CROP CANOPY SPECTRAL INFORMATION PREDICTION BASED ON EEMD AND CNN-LSTM

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Abstract. The utilization of the Normalized Difference Vegetation Index (NDVI) derived from canopy spectral information during crop growth helps identify growth conditions in farmland areas and facilitates management zone establishment. Targeted fertilizer application is possible based on observed growth patterns. Accurate NDVI prediction from canopy spectral information is crucial for real-time zone delineation and precision fertilization. Long Short-Term Memory (LSTM) neural networks can predict NDVI time series, but have limitations in handling non-stationary signals. A prediction model integrating modal decomposition with Convolutional Neural Network and Long Short-Term Memory (CNN-LSTM) is proposed to address these issues. This model uses Ensemble Empirical Mode Decomposition (EEMD) to decompose NDVI data into Intrinsic Mode Functions (IMFs), Convolutional Neural Network (CNN) to extract spatial features from IMFs, and LSTM to predict NDVI. Evaluation against standalone CNN, CNN-LSTM, and EEMD-CNN models using MAPE, RMSE, and R^2 metrics showed the proposed CNN-LSTM model with modal decomposition outperformed the others in prediction accuracy. For soybean and maize NDVI prediction, the model achieved MAPE of 2.111% and 2.425%, RMSE of 0.012, and R^2 of 0.971 and 0.968, respectively. This model provides a robust foundation for real-time management and precision fertilization, ensuring optimal crop growth and yield.

Keywords: *modal decomposition, CNN-LSTM model, feature extraction, precision fertilization, management zones*

Introduction

With the continuous development of precision agriculture technology, crop canopy spectral information has become an important data source for precision agriculture management(Sishodia et al., 2020). By analyzing this spectral information, one can ascertain the nutritional and growth status of crops, predict crop yield, and monitor pest and disease situations. The Greenseeker plant spectral detector can collect the Normalized Difference Vegetation Index (NDVI) of crop canopy spectral information. The NDVI data effectively mirrors crop growth. Based on growth differences across various farmland areas, farmland can be segmented into several management zones for targeted fertilizer application, thereby achieving precise management (Liu and Wang, 2019). However, due to the time-consuming transmission of spectral information detection and variable fertilization control by fertilization devices, achieving real-time management of zoning and precise variable fertilization is difficult. Therefore, it is necessary to predict the spectral information of crop canopy and the growth of crops, and reserve the time for fertilizer application devices to regulate the amount of fertilizer applied in order to achieve the goal of on-demand fertilization. As a type of time series data, NDVI has complex spatiotemporal characteristics and contains various forms of noise and outliers. These noise and outliers may come from various factors such as sensor errors, atmospheric conditions, and changes in land cover. Therefore, improving

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the prediction model is necessary, as well as improving prediction accuracy and stability(Li et al., 2021).

As a deep learning model, the long short term memory (LSTM) neural network has shown certain advantages in predicting time series data(Fischer and Krauss, 2018). Through its unique memory unit and gating mechanism, it can effectively capture hidden information in time series and achieve prediction of time series data(Hua et al., 2019). However, the LSTM model still has certain limitations in processing non-stationary signals and feature extraction. The statistical characteristics of non-stationary signals change over time, and the LSTM model cannot accurately capture the inherent laws of this data. Complex non-stationary signals also make it challenging to learn valuable features to extract critical information, which can lead to a decrease in prediction accuracy. To address the limitations of LSTM model prediction, a crop canopy spectral information prediction method combining modal decomposition and convolutional neural network and long short-term memory (CNN-LSTM) is proposed. This method fully combines and utilizes the advantages of modal decomposition and neural network prediction models, enabling more in-depth data preprocessing and feature extraction, improving the performance and stability of the prediction model. Modal decomposition is an effective method for processing time series data. Decomposing the time series can reveal data characteristics such as trends, periodicity, and random fluctuations and better capture the internal patterns of data(Hawinkel et al., 2015). In predicting crop canopy spectral information, modal decomposition can separate long-term trends and short-term fluctuations of spectral data. The long-term trends usually reflect the growth cycle, nutrient absorption, and photosynthesis of crops. Short term fluctuations are usually caused by various factors such as weather changes, pests and diseases, and human intervention. Modal decomposition can generally be achieved through various methods, such as time-frequency analysis, statistical model-based, and machine learning-based methods. Ensemble empirical mode decomposition (EEMD) is a time-frequency analysis-based modal decomposition method with significant advantages in handling nonlinear and non-stationary signals(Lang et al., 2020; Huang et al., 2016). Introducing white noise to overcome modal aliasing and other problems can effectively improve the stability and accuracy of decomposition during modal decomposition. Based on the advantages and characteristics of the EEMD method, it is selected to decompose the canopy spectral data and extract the Intrinsic mode function (IMF) through decomposition. IMF represents the components of different frequencies and amplitudes in the signal. Each IMF may correspond to different vegetation information or influencing factors for canopy spectral data. Convolutional neural network (CNN) models for feature extraction of IMF are effective post-decomposition data processing methods, especially for one-dimensional time series data such as NDVI(Ramachandran et al., 2024; Wu et al., 2022). By extracting local features and global trends from the IMF through components such as one-dimensional convolutional layer, pooling layer, activation function, and fully connected layer of the CNN model, the CNN model is used for feature extraction of IMF. Then, the LSTM model is used to make predictions. To verify the effectiveness of the proposed method, CNN, CNN-LSTM, and EEMD-CNN were selected as comparison models, and MAPE, RMSE, and R^2 were used as evaluation indicators to each model. The evaluation showed that the prediction model combining modal decomposition and CNN-LSTM showed superiority in all indicators and could efficiently and accurately predict canopy spectral information. Through the research on the prediction of NDVI data, this paper aims to anticipate the growth trend of crops in the subsequent fertilization area, thereby allocating sufficient time for the fertilization equipment to adjust the fertilizer application rate, ultimately achieving the objective of precise variable-rate fertilization for crops.

