

Article

Construction of a Winter Wheat Comprehensive Growth Monitoring Index Based on a Fuzzy Degree Comprehensive Evaluation Model of Multispectral UAV Data

Jing Yu ¹, Shiwen Zhang ^{2,*}, Yanhai Zhang ³, Ruixin Hu ² and Abubakar Sadiq Lawi ² 

¹ School of Spatial Informatics and Geomatics Engineering, Anhui University of Science and Technology, Huainan 232001, China; jingyust@163.com

² School of Earth and Environment, Anhui University of Science and Technology, Huainan 232001, China; hrx19960429@163.com (R.H.); abubakarsadiq830@yahoo.com (A.S.L.)

³ Huaibei Mining (Group) Co., Ltd., Huaibei 235001, China; zyh_1234560815@163.com

* Correspondence: mamin1190@126.com

Abstract: Realizing real-time and rapid monitoring of crop growth is crucial for providing an objective basis for agricultural production. To enhance the accuracy and comprehensiveness of monitoring winter wheat growth, comprehensive growth indicators are constructed using measurements of above-ground biomass, leaf chlorophyll content and water content of winter wheat taken on the ground. This construction is achieved through the utilization of the entropy weight method (EWM) and fuzzy comprehensive evaluation (FCE) model. Additionally, a correlation analysis is performed with the selected vegetation indexes (VIs). Then, using unmanned aerial vehicle (UAV) multispectral orthophotos to construct VIs and extract texture features (TFs), the aim is to explore the potential of combining the two as input variables to improve the accuracy of estimating the comprehensive growth indicators of winter wheat. Finally, we develop comprehensive growth indicator inversion models based on four machine learning algorithms: random forest (RF); partial least squares (PLS); extreme learning machine (ELM); and particle swarm optimization extreme learning machine (PSO-ELM), and the optimal model is selected by comparing the accuracy evaluation indexes of the model. The results show that: (1) The correlation among the comprehensive growth indicators (CGIs) constructed by EWM (CGI_{ewm}) and FCE (CGI_{fce}) and VIs are all improved to different degrees compared with the single indicators, among which the correlation between CGI_{fce} and most of the VIs is larger. (2) The inclusion of TFs has a positive impact on the performance of the comprehensive growth indicator inversion model. Specifically, the inversion model based on ELM exhibits the most significant improvement in accuracy. The coefficient of determination (R^2) values of ELM- CGI_{ewm} and ELM- CGI_{fce} increased by 20.83% and 20.37%, respectively. (3) The CGI_{fce} inversion model constructed by VIs and TFs as input variables and based on the ELM algorithm is the best inversion model (ELM- CGI_{fce}), with R^2 reaching 0.65. Particle swarm optimization (PSO) is used to optimize the ELM- CGI_{fce} (PSO-ELM- CGI_{fce}), and the precision is significantly improved compared with that before optimization, with R^2 reaching 0.84. The results of the study can provide a favorable reference for regional winter wheat growth monitoring.

Keywords: comprehensive growth; UAV; fuzzy degree comprehensive evaluation; machine learning



Citation: Yu, J.; Zhang, S.; Zhang, Y.; Hu, R.; Lawi, A.S. Construction of a Winter Wheat Comprehensive Growth Monitoring Index Based on a Fuzzy Degree Comprehensive Evaluation Model of Multispectral UAV Data. *Sensors* **2023**, *23*, 8089. <https://doi.org/10.3390/s23198089>

Academic Editor: Yong He

Received: 14 August 2023

Revised: 20 September 2023

Accepted: 24 September 2023

Published: 26 September 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Rapid, accurate and real-time monitoring of crop growth is of great significance in guiding field crop management and crop quality assurance. Traditional methods of monitoring crop growth, including manual sampling and qualitative identification by human eyes, are not only time-consuming and labor-intensive but can also cause damage to the original crop growth [1]. At present, remote sensing technology has been widely

used in crop growth monitoring by virtue of its advantages of fast, non-destructive and large monitoring area [2].

Remote sensing technology allows for the acquisition of a wide range of remote sensing data through ground-based, airborne and satellite platforms with different sensors. The ground sensor used for crop monitoring is mainly a canopy optical instrument, which is simple to operate and can realize rapid access. However, the monitoring range of canopy optical instruments is small, requires more labor, and makes it more difficult to obtain high-throughput crop phenotypic information [3]. A satellite remote sensing platform is used for acquiring large-scale remote sensing data. In addition, it has limitations in achieving real-time monitoring of crops with multiple temporal phases for precise operational management due to revisit cycles, weather conditions and resolution. In contrast, unmanned aerial vehicle (UAV) remote sensing monitoring technology has the advantages of high stability, flexible take-off and landing and low cost. It can be equipped with multi-spectral, hyperspectral and other sensors to accurately obtain high-resolution multi-temporal remote sensing image data of crops in real-time, which can account for the deficiency of satellite remote sensing monitoring technology. UAV remote sensing technology has found extensive applications in fields such as agriculture and environmental monitoring [4]. Hasan et al. conducted a study demonstrating the significant potential of UAVs equipped with RGB imagery for estimating the leaf area index of winter wheat during the nodulation stage in mono-crop fields [5]. Wang et al. showed that UAV multispectral imagery could accurately estimate high-throughput phenotypes of other crops in the field, such as the nitrogen content of rice leaves [6]. Zhu et al. reached the conclusion that images captured by a hyperspectral camera mounted on the UAV can effectively monitor the leaf chlorophyll content of maize and wheat with a high level of accuracy [7].

Previous studies on crop monitoring using UAV remote sensing imagery have shown that there is a good correlation among the spectral bands of the imagery, as well as the vegetation indexes (VIs) derived from linear or non-linear combinations of these bands and crop growth indicators. However, it has also been observed that the correlation decreases when the crops are either sparse or overly dense [8]. To address this issue, Sapkota et al. extracted plant height information from the digital surface model obtained from drones and utilized vegetation indices to estimate maize biomass [9]. Dilmurat et al. collected both LIDAR and hyperspectral data from drones and used the LIDAR point cloud to extract canopy structure information, thereby improving the accuracy of maize yield prediction [10]. However, these methods increase the cost and complexity of image acquisition and processing. Texture information extraction is a rapid image processing technique. Texture information can describe the spatial variations in grayscale within an image [11]. Crops with different growth form canopy and horizontal structure differences leading to changes in image texture information [12]. Texture information has been used in fields such as vegetation classification and biomass estimation of forests. There have also been studies that utilize texture features (TFs) for monitoring the single growth indicator of crops. Yue et al. indicated that combining the vegetation index with texture characteristics could improve the prediction accuracy of the above-ground biomass of winter wheat with high canopy coverage [13]. Biomass, chlorophyll content and leaf water content are crucial indicators for monitoring crop growth.

In recent years, there have been studies using UAV remote sensing technology to monitor these growth indicators, and significant progress has been made. Yue et al. used the UAV digital camera and an imaging spectrometer to obtain the remote sensing spectral index of winter wheat, and then the images were subjected to wavelet decomposition and continuous wavelet variations, and finally, the combination of the acquired variables improved the biomass estimation accuracy of winter wheat [14]. Huang et al. utilized a UAV to capture RGB images of rapeseed and combined the R, G and B bands to extract different feature parameters for constructing various inversion models. This study provided a viable reference for estimating chlorophyll content in rapeseed [15]. Ndlovu et al. showed that near-infrared and red-edge-derived spectral variables extracted from UAV

multispectral imagery are crucial for characterizing maize moisture indicators [16]. Most studies evaluate crop growth using a single growth indicator, which overlooks the influence of other factors and leads to a one-sided characterization of crop growth. Currently, many studies construct comprehensive growth indicators by assigning equal weights to different indicators. However, this approach overlooks the contribution rates of each indicator and subjective biases in the weighting process. Considering the contribution rate and combining various indicators to construct a comprehensive growth indicator to monitor crop population information more comprehensively needs to be studied in depth [17]. Fuzzy comprehensive evaluation (FCE) is a non-linear multi-objective evaluation method that employs the theory of fuzzy mathematical membership degree to address the uncertainty and inaccuracy in quantitative problems. FCE has found extensive applications in the fields of system evaluation and environmental assessment. Sun et al. utilized FCE to calculate the comprehensive advantages of multiple agronomic trait evaluations, constructed a comprehensive lodging evaluation index and effectively monitored the severity of corn lodging using UAV multispectral imagery [18]. Wang et al. combined the analytic hierarchy process (AHP) with FCE to optimize the irrigation and fertilization quantities for potatoes [19].