Materials and methods

Study area

The NDVI data collection location for crop canopy spectral information is the fourth management area of Zhaoguang Farm(126°26'-127°6' E, 47°54'-48°12' N) in Bei'an City, Heilongjiang Province, China. Zhaoguang Farm is located at the southern foothills of Xiaoxing'an Ridge, with a higher terrain in the southwest and lower terrain in the northeast, belonging to a cold and warm monsoon climate. The average annual temperature is lower, the frost free period is relatively short, and the rainfall and sunshine time are moderate. Solid winds and dryness characterize spring, while summer presents a hot and humid climate. Autumn is characterized by rapid cooling, while winter is characterized by persistent and severe cold. The soil types are rich, mainly brown, black, meadow, and swamp, with black soil accounting for a significant proportion(Liu and Wang, 2019). The natural conditions of Zhao Guang Farm are conducive to the cultivation of crops such as soybeans and maize, and the terrain conditions are also conducive to the collection of crop canopy spectral information. In the experiment, NDVI data of soybeans and maize were collected separately, and the specific plot distribution is shown in *Figure 1*. The two plots are open and unobstructed by buildings, which is conducive to satellite signal reception. The cultivated maize variety is DeMeiYa 3, for which NDVI data were acquired on June 18, 2019, corresponding to the six-leaf growth stage. The cultivated soybeans variety is HeiHe 43, with NDVI data recorded on June 22, 2019, during the initial pod-setting phase of growth. Both maize and soybeans were planted using a wide-ridge, double-row planting configuration, with a ridge-to-ridge spacing of 1.1m. The planting density of maize is 67,500 plants per hectare, and the planting density of soybeans is 350,000 plants per hectare.

Figure 1. *Location of Crop Canopy Spectral Information NDVI Data*

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Data collection

The NDVI data acquisition system collected the experimental data for crop canopy spectral information, which Trimble Company developed in the United States. The system comprises a plant spectral detector Greenseeker, a control computer, a Trimble satellite positioning and navigation system, a vehicle-mounted CAN data recorder, and a master's and doctoral motion controller. The control computer is used for statistical and predictive calculations of NDVI data, using the fourth generation Bay Trail single-chip processor from Lingdong, with 4GB of DDR3 high-speed memory onboard, 10.1-inch capacitive touch screen, HD Graphics series core display, and 8 GPIO input/output interfaces. Greenseeker is a car-mounted plant spectral detector that calculates NDVI values by measuring vegetation's red and near-infrared reflectance(Tagarakis et al., 2022). It can effectively evaluate the growth and health status of crops. Greenseeker has been widely used in precision agriculture management, assisting scientific decision-making in agricultural production and improving crop yield and quality(Farid et al., 2023; Viana et al., 2019). Due to the use of active light sources for signal acquisition, Greenseeker can generally operate under poor lighting conditions such as cloudy, cloudy, and even nighttime, without being affected by interference factors such as cloud cover and soil reflection, achieving accurate all-weather plant spectral information collection(Yao et al., 2020; Barker and Sawyer, 2013). When conducting data collection experiments, the NDVI data collection system for crop canopy spectral information will be installed on the Case 2254 tractor, with Greenseeker in front of the tractor, satellite positioning and navigation system antenna above the tractor, and other equipment located in the tractor cab, as shown in *Figure 2*. As illustrated in *Figure 2*, the spectral sensor is mounted at the front of the tractor, whereas the variable-rate fertilization system is located at the rear, with a certain distance between the two. This study applies variable-rate fertilization based on real-time management zone delineation results. However, the variable-rate fertilization system requires a certain response time to adjust the fertilizer application rate. If fertilization decisions rely solely on the NDVI data collected from the front, it would be challenging to adjust the fertilizer rate for the target area promptly. Therefore, predicting the NDVI data ahead of the tractor's current position is necessary, providing the variable-rate fertilization system with sufficient time to make adjustments and apply fertilizer precisely to the target area.

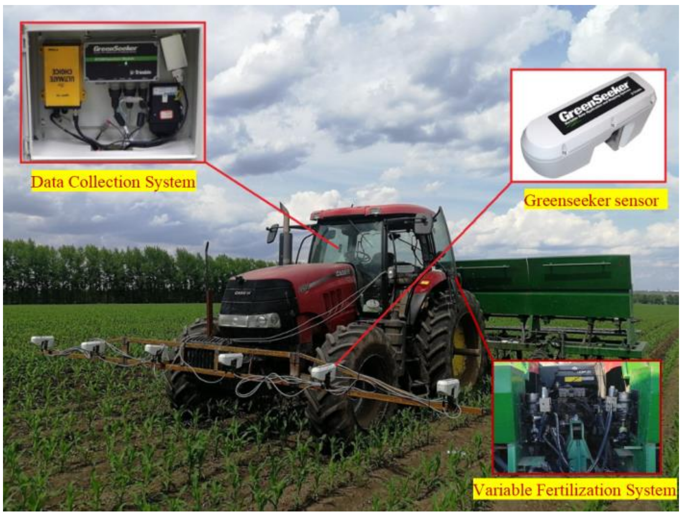

Figure 2. *Acquisition system of Crop Canopy Spectral Information NDVI Data*

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The management partition program written in the industrial control integrated computer can process the NDVI data collected by Greenseeker in real time and partition the management partition. In order to ensure the integrity and traceability of the data, the data is recorded in the CAN data recorder during the collection process. The CAN data recorder has high stability and reliability and can receive and store NDVI and other data from Greenseeker in real time. The data collected in the experiment includes longitude, latitude, elevation, tractor speed, and NDVI values. The data is collected once per second, and the high-frequency data collection method can capture subtle changes in different areas of the crop canopy, providing data support for subsequent research on canopy spectral information prediction. A total of 12,651 sets of soybean NDVI data and 20,447 sets of corn NDVI data were collected. Some of the data collected in the experiment are shown in *Table 1*.

Table 1. *Part of experimental data*

Time	Longitude	Latitude	Elevation/m	Velocity/km·h^{-1}	NDVI
14:38:39	126.6272425	48.0360503	305.63	4.24219	0.462
14:38:40	126.6272369	48.0360717	310.88	4.15234	0.452
14:38:41	126.6272405	48.0360869	314.50	5.06250	0.453
14:38:42	126.6272484	48.0360984	316.75	4.78125	0.418
14:38:43	126.6272564	48.0361087	318.25	4.86719	0.416
			…		
18:18:57	126.6267928	48.036857	292.50	4.39063	0.414
18:18:58	126.6267755	48.0368535	292.13	4.31250	0.417
18:18:59	126.6267587	48.0368497	292.00	4.57422	0.414
18:19:00	126.626747	48.0368446	291.88	4.64453	0.401
18:19:01	126.6267361	48.0368393	292.25	4.53125	0.389

To conduct predictive research on NDVI data, it is first necessary to confirm whether there is spatial correlation between NDVI data. If there is spatial correlation in NDVI data, relevant time series prediction algorithms can be used to predict NDVI data. However, if there is no spatial correlation in NDVI data, the prediction algorithm is meaningless and cannot predict future data based on existing data. NDVI data is a vegetation index calculated using the difference between infrared and visible light bands, which can characterize the physical state and growth status of surface vegetation, thereby reflecting the vegetation coverage of the region. The usual method for conducting spatial correlation analysis of NDVI data is to calculate Moran's I to evaluate the spatial distribution and correlation of vegetation index changes, reflecting the differences and similarities in vegetation cover between different regions, as well as the relationship between vegetation cover and other environmental factors such as climate, soil conditions, etc.

The Moran's index, as a commonly used spatial correlation analysis indicator, can be used to evaluate spatial correlation in spatial distribution data. Its basic principle is to measure the similarity between the regionalization variable of a spatial location and its

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neighborhood, that is, whether each geographical location of a target data is similar or different from each other. This index can be used for any spatial data, including geographical and non geographical data. Using ARGIS to calculate the Moran index and related indices of soybeans and corn, the results showed that the Moran index of soybeans was 0.7342, with a z-score of 519.6983 and a p-value of 0, while the Moran index of corn was 0.7679, with a z-score of 378.0764 and a p-value of 0. The Moran's index is used to measure spatial autocorrelation, typically ranging from -1 to 1, with values close to 1 indicating strong positive spatial autocorrelation. The z-score is used to test the statistical significance of the Moran's index. When the absolute value of the z-score is greater than 1.96, it is considered significant spatial autocorrelation. The p-value is used to determine the significance of spatial autocorrelation, and a p-value less than 0.05 indicates significant spatial autocorrelation. From the calculation results, it can be concluded that there is a strong spatial positive correlation between the NDVI data of soybeans and corn, which can be used for prediction calculations.