In this study, UAV remote sensing is utilized to obtain multispectral ortho imagery of the study area. The research focuses on the above-ground biomass (AGB), leaf chlorophyll content and leaf water content (LWC) of winter wheat. This study employs two methods, namely the entropy weight method (EWM) and the FCE model, to construct comprehensive growth indicators for winter wheat. The input variables include VIs, TFs and a combination of VIs and TFs. Four inversion models are developed, specifically random forest (RF); partial least squares (PLS); extreme learning machine (ELM); and particle swarm optimization extreme learning machine (PSO-ELM), to estimate the comprehensive growth indicators of winter wheat. Finally, the best inversion model is selected based on accuracy comparison in order to investigate the effectiveness of UAV multispectral imagery in monitoring the comprehensive growth indicator of winter wheat. This study provides valuable insights into the application of UAV remote sensing technology in monitoring and managing the growth of winter wheat.

2. Materials and Methods

2.1. Overview of the Study Area

The study area is located in Suixi County, Huaibei City, Anhui Province, China, with geographic coordinates ranging from 116°24' to 117°03' E, 33°16' to 34°10' N, and an area of about 0.24 km². The study area has a monsoon warm-temperate semi-humid climate, with mild rain in spring and fall, hot and rainy summer and cold and windy winter. The average annual temperature is 17 °C, the average wind speed is 2.2 m/s, the average precipitation is 737 mm, rainfall is mostly concentrated in June–August and the annual frost-free period is about 218 days.

Crops in the study area are planted in the rotation of winter wheat and summer corn, and the irrigation method is rain-fed. The location of the study area and the distribution of sampling points are shown in Figure 1. After field research, the study area has some land collapse and land destruction due to long-term underground coal mining. Therefore, its elevation shows a gradual decline towards the center collapse area. In order to repair the ecological safety problems caused by coal mining, a series of land reclamation measures have been carried out in the collapsed area.

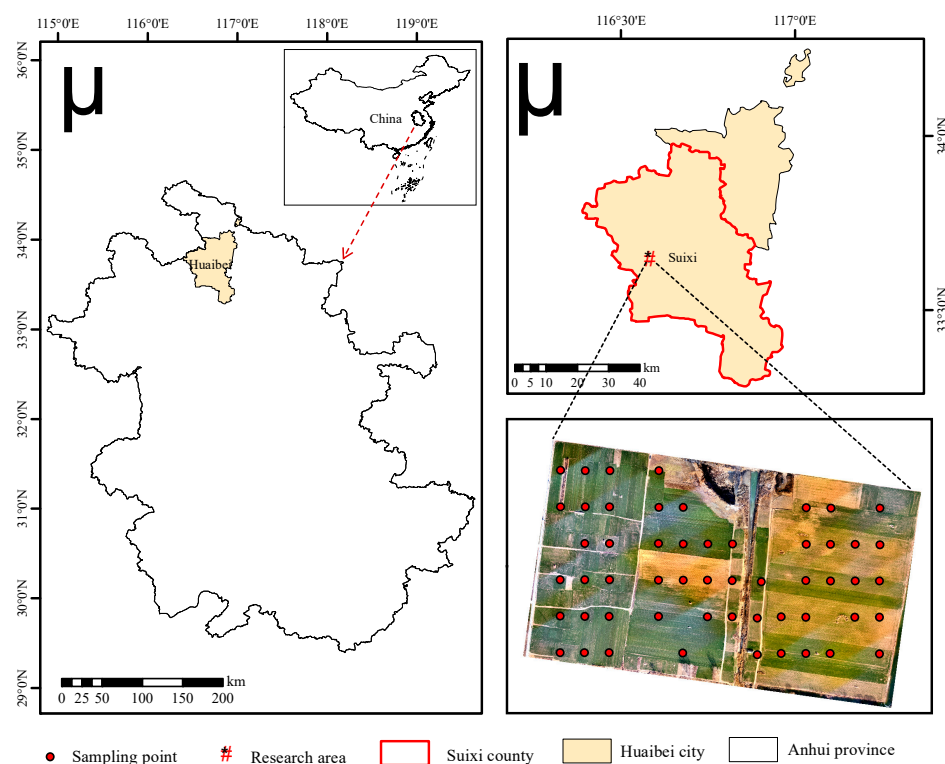


Figure 1. Location of the study area and distribution of sampling points.

2.2. Data Acquisition

2.2.1. UAV Multispectral Imagery

In this study, the DJ-Innovations (DJI) Phantom 4 multispectral drone real-time kinematic (RTK) was used with an integrated visible light sensor and 5 multi-spectral sensors (blue, green, red, red-edge and near-infrared). The drone also had a built-in global positioning system (GPS) and inertial measurement unit (IMU) system. The parameters of the five bands of the sensor are shown in Table 1.

Table 1. Multispectral Camera Parameters.

Band Name	Blue	Green	Red	Red Edge	Near Infrared
Center Wavelength (nm)	450	560	650	730	840
Band Width (nm)	32	32	32	32	52

To avoid bad weather such as rain, snow and high winds, we chose to conduct aerial photography operations when the weather was clear and cloudless and the wind was light. We conducted a survey of the geographical conditions of the study area and the surrounding structures to ensure avoidance of interference from objects such as high-voltage power lines and tall trees during the drone flight. The collection of multispectral imagery by the drone took place on 10 January 2021, with a flight time between 11:00 a.m. and 2:00 p.m. Before takeoff, the drone was manually controlled to fly approximately 2.5 m directly above the calibration whiteboard. The camera was set to single-shot mode to capture images of the standard whiteboard. The whiteboard model used in this study was an SRT-99-100 with a diffuse reflectance of 99% and a size of 25.4 cm × 25.4 cm. The drone's flight mode followed a pre-planned S-shaped flight path. The heading overlap was set to 75% and the side lap was set to 60%. The drone flew at a height of 100 m with the sensor lens facing vertically downward. The camera was set to capture images at equal

time intervals, with a time interval of 3 s. Photographs of the operational site for UAV field data collection are shown in Figure 2.



Figure 2. Photographs of drone field sites. UAV operation (a), UAV (b), UAV flight (c).

After acquiring the image, Pix4D-mapper 4.5.6 software was used to assemble the image to obtain the orthographic image of the study area. Using ArcMap 10.6 software and referencing the orthoimage as the base image, 30 reference points were uniformly selected for geometric correction on each of the five single-band images. The geometric correction error was within 0.5 pixels. Afterward, the digital number (DN) values of the whiteboard were obtained for each band, and the average DN values of the five bands were calculated. The multispectral images were then radiometrically corrected using the Band Math functionality in ENVI 5.3 software. The pre-processed UAV multispectral images were acquired after the above processing with a resolution of 0.05697 m. Finally, the pre-processed multispectral images, as well as the GPS point locations of the sampling points, were imported into the ENVI 5.3 software. An 18×18 (pixel) image centered on the sampling point, corresponding to the sample quadrat size and image resolution, was cropped as the region of interest. The average reflectance of each band within each sample quadrat was extracted.

2.2.2. Ground Data Acquisition

Sample point layout was conducted before the UAV aerial survey. After the image collection was completed, the data collection for winter wheat growth indicators was immediately carried out. The sample point layout in the study area adopted the method of uniform distribution, and the positions of the sample quadrats were recorded using the GPS. Fifty-four sample quadrats were laid out in the area, each with a size of $1 \text{ m} \times 1 \text{ m}$. The sampling and testing methods for ground-based measurements were as follows.

(1) Above-ground biomass (AGB)

The five-point sampling method was applied to the 54 sample quadrats laid out in this study, and the locations of the 54 sample quadrats in the study area are shown in Figure 1. A representative number of 20 winter wheat plants were selected from each sample quadrat. The plants were removed flush with the ground and the leaves and stems were separated

and stored in sealed bags. The temperature of the laboratory oven was set at 105 °C for 30 min of greening treatment, and then the plants were placed in an oven at 80 °C for 24–48 h until a constant dry biomass was obtained [20,21].

(2) Leaf chlorophyll content (SPAD)

The SPAD-502 chlorophyll instrument determines plant leaf SPAD values. Its measured leaf SPAD values are highly significantly correlated with leaf chlorophyll content [7]. Therefore, this instrument was used in this study to determine the chlorophyll content of winter wheat leaves. Five winter wheat plants were selected in each sample quadrat using the five-point sampling method. Then, the SPAD values of the leaf tip, leaf center and leaf base of each winter wheat plant were measured, and the average of the SPAD values of these three parts was calculated as the SPAD value of the winter wheat plant. Finally, the average of the SPAD values of the five winter wheat plants was taken as the chlorophyll content of the winter wheat in the sample quadrat [22].

(3) Leaf water content (LWC)

After leaf stem separation, the fresh leaf weight of the winter wheat plant sample was weighed. Dry leaf dry weight was obtained after drying. The leaf water content was calculated according to Equation (1) [23]:

$$LWC = \frac{FW - DW}{FW} \quad (1)$$

where *FW* is the fresh weight of the leaf; *DW* is the dry weight of the leaf.