Construction of EEMD-CNN-LSTM prediction model

Ensemble Empirical Mode Decomposition （EEMD）

Empirical Mode Decomposition (EMD) was proposed by Huang E and others in the United States in 1998(Huang, 2000). It is a signal decomposition method based on local signal characteristics, which can decompose a complex signal into several intrinsic mode functions (IMFs), representing vibration modes with different scale or frequency characteristics, and each IMF is independent of the other(Huang et al., 1998). The basic idea of EMD is that any complex signal is composed of a combination of independent and simple nonsinusoidal component signals, and multi-scale features are automatically extracted based on the specific shape of the signal without the need to set a basis function in advance. Therefore, it is particularly suitable for processing nonlinear, non-stationary, and transient signals. The EMD method has good local adaptability and adaptability, with high resolution for local features of signals, and can be applied in fields such as signal processing, image processing, and time series analysis. However, the EMD method also has limitations: signal components of different scales may need to be more effectively separated and mixed during the modal decomposition process, resulting in inaccurate decomposition results and causing modal aliasing problems(Barbosh et al., 2020). Ensemble Empirical Mode Decomposition (EEMD) is an improved method of EMD, which introduces the Noise Assisted Data Analysis (NADA) strategy(Wu and Huang, 2009). By adding a certain level of white noise to the EMD process, the denoised signal is subjected to multiple EMD decompositions. Finally, the set average of IMFs of the same order is taken, which can effectively reduce mode aliasing and improve the stability and accuracy of the decomposition. The decomposition process of the EEMD method is as follows(Gaci, 2016):

(1)Add a certain intensity of Gaussian white noise $h_i(t)$ to the original signal $x(t)$ to obtain a new signal $XI(t)$:

$$XI(t) = x(t) + h_i(t) \tag{Eq.1}$$

where i is the i-th addition of Gaussian white noise;

(2)Perform EMD decomposition on the noisy signal $XI(t)$ to obtain a series of IMF components $Mij(t)$, where j is the j-th IMF component;

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(3)Repeat steps (1) and (2), adding different Gaussian white noise each time, and perform EMD decomposition on the obtained signal each time;

(4)Average each IMF component obtained from N decompositions to obtain the final IMF component *Mj*(*t*):

$$Mj(t) = \frac{1}{N}\sum_{i=1}^{N} Mij(t) \tag{Eq.2}$$

where *Mj*(*t*) is the j-th final IMF component, and N is the total average number of times.

CNN-LSTM prediction model

CNN models use their convolutional layers to automatically extract critical local features from time series data using convolutional kernels, identifying periodic, seasonal, and repetitive features in time series(Kareem et al., 2021). The same convolution kernel in CNN will slide and perform convolution operations on the entire input sequence, thereby achieving parameter sharing(Ketkar et al., 2021). This sharing mechanism can effectively reduce the complexity of the model, reduce the number of parameters, avoid overfitting, and make the model more adaptable to sequences of different lengths. When processing multivariate time series prediction, CNN can use the weights in its convolutional layers to capture the interactions between different variables without the need to design a separate network structure for each variable(Wang et al., 2019). This effectively extracts features from multiple related time series, learns the time series relationships and mutual influences between different variables, and improves the accuracy of prediction(Zhao et al., 2021).

The LSTM neural network model has a unique network structure by introducing memory units and gating mechanisms, which can effectively process time series data with long-term dependencies for time series prediction(Vasilakos et al., 2022; Yu et al., 2019). The network structure of the LSTM model is shown in *Figure 3*. In the figure, C_t denotes the memory unit at the temporal instance t, x_t signifies the input at time t, h_t represents the output at time t, tanh indicates the hyperbolic tangent activation function, and σ signifies the logistic sigmoid function. The memory unit of the LSTM model can remember and effectively utilize information with long time intervals, avoiding the problem of gradient vanishing or exploding that traditional recurrent neural networks may encounter when processing long time series(Zha et al., 2022). The LSTM model has a unique gating mechanism, including forget, input, and output gates(Landi et al., 2021). The role of each gate is: the forget gate determines which information in the memory unit C_{t-1} at time t-1 should be forgotten; The input gate determines which information in the input x_t at time t should be stored in the memory unit C_t; The output gate controls which information in the memory unit C_t at time t should be activated and output, and the output ht can be regarded as the current output at time t. By using the gating mechanism of the LSTM model to forget and update inputs at specific time steps selectively, the flow of information can be flexibly controlled, ensuring that crucial information can be retained and transmitted to subsequent calculations, enabling the LSTM model to capture complex features and dynamic changes in time series data. LSTM models also have certain advantages in terms of nonlinear modeling, as they can learn and capture nonlinear relationships in time series data, further improving prediction accuracy. Through end-to-end training, they can directly learn features from

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the original time series data without the need for complex manual feature extraction or preprocessing steps. The LSTM model has become excellent for processing time series data and making predictions. It relies on its advantages of memory ability, gating mechanism, nonlinear modeling ability, and end-to-end training(Van Houdt et al., 2020).

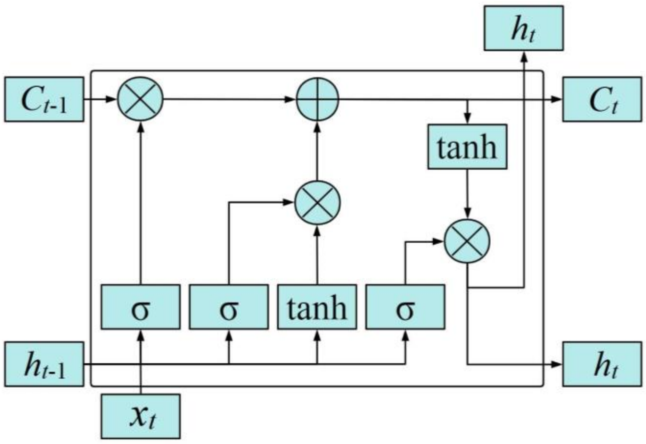

Figure 3. *Network structure of LSTM model*

The CNN-LSTM model combines the advantages of local feature extraction from CNN models and time series prediction modeling from LSTM models, enabling it to effectively extract features from time series data and fully explore time-dependent information in the data, improving the stability and accuracy of prediction. During data processing, the convolutional layer of the CNN model extracts local features from the original time series data, captures spatial correlations in the data through convolutional operations, reduces feature dimensions through pooling operations while retaining critical information, and extracts effective feature representations. Afterward, the extracted compelling features are passed on to the LSTM model, which captures long-term dependencies in the time series through its internal memory unit and gating mechanism to establish a prediction model.

EEMD-CNN-LSTM prediction model

The EEMD-CNN-LSTM model is a deep learning neural network time series prediction model that combines the EEMD method, CNN model, and LSTM model. The prediction process of this model is as follows: First, the original time series data is decomposed using the EEMD method to extract multiple IMFs, revealing the data's local features and periodic components. Then, a CNN model is used to extract features from each IMF, and the spatial structure information of the data is captured through convolution and pooling operations. Next, the features extracted by the CNN model are inputted into the LSTM model, and its memory unit and gating mechanism are used to learn and capture long-term dependencies in time series data. Finally, LSTM predicts future time series data using the learned time series prediction model. Through the above prediction process, the EEMD-CNN-LSTM model can fully utilize the spatiotemporal characteristics of data to achieve high-precision time series prediction and analysis. The prediction process of the EEMD-CNN-LSTM model is shown in *Figure 4*.

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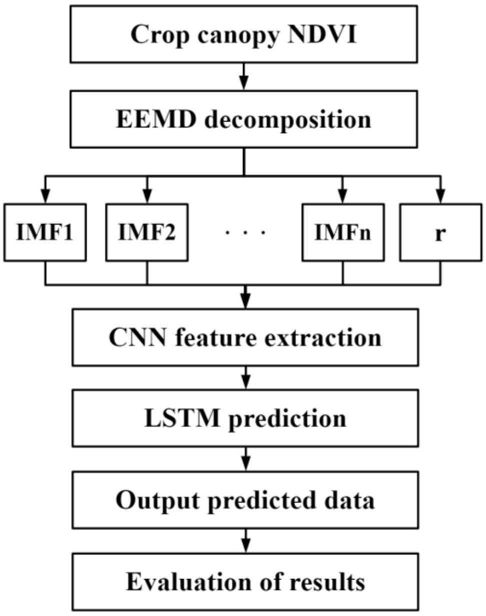

Figure 4. *Flowchart of EEMD-CNN-LSTM Model Prediction*

Results and discussion

NDVI data decomposition

Performing EEMD modal decomposition on NDVI data of soybean and maize canopy spectral information can obtain multi-scale changes in vegetation coverage and growth characteristics of the two crops at different growth stages. Write an EEMD modal decomposition program using Matlab, explicitly using Matlab's Complete Ensemble Empirical Mode Decomposition (CEEMD) function.The first 900 sets of data were decomposed and used for training, while the last 100 sets of data were used as test data to verify the predictive performance of the model. In general, the proportion of data used for training and validating predictive models is 90% and 10%, respectively. The specific decomposition results are shown in *Figure 5*. By decomposing EEMD, a series of IMF data were obtained, which reflect the characteristics of NDVI data for soybeans and maize at different time scales and frequencies and their responses to environmental factors. IMF1 usually reflects the high-frequency components in NDVI data, which generally correspond to short-term fluctuations or noise during the growth process of soybeans or maize. IMF2 displays intermediate frequency components, revealing specific stage changes in the soybean growth cycle, such as accelerated or slowed growth. IMF3 represents the low-frequency component and reflects the long-term trend or periodic changes of NDVI. The high-frequency components in the IMF usually reflect the impact of short-term weather changes, pests, and diseases on crop growth, which is of great significance for short-term forecasting. The mid-frequency and low-frequency components in the IMF reflect the long-term effects of factors such as growth cycle and soil conditions on crop growth, which are crucial for long-term prediction. The residual term (res) represents the remaining signal after EEMD decomposition, usually containing components that cannot be decomposed into IMF. These remaining signals generally contain some unpredictable factors. The robustness and generalization

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ability can be improved by incorporating them into the prediction model. From *Figure 5*, it can be seen that a high IMF1 value represents the occurrence of short-term environmental disturbances (such as cloud cover or wind-blown vegetation blades), while a low value indicates a stable environment, normal sensor operation, and no significant noise. A high IMF2 value indicates changes in lighting conditions, with strong light causing significant fluctuations in NDVI values, while a low value indicates a stable vegetation physiological status with no significant changes in vegetation reflectance. A high IMF3 value indicates environmental changes, and sensor temperature drift leads to systematically high NDVI values. A low value indicates stable environmental conditions, normal sensor operation, and no significant drift. A high res value may indicate a significant increase in vegetation coverage, while a low value indicates a stable vegetation coverage.