2.3. Methods

The research framework is shown in Figure 3. The following work is illustrated in the figure:

- (1) Acquisition and preprocessing of UAV multispectral data in the study area, which is in Section 2.2.1 of the article. Based on the preprocessed multispectral images, vegetation indices (VIs) and texture features (TFs) are extracted as input feature variables for the inverse model of comprehensive growth indicators;
- (2) Construction of two kinds of winter wheat comprehensive growth indicators. The above-ground biomass (AGB), leaf chlorophyll content (SPAD) and leaf water content (LWC) of winter wheat are measured using field samples, and CGI_{ewm} and CGI_{fce} are constructed based on the entropy weight method (EWM) and fuzzy degree comprehensive evaluation model (FCE), respectively;
- (3) Construction and validation of the inversion model of comprehensive growth indexes. The features were categorized into three feature groups: vegetation index; texture features; and the combination of the two, which are used as input variables to construct the inversion models of CGI_{ewm} and CGI_{fce} , with ①, ② and ③ indicating the variable groupings and the order of model construction, respectively. The four regression algorithms selected in this study are partial least squares (PLS), random forest (RF), extreme learning machine (ELM) and particle swarm optimization extreme learning machine (PSO-ELM) for model construction. The accuracy of the inverse model is verified by R^2 and nRMSE.

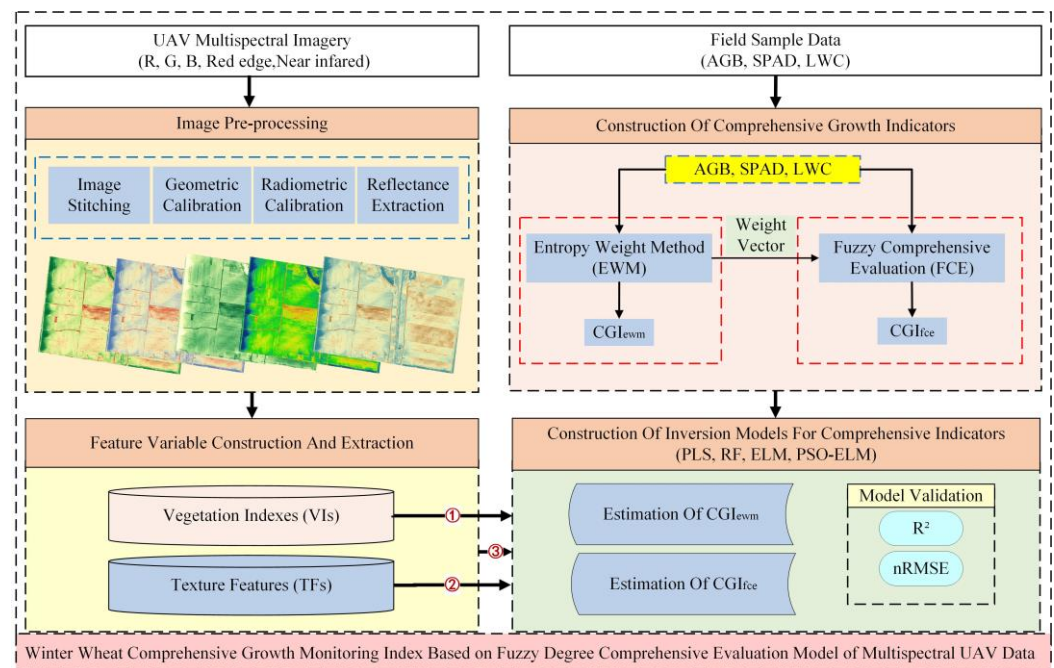


Figure 3. Research framework. Note: AGB stands for above-ground biomass; SPAD indicates leaf chlorophyll content; LWC stands for leaf water content; ①: VIs used as input variables; ②: TFs used as input variables; ③: a combination of VIs and TFs used as an input variable.

2.3.1. Vegetation Indexes (VIs) Construction

Different vegetation species and different growth conditions cause different absorption and scattering effects of incident light in different wavelength bands to enable the characterization of the spectral response between vegetation and incident light [24]. Vegetation indexes (VIs) are calculated by combining the reflectance of different wavelength bands in a linear or nonlinear manner. Therefore, compared with a single spectral reflectance, the VI has a more sensitive response to vegetation growth and can weaken the influence of environmental background on the spectral reflectance of the canopy [25,26]. Based on the results of previous studies, 12 VIs were selected for vegetation growth monitoring (Table 2).

Table 2. VIs and formula.

Vegetation Index	Abbreviations	Formula	Reference
Re-Normalized Vegetation Index	RDVI	$RDVI = (NIR - R) / (NIR + R)^{0.5}$	[27]
Ratio Vegetation Index	RVI	$RVI = NIR / R$	[28]
Normalized Difference Vegetation Index	NDVI	$NDVI = (NIR - R) / (NIR + R)$	[29]
Difference vegetation index	DVI	$DVI = NIR - R$	[30]
Soil-Adjusted Vegetation Index	SAVI	$SAVI = 1.5(NIR - R) / (NIR + R + 0.5)$	[31]
Optimized Soil-Adjusted Vegetation Index	OSAVI	$OSAVI = 1.16(NIR - R) / (NIR + R + 0.16)$	[32]
Triangular vegetation index	TVI	$TVI = 60(NIR - G) - 100(R - G)$	[33]
Excess Red Index	EXR	$EXR = 1.4R - G$	[34]
Normalized Difference Red Edge Index	NDRE	$NDRE = (NIR - RE) / (NIR + RE)$	[35]
Normalized Pigment Chlorophyll Index	NPCI	$NPCI = (R - B) / (R + B)$	[36]
Enhanced Vegetation Index2	EVI2	$EVI2 = (NIR - R) / (1 + NIR + 2.4R)$	[37]
Modified Vegetation Index	MVI	$MVI = \sqrt{\frac{NIR - R}{NIR + R}} + 0.5$	[37]

Note: R, G, B, RE and NIR represent the reflectance of the red band, green band, blue band, red edge band and near-infrared band, respectively.

2.3.2. Texture Features (TFs) Extraction

Texture refers to the repeated sequence patterns and regular arrangement and distribution in an image, which can reflect the spatial distribution information of the image grayscale [38]. In this study, one of the most widely used texture extraction techniques, the gray-level co-occurrence matrix method, was used to obtain the texture parameters

of multispectral images. This method is based on the comprehensive acquisition of local features and arrangement rules of image pixels [39]. In this study, eight texture features in R-band and G-band were extracted using ENVI 5.3 software. The bit-depth of both the R-band and G-band was 8-bits. The formula for each texture feature is shown in Table 3.

Table 3. TF and its calculation formula.

Parameters	Abbreviations	Formula
Mean	<i>mean</i>	$mean = \sum_{i,j}^{N-1} i P_{i,j}$
Variance	<i>var</i>	$var = \sum_{i,j=0}^{N-1} i P_{i,j} (i - mean)^2$
Contrast	<i>con</i>	$con = \sum_{i,j=0}^{N-1} i P_{i,j} (i - j)^2$
Dissimilarity	<i>dis</i>	$dis = \sum_{i,j=0}^{N-1} i P_{i,j} i - j $
Homogeneity	<i>hom</i>	$hom = \sum_{i,j=0}^{N-1} i \frac{P_{i,j}}{1 + (i - j)^2}$
Entropy	<i>ent</i>	$ent = \sum_{i,j=0}^{N-1} i P_{i,j} (-\ln P_{i,j})$
Second moment	<i>sm</i>	$sm = \sum_{i,j=0}^{N-1} i P_{i,j}^2$
Correlation	<i>corr</i>	$corr = \sum_{i,j=0}^{N-1} i P_{i,j} \left[\frac{(i - mean)(j - mean)}{\sqrt{var_i * var_j}} \right]$

Note: $P_{i,j} = \frac{V_{i,j}}{\sum_{i,j=0}^{N-1} V_{i,j}}$; $V_{i,j}$ represents the brightness value of the pixel at the i th row and j th column; and N is the size of the moving window used to calculate texture features.

2.3.3. Entropy Weight Method and Fuzzy Comprehensive Evaluation Model

(1) Entropy weight method (EWM)

Entropy can be used in information theory to measure the amount of useful information provided by various indicators. When using entropy to calculate the weights of indicators, the magnitude of entropy weight corresponds to the amount of information that the selected indicators provide for evaluating the growth status of winter wheat. The larger the entropy weight, the greater the amount of information [40,41]. Therefore, the EWM was used to assign weights to each indicator in this study. The steps for calculating the weights are as follows:

(i) Normalize the original data to obtain a standard matrix:

$$X' = \{x'_{ij}\} \quad (2)$$

where x'_{ij} represents the normalized value of the j th sample quadrat for the i th index;

(ii) Calculate the entropy of the indicator e_i . Calculate the information entropy of the three longevity indicators: AGB; SPAD; and LWC. e_i denotes the information entropy of each longevity indicator of i . The smaller the value of information entropy and the larger the value of entropy weight, the more informative the indicator is for the constructed comprehensive growth indicator:

$$e_i = -k \sum_{j=1}^m x'_{ij} \ln x'_{ij} \quad j = 1, 2, \dots, m \quad (3)$$

$$k = 1 / \ln n \quad (4)$$

where k is the standardized coefficient, m is the number of sample quadrats and n is the number of indicators;

(iii) The weight of each indicator is: $w_i = (1 - e_i) / \left(n - \sum_{i=1}^n e_i \right)$.

The weight vector $W = [w_1, w_2, w_3]$ is obtained, and w_1, w_2 and w_3 are the weights of each indicator, respectively.

The comprehensive index constructed by the entropy weight method (CGI_{ewm}) is represented as Equation (5):

$$CGI_{ewm} = w_1x'_1 + w_2x'_2 + w_3x'_3 \quad (5)$$

where, x'_1 , x'_2 and x'_3 are the respective normalized values of the indicators.

(2) Fuzzy comprehension evaluation method (FCE)

The fuzzy comprehension evaluation (FCE) method is based on fuzzy mathematics. It utilizes the theory of membership degrees in fuzzy mathematics to transform qualitative evaluations into quantitative ones, enabling a comprehensive evaluation of objects that are influenced by multiple factors [42,43]. The above-ground biomass, leaf chlorophyll content and leaf water content of winter wheat were measured in this study. The weights of the EWM combined with the fuzzy degree comprehensive evaluation model were used to construct a comprehensive indicator to quantify the winter wheat growth information. The steps of constructing the comprehensive fuzzy evaluation model are as follows:

(i) Determine the set of factors and weight vector. The set of factors composed of the evaluation object's elements is referred to as the factor set. If there are n evaluation factors, the factor set can be represented as follows: $U = \{u_1, u_2, \dots, u_n\}$. As this study involves three influencing factors, the factor set can be defined as follows: $U = \{u_1, u_2, u_3\}$. u_1 , u_2 and u_3 are winter wheat AGB, SPAD and LWC, respectively.

$$CGI_{fce} = f(AGB, SPAD, LWC) \quad (6)$$

where CGI_{fce} is a comprehensive growth indicator constructed by FCE;

(ii) Determine the evaluation level. The collection of evaluation results is called the evaluation set. Based on the actual growth of winter wheat in the study area. The growth indicators are categorized into five evaluation levels: $V = \{v_1, v_2, v_3, v_4, v_5\}$. The v_1 , v_2 , v_3 , v_4 and v_5 represent poor growth, relatively poor growth, medium growth, relatively good growth and good growth, respectively;

(iii) Determine the fuzziness matrix and membership functions. The fuzzy matrix is denoted as $R_{nm} = \{r_{nm}\}$, where r_{nm} represents the evaluation result in the m th evaluation set for the n th evaluation factor. Based on the defined set of factors and evaluation sets, the fuzzy matrix for this study can be obtained as shown in Equation (7):

$$R = \begin{bmatrix} r_{11}r_{12}r_{13}r_{14}r_{15} \\ r_{21}r_{22}r_{23}r_{24}r_{25} \\ r_{31}r_{32}r_{33}r_{34}r_{35} \end{bmatrix} \quad (7)$$

The membership function is utilized in fuzzy set theory to accurately represent and address real-world evaluation problems through the ranking and partitioning of fuzzy concepts. Considering the ambiguity in determining membership based on interval boundaries, this study utilized trapezoidal membership functions to construct the fuzzy degree matrix. The [0,1] was divided equally into 5 intervals corresponding to 5 rating levels. The fuzzy boundary gap between the head and tail was 0.15, and the center point gap was 0.1. The fuzzy boundary centers for adjacent rating levels were 0.2, 0.4, 0.6 and 0.8, respectively, as shown in Figure 4.

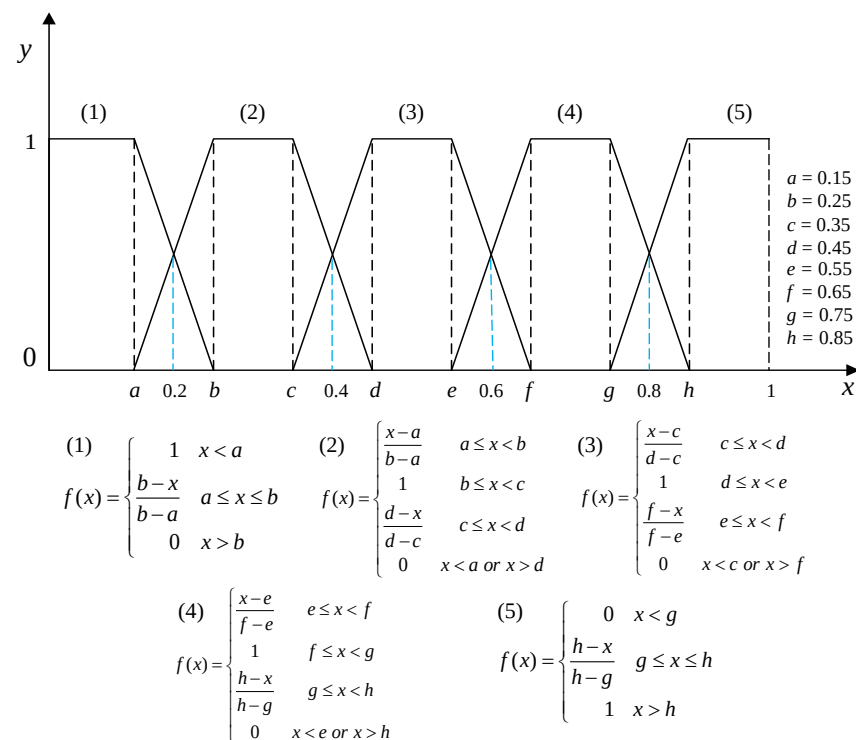


Figure 4. Membership function graphs.

(4) Construct a comprehensive evaluation model of fuzziness and assessment values. Multiply the weight vector obtained by the entropy weighting method with the fuzziness matrix to obtain the fuzzy vector B of the evaluation set. Quantify the score values to a percentage using the score vector as $F = [100 \ 75 \ 50 \ 25 \ 0]$. S represents the evaluation value, which is the final numerical value of various comprehensive growth indicators for winter wheat sample quadrats, as shown in Equations (8) and (9):

$$B = W \bullet R \quad (8)$$

$$S = B \bullet F^T \quad (9)$$

where W is the weight vector of the evaluation factors obtained using the EWM.

2.3.4. Machine Learning Algorithms

Using regression analysis, the inversion models of winter wheat comprehensive growth indexes constructed based on EWM and FCE were established, respectively. Four algorithms were selected to construct the inversion models, namely partial least squares (PLS), random forest (RF), extreme learning machine (ELM) and particle swarm optimization extreme learning machine (PSO-ELM) regression algorithms, respectively. In this study, the above algorithms were completed in MATLAB 2022a software for the inversion model of comprehensive growth indicators of winter wheat.

PLS is a multivariate linear regression analysis method that can simplify data structure and analyze the correlation among variables. When building regression models, it can achieve data dimensionality reduction, information synthesis and screening techniques to extract new composite components that best explain the system [44].

RF is an ensemble learning method that combines multiple decision tree algorithms to generate repeated estimations, which solves the problem of multicollinearity among variables. By calculating the importance of variables, RF can be used to select variables and perform complex nonlinear regression [45]. In this study, the RF model was configured with 100 decision trees and a minimum leaf size of 5.

ELM is a feedforward neural network algorithm with a single hidden layer. The model structure consists of an input layer, a hidden layer and an output layer. The input weights and hidden layer have random values and do not require adjustment. Each layer is connected through a feature mapping function, which offers the advantages of efficient and fast learning [46]. Previous research has indicated that ELM demonstrates better predictive accuracy for monitoring vegetation growth phenotypic traits compared to several typical empirical models. After multiple runs, the optimal number of neurons in the hidden layer was determined to be 5, and the activation function was set as the “sigmoid” function.