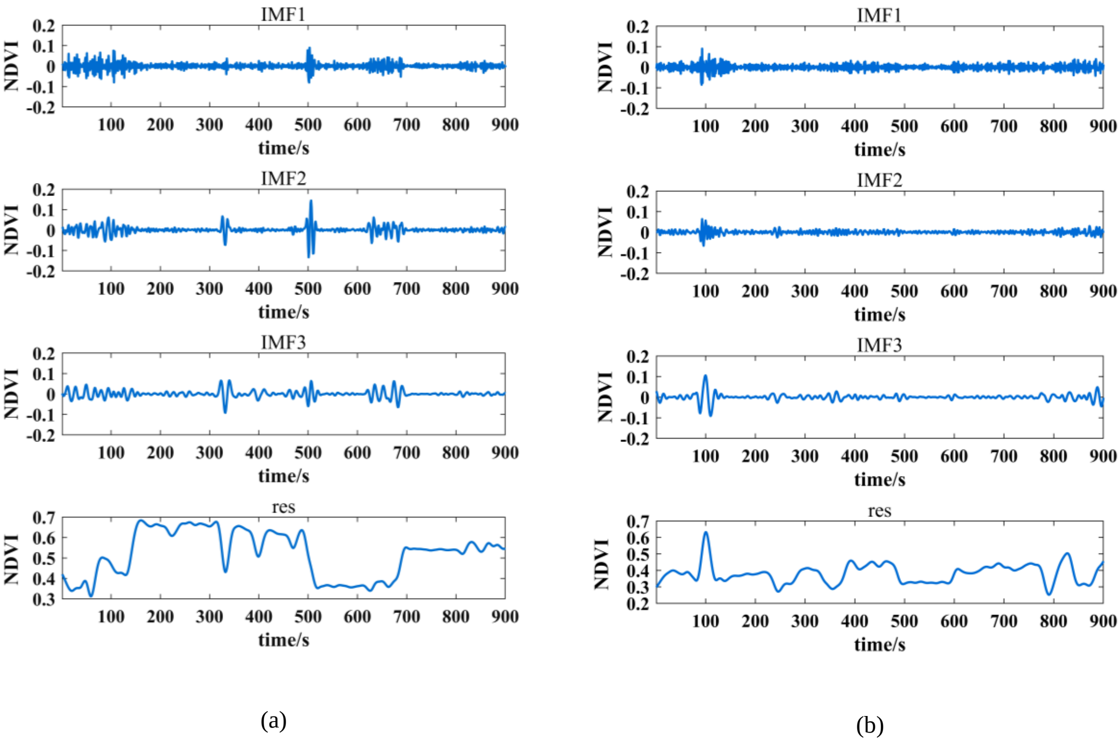

Figure 5. *Decomposition results of canopy spectral information NDVI data*
(a):*Soybean;* (b):*Maize*

NDVI data prediction

Write an EEMD-CNN-LSTM prediction model program using Matlab. Select the first 900 sets of data from the intercepted NDVI data of soybean and maize canopy spectral information and input them into the EEMD-CNN-LSTM prediction model for training. First, IMF1, IMF2, IMF3, and res are obtained through EEMD modal decomposition, then the CNN model is used for feature extraction, and finally, the LSTM model is used for prediction. Select the last 100 groups of NDVI data as test data to test the model's predictive performance. The curves of NDVI predicted values and actual values for soybeans and maize are shown in *Figure 6*. The graph shows that the predicted and actual value curves have similar upward and downward trends, with a

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high degree of agreement and no significant outliers. This indicates that the EEMD-CNN-LSTM prediction model has good prediction accuracy and stability.

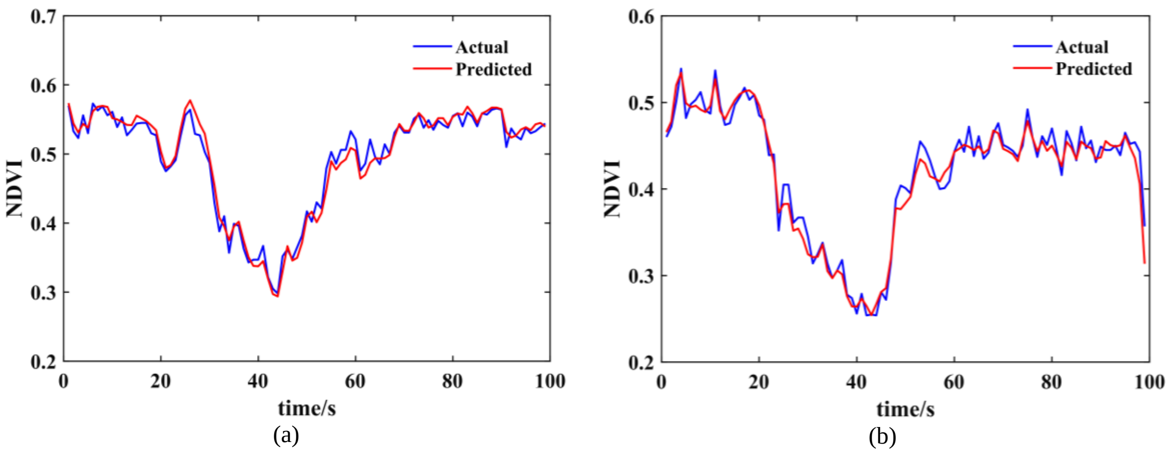

Figure 6. *Curve of variation between predicted value and actual value of EEMD-CNN-LSTM model*
(a):*Soybean*; (b):*Maize*