PSO-ELM regression algorithm combines the PSO algorithm with ELM to address the issue of randomness in the input weights and hidden layer [47]. The PSO optimization algorithm mimics the behavior of a flock of birds searching for food using a stochastic optimization technique. Each bird in the flock is represented as a particle. In the optimization process, each particle searches for the global best position with a certain flying speed. They explore the solution space based on the fitness function and iteratively update their velocity and position by tracking individual and global extreme values. The principle is as follows: In a D-dimensional search space, a population consisting of n particles, denoted as $X = (x_1, x_2, \dots, x_D)$, is present. The position of the i th particle is represented by the vector $X_i = (x_{i1}, x_{i2}, \dots, x_{iD})^T$, $i = 1, 2, \dots, n$, while its velocity is represented $V_i = (v_{i1}, v_{i2}, \dots, v_{iD})^T$, $i = 1, 2, \dots, n$. The fitness function $f(X_i)$ calculates the fitness value of the particle's position. Each particle has an individual best value $p_{besti} = (p_{i1}, p_{i2}, \dots, p_{iD})$, and the entire population has a global best value $g_{besti} = (g_{i1}, g_{i2}, \dots, g_{iD})$. The particles update their velocity and position iteratively based on Equations (10) and (11).

$$V_{id}^{k+1} = wV_{id}^k + c_1r_1(p_{id}^k - X_{id}^k) + c_2r_2(g_{id}^k - X_{id}^k) \quad (10)$$

$$X_{id}^{k+1} = X_{id}^k + V_{id}^{k+1} \quad (11)$$

where k represents the current iteration count, c_1 and c_2 are non-negative constant acceleration factors, w is the inertia weight factor, r_1 and r_2 are random uniform numbers between 0 and 1 and p_{id}^k and g_{id}^k represent the individual best position and global best position of the i th particle in the d th dimension during the k th iteration. The optimization steps are as follows:

- (1) Initialize the particle swarm. PSO parameters include acceleration constants, inertia weight, particle dimensions, maximum iteration count and population size;
- (2) Train the ELM algorithm with random input weights and thresholds for each particle to obtain the output weight prediction. The root mean square error calculated from the training samples is used as the particle fitness. Update the individual and global best values based on the higher fitness value. During the iteration process, update the particle's velocity and position using Equations (10) and (11). Stop the iteration when reaching the maximum iteration count or the best fitness;
- (3) Obtain the optimal fitness and hidden layer thresholds and input them into the ELM structure to calculate the weight matrix and obtain the prediction results.

After multiple training sessions, the parameters of the particle swarm were determined as follows: the maximum iteration count was set to $k = 100$; the number of particles in the population was set to $n = 40$; the acceleration constant was set to $c_1 = 2.8$; the inertia weight was set to $c_2 = 1.3$; and the velocity range was $[-1, 1]$.

2.3.5. Evaluation of Model Accuracy

In this study, a random sample of 40 out of 54 data points was selected for model training, while the remaining 14 were used for model validation. The model performance was quantitatively evaluated using the coefficient of determination (R^2) and the normalized root mean square error (nRMSE), as shown in Equations (12) and (13). R^2 represents the degree of fit of the model, while nRMSE indicates the magnitude of the error between

predicted and actual values. A higher R^2 and lower nRMSE indicate higher accuracy of the model [48].

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (12)$$

$$\text{nRMSE} = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}}{\bar{y}} \times 100\% \quad (13)$$

where y_i is the measured value, $\hat{y}_i$ is the predicted value, $\bar{y}$ is the mean of the measured value and n is the number of samples.

3. Results and Analysis

3.1. Comprehensive Growth Indicator Construction

In this study, the entropy weight method and fuzzy comprehensive evaluation model were used to construct winter wheat comprehensive growth indicators, which are represented by CGI_{ewm} and CGI_{fce} , respectively. The result of comprehensive growth index constructed by the entropy weight method is shown in Equation (14). The comprehensive growth indicator values of various methods constructed by the two methods are shown in Figure 5.

$$\text{CGI}_{\text{ewm}} = 0.624u'_1 + 0.093u'_2 + 0.283u'_3 \quad (14)$$

where u'_1 represents the normalized above ground biomass of winter wheat, u'_2 represents the normalized leaf water content and u'_3 represents the normalized chlorophyll content of winter wheat.

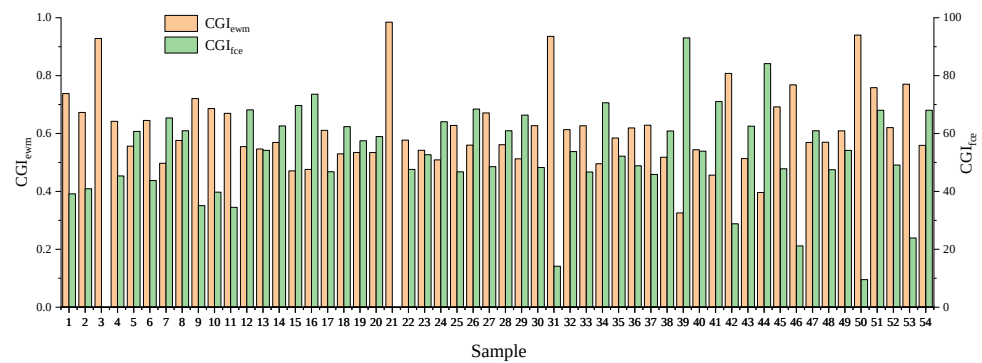


Figure 5. The results of constructing the comprehensive growth index.

According to Equation (14), it can be observed that compared to leaf water content and chlorophyll content, the above-ground biomass had the highest contribution rate to the comprehensive growth indicator, with a weight of 0.624. The chlorophyll content followed next with a weight of 0.283, while leaf water content had the lowest contribution rate with a weight of 0.093. Figure 5 shows that most of the values of CGI_{ewm} were concentrated between 0.4 and 0.8, and most of the values of CGI_{fce} were concentrated between 25 and 65. The figure illustrates that CGI_{ewm} and CGI_{fce} exhibited opposite trends, suggesting that a smaller value of CGI_{fce} indicates better winter wheat growth. The CGI_{fce} values of Sample 3 and Sample 21 in the figure were zero and the values of CGI_{ewm} were high, indicating that the winter wheat in the sample quadrat was growing well.

3.2. Correlation Analysis

To analyze the correlation between the composite growth indicators CGI_{ewm} and CGI_{fce} (CGIs) constructed using two different methods and vegetation indexes, we performed a correlation analysis using the Pearson correlation coefficient among AGB, LWC,

SPAD, CGI_{ewm} , CGI_{fce} and the selected 12 VIs. The results of the analysis are shown in Figure 6.

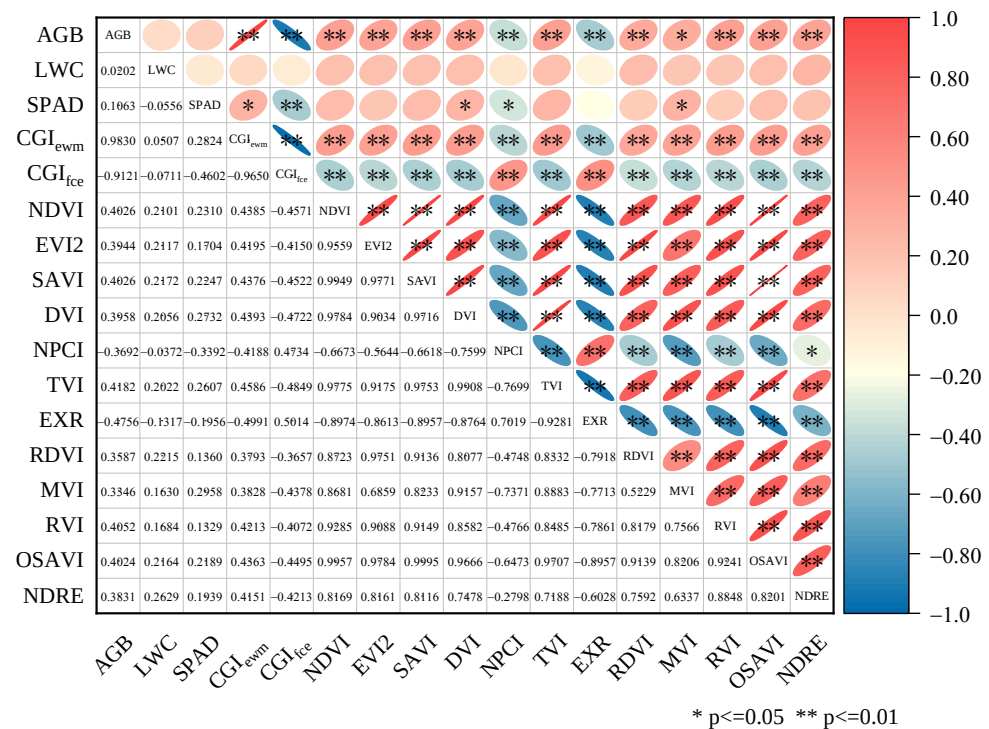


Figure 6. Correlation between growth indicators and vegetation indexes. Note: * indicates significant correlation at the 0.05 level; ** indicates significant correlation at the 0.01 level; red color indicates positive correlation and blue color indicates negative correlation; right tilted ellipse indicates positive correlation and left tilted ellipse indicates negative correlation; flatter ellipse indicates higher correlation and wider ellipse indicates lower correlation.