Using CNN, LSTM, CNN-LSTM, EEMD-CNN, and EEMD-LSTM are used as comparative models for EEMD-CNN LSTM. Calculate the relative errors between the predicted and actual values of the four models, as shown in *Figure 7*. From the relative error variation curves of the four prediction models, it can be seen that for the prediction of soybean NDVI data, the CNN model, LSTM model and CNN-LSTM model have relatively large relative errors, with the maximum relative error of the CNN model and LSTM model exceeding 25% and the maximum relative error of the CNN-LSTM model reaching 20%. The relative errors of the EEMD-CNN model, EEMD-LSTM model and the EEMD-CNN-LSTM model are relatively small, within 10%. For the prediction of maize NDVI data, the CNN and CNN-LSTM models have relatively large relative errors, with maximum relative errors exceeding 20%. The relative errors of the EEMD-CNN model are within 15%, and the relative errors of the EEMD-LSTM model and EEMD-CNN-LSTM model are within 10%.

The comparison of prediction models for soybean and maize NDVI data reveals significant differences in their performance. The CNN, LSTM, and CNN-LSTM models exhibit relatively large errors in predicting soybean NDVI data, while the EEMD-CNN, EEMD-LSTM, and EEMD-CNN-LSTM models demonstrate smaller errors. This suggests that integrating EEMD with deep learning models enhances the prediction accuracy for soybean NDVI data. For maize NDVI data prediction, the CNN and CNN-LSTM models again show large errors, whereas the EEMD-CNN, EEMD-LSTM, and EEMD-CNN-LSTM models maintain smaller errors. This further highlights the effectiveness of combining EEMD with LSTM for maize NDVI prediction. The superior performance of EEMD-CNN-LSTM in both soybean and maize predictions indicates its robustness and adaptability across different crops. Despite the promising results, it is important to note the limitations of this study. The performance of the EEMD-CNN-LSTM model may be influenced by the quality and resolution of the NDVI data, as well as the specific parameters used in the EEMD decomposition.

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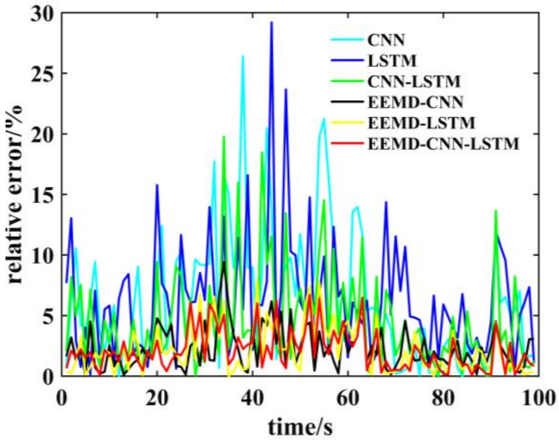
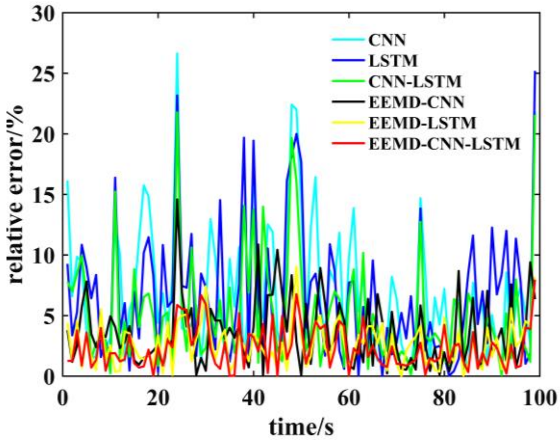


(a)



(b)

Figure 7. *Relative error variation curves of various prediction models*
(a):*Soybean*; (b):*Maize*

Prediction effect evaluation

The predictive performance evaluation index is a type of indicator used to measure the difference between the predicted results of a model and the actual values. It can systematically evaluate the predictive performance and accuracy of the model. Considering the characteristics of NDVI data, MAPE, RMSE, and R^2 are selected to evaluate the predictive model. MAPE reflects the average deviation of predicted values from actual values, with smaller values indicating more accurate predictions; RMSE measures the average deviation between predicted and actual values, with smaller values indicating higher prediction accuracy; R^2 describes the degree to which the model fits the data, and the closer its value is to 1, the stronger the model's predictive ability. The calculation formulas for the three indicators MAPE, RMSE, and R^2 are as follows:

$$\mathrm{MAPE} = \frac{100\ \%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad \text{(Eq.3)}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \quad \text{(Eq.4)}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad \text{(Eq.5)}$$

where *n* is the number of data, $\hat{y}_i$ is the predicted value, and y_i is the observed true value.