As can be seen in Figure 6, there were different degrees of correlation between the three single indicators and the VIs. Among them, the correlation between AGB and VIs was generally larger, and the correlation between SPAD and most of the VIs were larger than that of LWC. CGI_{ewm} and CGI_{fce} passed the significance test with the 12 VIs, and the correlation between the two composite indicators and the VIs increased to different degrees compared to the single indicators, and the increase was the most obvious compared to LWC, and all were correlated with the selected VIs up to the 0.01 level of significant correlation. The correlations between the VIs and CGI_{fce} were greater than those of CGI_{ewm} , except for RVI, RDVI and EVI2.

3.3. Input Variables

To address the issues of limited input features and the problem of spectral feature saturation, this study introduced TFs as additional input variable for the model. The final selection of VIs as input variables for the VI was based on their significant correlation at the 0.01 level with both CGI_{ewm} and CGI_{fce} (CGIs). Performing correlation analysis between the composite indicators and individual bands (Figure 7a) revealed that both the G and R bands showed significant correlation at the 0.01 level with the two constructed composite indicators. Therefore, the texture information of the G and R bands was further analyzed for correlation with the composite indicators (Figure 7b). The TFs that exhibited significant correlation at the 0.01 level with both composite indicators were selected as the final texture feature selection results.

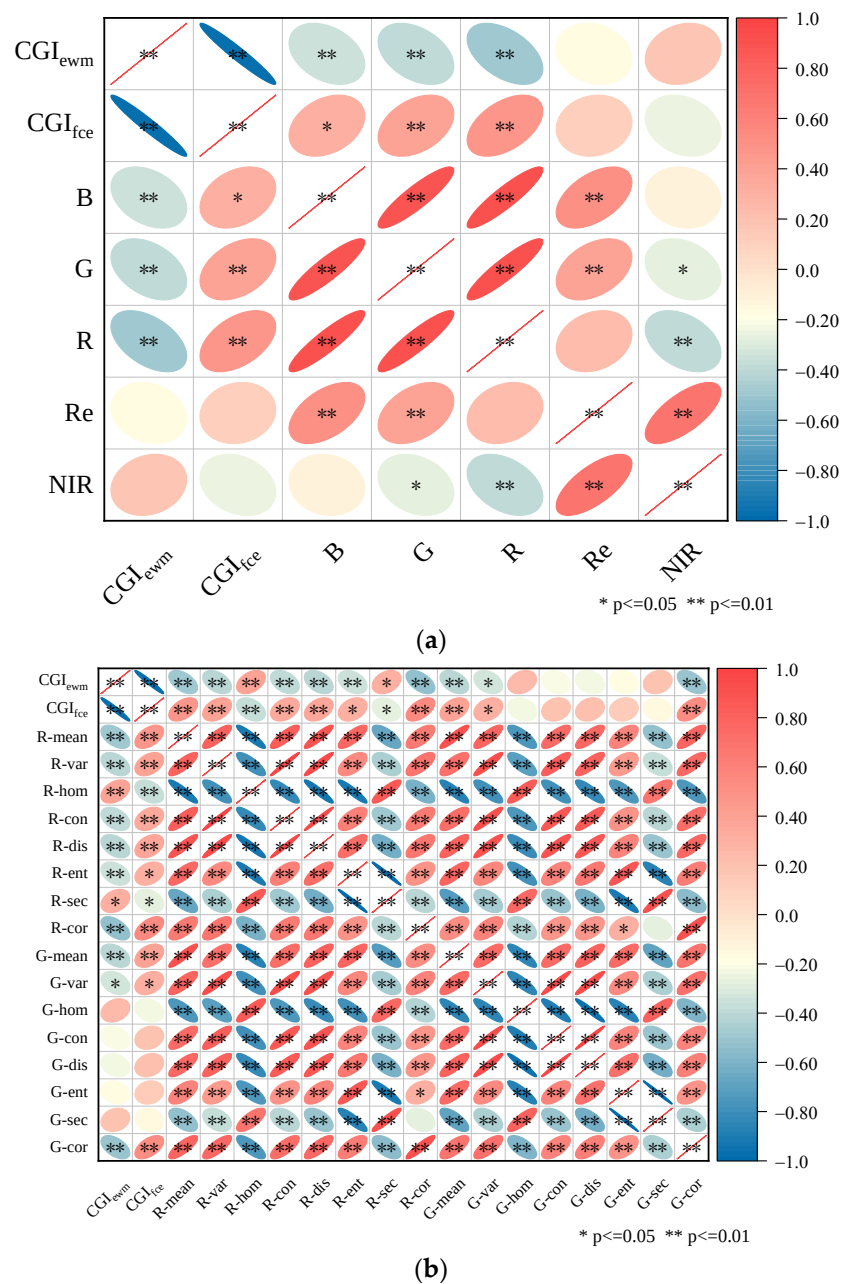


Figure 7. Texture feature correlation analysis. Note: * indicates significant correlation at the 0.05 level; ** indicates significant correlation at the 0.01 level; red color indicates positive correlation and blue color indicates negative correlation; right tilted ellipse indicates positive correlation and left tilted ellipse indicates negative correlation; flatter ellipse indicates higher correlation and wider ellipse indicates lower correlation. (a) Correlation between CGIs and single bands. (b) Correlation between CGIs and TFs.

3.4. Model Construction

3.4.1. Inversion Model Construction of Comprehensive Indicators Based on the EWM

According to the above method, the final input variables of the vegetation index and texture feature were determined. A CGI_{ewm} inversion model was constructed based on vegetation index, texture feature and the combination of vegetation index and texture feature. The accuracy of the constructed model is shown in Figure 8.

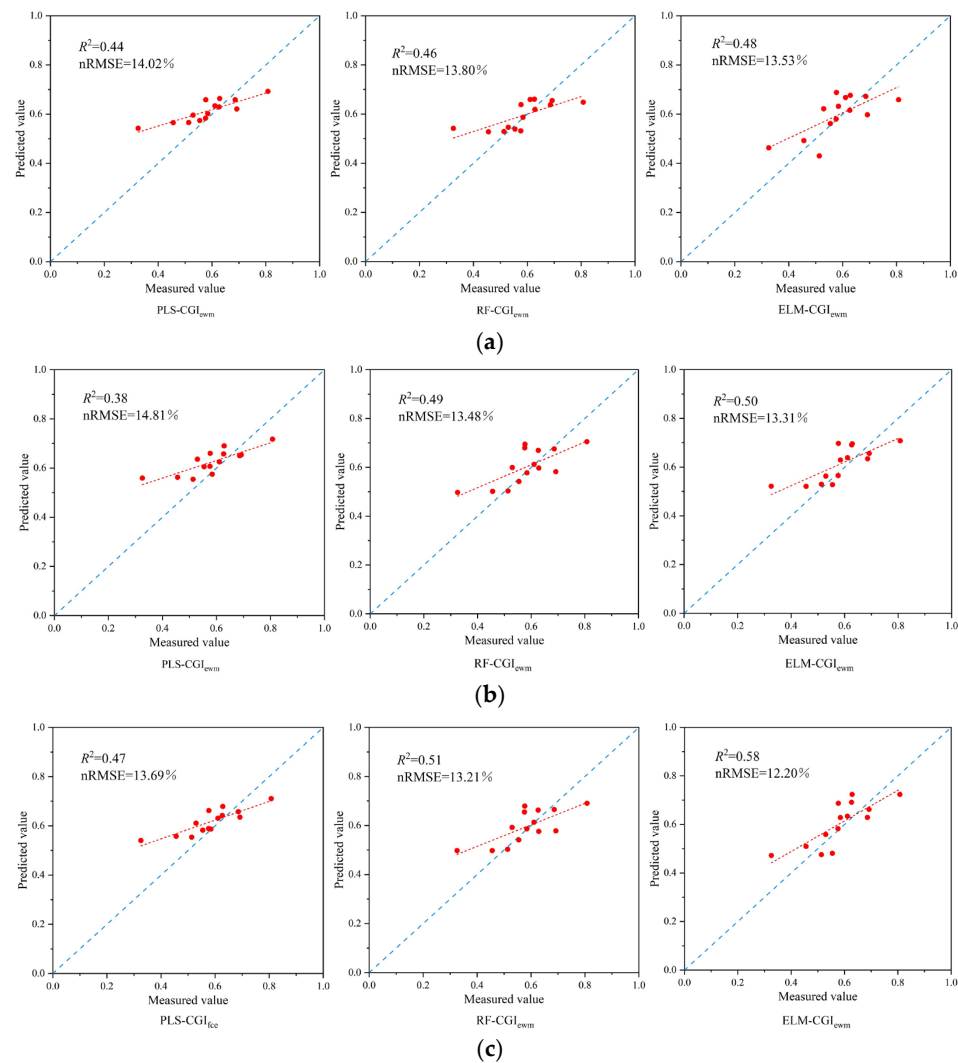


Figure 8. Accuracy verification of the CGI_{ewm} inversion model. (a) Model construction based on Vis. (b) Model construction based on TFs. (c) Model construction based on VIs and TFs.

As can be seen from the inversion validation results displayed in Figure 8a,b, when the CGI_{ewm} inversion model was constructed using Vis and TFs as model input variables, respectively, the accuracy of the models constructed based on the ELM algorithm were both the highest. This was followed by the RF algorithm. PLS constructed the model with the lowest accuracy.

Figure 8c presents the results of constructing the CGI_{ewm} inversion model by combining VIs and TFs as input variables using three different machine learning algorithms. From the figure, it can be observed that compared to using VIs feature as input variable, all models showed varying degrees of improvement in accuracy. Among them, the ELM- CGI_{ewm} model exhibited a significant improvement in accuracy.

The inclusion of the texture feature variable improved the R^2 of the ELM- CGI_{ewm} model by 20.83% and reduced the nRMSE by 9.83% compared to using VIs as the input variable.

Comparing the results of constructing the inversion model using three different algorithms, the ELM- CGI_{ewm} model, which combined VIs and TFs, achieved the highest accuracy in predicting the comprehensive growth indicator.

3.4.2. Inversion Model Construction of Comprehensive Indicators Based on the FCE

The FCE was used to construct the comprehensive growth indicator of winter wheat, also with three variable inputs based on PLS, RF and ELM machine learning algorithms to

construct the inverse model of the growth indicator. The results of the construction of each model are shown in Figure 9.

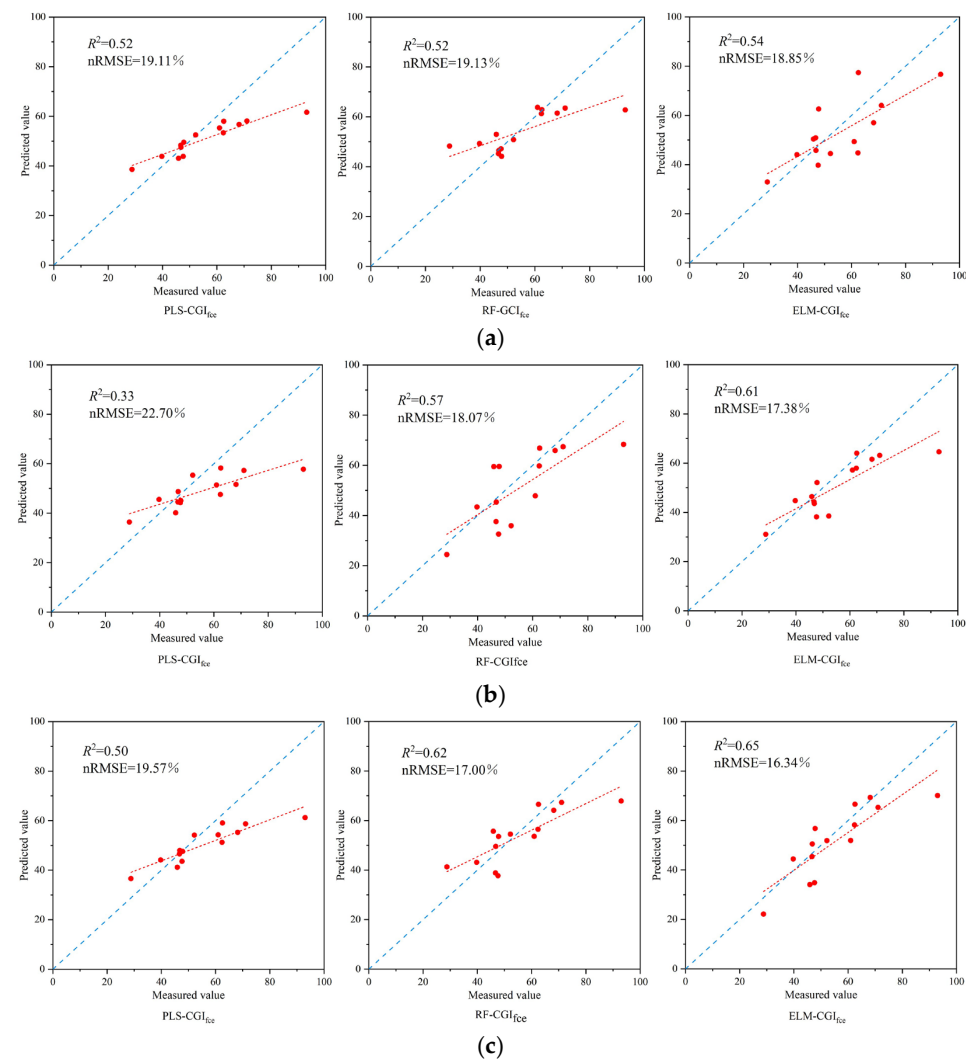


Figure 9. Accuracy verification of the CGI_{fce} inversion model. (a) Model construction based on Vis. (b) Model construction based on TFs. (c) Model construction based on VIs and TFs.

Figure 9a,b represents the model validation results of constructing CGI_{fce} inversions with VIs and TFs input variables, respectively. As can be seen from the figures, ELM- CGI_{fce} exhibited optimal model performance compared to both the PLS- CGI_{fce} and RF- CGI_{fce} models.

Figure 9c shows the results of the comprehensive indicator inversion model construction when the combination of VIs and TFs were used as input variables. Except for the PLS- CGI_{fce} model, the accuracy of all inversion models improved compared with only using a single feature as the input variable. The accuracy of the ELM- CGI_{fce} model was the highest compared with the other eight comprehensive indicator inversion models, with an R^2 of 0.65 and an nRMSE of 16.34%. And the R^2 of the ELM- CGI_{fce} model improved by 20.37%, and the nRMSE reduced by 13.32% compared to when only VIs was used as the input variable.

The comparison of the performance of inversion models for the comprehensive growth indicator of winter wheat constructed in different ways revealed that the CGI_{fce} inversion models, built using the RF and ELM algorithms with various feature input variables, exhibited improved accuracy compared to the CGI_{ewm} inversion model. Thus, it can be concluded that the comprehensive growth indicator constructed using the fuzzy compre-

hensive evaluation model more effectively reflects the growth information of winter wheat in comparison to the entropy weight method.

3.4.3. Construction of the PSO-ELM-CGI_{fce} Inversion Model

Based on the construction results mentioned above, the ELM-CGI_{fce} inversion model, built using a combination of VIs and TFs as input variables, exhibited good performance. However, due to the random generation of initial weights and thresholds in the ELM model structure, it may suffer from the disadvantage of ineffective hidden nodes and insufficient generalization ability.

To overcome this issue, this study introduced the PSO algorithm to optimize the initial input weights and thresholds of the ELM-CGI_{fce} model, aiming to achieve a higher accuracy inversion model for CGI_{fce}. The fitting effect of the PSO-ELM-CGI_{fce} inversion model on the validation samples is shown in Figure 10.