According to the above calculation formula, write three evaluation index calculation programs using Matlab, and each prediction model's evaluation index calculation results are shown in *Table 2*. For the prediction of soybean NDVI, based on the MAPE value,

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the error rate of the CNN model is 6.317%. In comparison, the CNN-LSTM model drops to 4.494%, indicating that introducing the LSTM model is conducive to reducing prediction errors. When the EEMD method is combined with the CNN or CNN-LSTM models, the error is significantly reduced. The MAPE of the EEMD-CNN model and the EEMD-CNN-LSTM model are reduced to 2.286% and 2.111%, respectively, indicating the superiority of the EEMD method in prediction accuracy. The RMSE values also showed a similar trend, with the EEMD-CNN model and EEMD-CNN-LSTM model having the lowest RMSE values of 0.013 and 0.012, respectively, indicating that their predicted values have the slightest difference from the actual values. This result further confirms the effectiveness of combining the EEMD method with deep learning models, especially in reducing prediction errors. From the coefficient of determination R^2, it can be seen that all models have relatively high R^2 values, indicating that they can better fit the trend of soybean NDVI data. The EEMD-CNN-LSTM model has the highest R^2 value, reaching 0.971, which once again proves the excellent performance of the prediction model combined with the EEMD method in soybean NDVI prediction. For the prediction of maize NDVI, the evaluation index results of each model are the same as the trend of soybean NDVI prediction. The EEMD-CNN-LSTM model has the lowest MAPE, the lowest RMSE value, and the highest R^2 value, demonstrating this model's superior performance in predicting maize NDVI.

Table 2. *Calculation results of evaluation metrics for each predictive model*

Prediction model	Soybean NDVI			maize NDVI		
	MAPE/%	RMSE	R^2	MAPE/%	RMSE	R^2
CNN	6.317	0.036	0.747	7.011	0.036	0.736
LSTM	6.302	0.036	0.764	6.678	0.035	0.760
CNN-LSTM	4.494	0.027	0.859	5.178	0.027	0.848
EEMD-CNN	2.286	0.013	0.967	3.576	0.018	0.935
EEMD-LSTM	2.198	0.013	0.968	2.617	0.013	0.965
EEMD-CNN-LSTM	2.111	0.012	0.971	2.425	0.012	0.968

Based on the evaluation indicators of the above prediction models, calculate the RMSE value in the results and conduct ablation experiments on key modules. Firstly, EEMD preprocessing significantly reduced prediction errors, with the MAPE of soybeans and corn decreasing from 6.317% and 7.011% to 2.111% and 2.425%, respectively. This indicates that EEMD effectively reduces noise interference and enhances feature extraction capabilities through signal decomposition. Secondly, the combination of CNN and LSTM (CNN-LSTM) is superior to the single model in soybean and corn, and the MAPE decreases from 6.317% and 7.011% to 4.494% and 5.178% respectively, which verifies the complementarity of CNN in spatial feature extraction and LSTM in time series modeling. Finally, the EEMD-CNN-LSTM model achieved optimal performance in both soybean and maize (MAPE of 2.111% and 2.425%, respectively), significantly outperforming other models, demonstrating the synergistic effect of EEMD, CNN, and LSTM. Overall, EEMD preprocessing is the core of improving model performance, while the combination of CNN-LSTM further

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enhances the predictive ability of the model. The excellent performance of EEMD-CNN-LSTM validates its generality and robustness in crop NDVI prediction.

Conclusions

A prediction method combining modal decomposition and CNN-LSTM model is proposed to address the issue of real-time management zoning and precise variable fertilization in farmland, which requires crop canopy spectral information prediction. Firstly, the EEMD method decomposes the canopy spectral data of the original maize and soybeans, and then the CNN-LSTM model is used for prediction. Finally, three evaluation indicators, MAPE, RMSE, and R^2, are used to evaluate the prediction results. The experimental results show that compared with CNN, CNN-LSTM, and EEMD-CNN models, the prediction model combining modal decomposition and CNN-LSTM shows higher accuracy and stability in predicting crop canopy spectral information NDVI. All evaluation indicators show that it has the best predictive ability. In soybean NDVI prediction, the MAPE, RMSE, and R^2 evaluation indicators are 2.111%, 0.012, and 0.971, respectively. In maize NDVI prediction, the MAPE, RMSE, and R^2 evaluation indicators are 2.425%, 0.012, and 0.968, respectively. The prediction method combining modal decomposition and CNN-LSTM model improves the accuracy of crop canopy spectral information prediction, predicts crop growth in advance, adjusts fertilization strategies promptly, and achieves on-demand fertilization, thereby improving agricultural production efficiency and resource utilization efficiency and reducing environmental pollution. Specifically, predicting NDVI data enables fertilization machinery to adjust the fertilizer application rate in advance, thereby compensating for the lag in fertilization control, reducing errors in variable-rate fertilization, and improving the accuracy of variable-rate fertilization. Future research can further explore applying other advanced modal decomposition methods and deep learning models in predicting canopy spectral information to optimize prediction models and improve prediction accuracy and stability. At the same time, we will also consider integrating canopy spectral information with other agricultural environmental data (such as meteorological data, soil data, etc.) to build a more comprehensive precision agriculture management system.

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