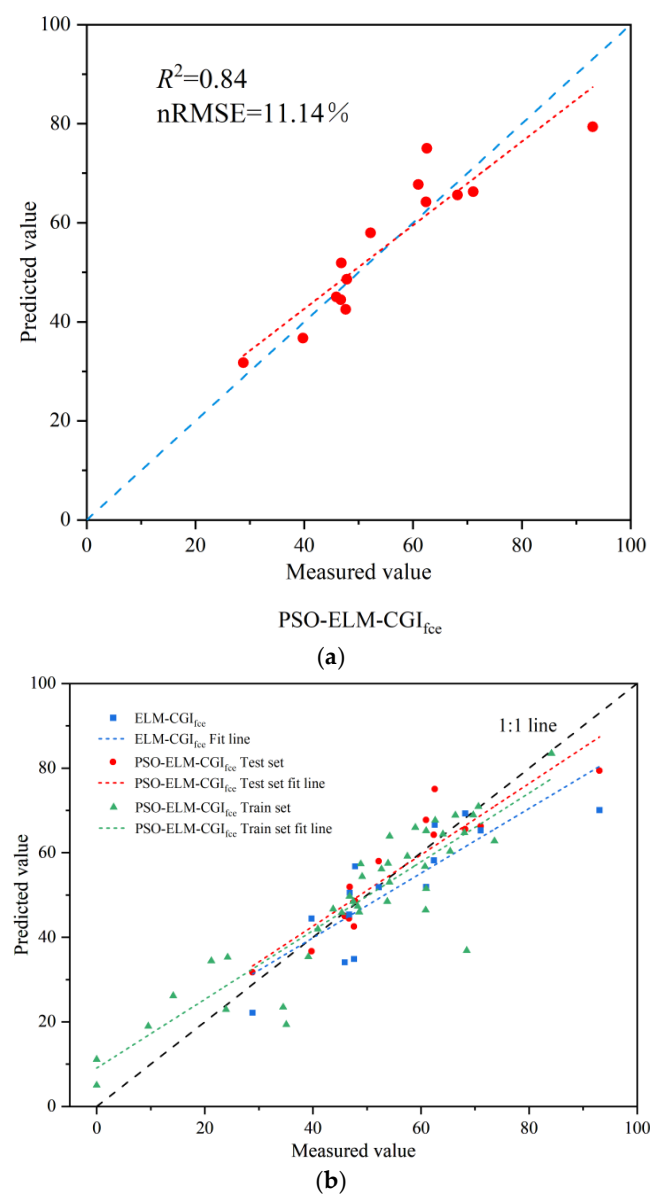


Figure 10. Inverse results of CGI_{fce} of PSO-ELM-CGI_{fce}. (a) Validation of the PSO-ELM-CGI_{fce} model. (b) Comparison of accuracy of the ELM-CGI_{fce} model and PSO-ELM-CGI_{fce} model.

As can be seen from Figure 10a, the CGI_{fce} inversion model R^2 constructed with PSO-ELM increased from 0.65 to 0.84, with an increase of 29.23% and a decrease of 31.82% in nRMSE.

As can be seen from Figure 10b, compared with the scatterplot of the PSO-ELM- CGI_{fce} model before optimization, most points were close to the 1:1 line after optimization of the algorithm, and the fitting line of the prediction point was closer to 1:1 line, indicating that after processing by the optimization algorithm, the difference between the predicted value and the measured value was reduced, and the PSO algorithm improved the prediction accuracy of the ELM- CGI_{fce} model. At the same time, from the scatterplot dispersion degree and fitting line of the measured and predicted values of the training set, it can be seen that the accuracy of the scatterplot was relatively high and similar to that of the test set, indicating that the model has strong generalization ability.

4. Discussion

4.1. Combination of VIs and TFs as Input Variables

A UAV multispectral remote sensing image interpretation technique can provide an efficient and reliable method for monitoring the growth of winter wheat. Many studies have focused on extracting spectral information to monitor crop growth. However, spectral information tends to saturate when vegetation canopy coverage is high and is easily affected by soil background reflectance in sparse plant areas. Additionally, previous research has shown that the texture information derived from UAV images can accurately predict winter wheat biomass [49,50]. Therefore, in this study, we introduced texture features based on vegetation indexes to construct an inversion model for comprehensive growth indicators of winter wheat that includes biomass. Based on the results of the correlation analysis, the TFs of R and G band were used in this study. Xu et al. found that the TFs of different bands have different effects on rice biomass monitoring, and that the red and green bands have advantages in characterizing texture information [51]. Taking into account that winter wheat is in the winter period and the plants are relatively sparse, the extraction of reflectance information is influenced by the soil background. The green band can reflect the spectral reflectance of background objects, indicating that considering texture features in the red and green bands is more reasonable. When the combination of vegetation index and texture features was used as input variables, the accuracy was significantly improved, except for the PLS- CGI_{fce} model. Among them, the ELM- CGI_{fce} model had a larger accuracy improvement. Compared to using VIs as input variables, R^2 was improved by 20.37%. It indicates that combining texture features with the vegetation index can improve the accuracy of the CGIs prediction. The reason is that image texture can represent the phenotypic information of crops, specifically the differences in field growth details. By incorporating both spectral and texture information, the limitations of relying solely on spectral data and its saturation can be overcome effectively. Additionally, texture information proves to be more stable compared to vegetation indices, even in the presence of noise and the influence of soil background, effectively diminishing the interference caused by weather conditions and soil background [52–54].

4.2. Comprehensive Growth Indicators Construction

A single growth index can only reflect the growth characteristics of winter wheat in a single aspect, such as morphological structure, physiology and biochemistry, and cannot comprehensively monitor winter wheat growth [55]. Therefore, in this study, EMW and FCE were used to construct CGI_{ewm} and CGI_{fce} . Correlation analysis was conducted between two comprehensive indicators and VIs. The results showed that compared with three single indicators, both comprehensive growth indicators had corresponding improvements in correlation. This indicates that CGI_{ewm} and CGI_{fce} contain more information about winter wheat growth, and the selected VIs have a better response relationship with them. Among them, CGI_{fce} has a higher correlation with most VIs, indicating that the comprehensive

growth indicator constructed by the fuzzy comprehensive evaluation model can more comprehensively respond to winter wheat growth [56].

The growth of winter wheat is influenced by multiple factors. However, evaluating the growth of winter wheat based on single indicator, such as biomass, plant water content and chlorophyll content, can be subjective and imprecise. To tackle the uncertainties, the FCE can be employed. Additionally, the EWM can objectively determine the weights of different indicators by considering their information entropy. In this study, we developed an FCE that combines the strengths of both approaches, making it more advantageous compared to the EWM.

4.3. Inversion Model Construction of Winter Wheat CGIs

The RF, PLS and ELM algorithms were selected to construct regression models, and the results showed that ELM modeling results have the best effect. Maimaitijiang et al. found that the ELM algorithm showed the best performance in estimating crop growth traits [57], which is consistent with the results of this study. The accuracy of the models constructed by the PLS algorithm was lower than the RF and ELM. The reason for this is that there is a nonlinear relationship among Vis, TFs and CGIs. The PLS algorithm used to describe the linear relationship to build the CGI inversion model is deficient [58]. On the other hand, RF and ELM use nonlinear functions to establish the functional relationship between input variables and output variables, which can explain the correlation among Vis, TFs and CGIs more accurately. The RF algorithm is suitable for prediction problems with large volumes of data, and it tends to experience overfitting issues when applied to small data volumes. This leads to poorer results in the construction of its inverse model compared to the ELM algorithm [59,60]. The ELM algorithm has poor generalization ability due to the randomness of input weights and hidden layer thresholds. The PSO algorithm can systematically optimize the input weights and hidden layer thresholds through the stochastic optimization technique of the population [61]. Therefore, from the results of model construction in this study, the accuracy of the PSO-ELM-CGI_{fce} model was significantly improved compared with that before optimization. This study specifically focused on the growth indicators of winter wheat during the overwintering period. However, since winter wheat crops exhibit variations in phenotypic traits throughout different growth stages, future research can delve into and refine monitoring methods for comprehensive growth indicators of winter wheat across multiple growth stages.

5. Conclusions

- (1) The biomass, leaf chlorophyll content and leaf water content of winter wheat were used to construct the CGIs (CGI_{ewm}, CGI_{fce}) by EWM and FCE. According to Pearson correlation analysis with VIs, CGI_{ewm} and CGI_{fce} are significantly correlated with each other. The correlation between CGI_{fce} and most VIs is greater than that of CGI_{ewm}, and the CGIs of winter wheat constructed by the two methods contain more growth information than the single index. CGI_{fce} has a better response relationship with the selected Vis;
- (2) When constructing the CGI_{ewm} inversion model, the model accuracy constructed by the RF, PLS and ELM algorithms is improved after introducing TFs as model input variables based on the VIs, and the R^2 is 0.47, 0.51 and 0.58, respectively, of which the ELM is improved the most, with the R^2 improved by 20.83%, and the nRMSE reduced by 9.83%. When constructing the CGI_{fce} inversion model, the accuracy of all algorithms, except PLS, is improved accordingly with the introduction of TFs. The ELM-CGI_{fce} of winter wheat can better reflect the growth of winter wheat in the study area, with R^2 of 0.65 and nRMSE of 16.34%. The combination of VIs and TFs effectively improves the inversion accuracy of the comprehensive growth indicators;
- (3) After optimizing the ELM-CGI_{fce} model of winter wheat growth by PSO, the prediction accuracy of the model is significantly improved. The R^2 increased from 0.65 to 0.84, which is 29.23% higher, and nRMSE reduced by 31.82%. The PSO algorithm opti-

mizes the parameters of the ELM algorithm, and PSO-ELM-CGI_{fce} more accurately estimates the CGI_{fce} of winter wheat.

In this study, the EWM and FCE were applied to the construction of a comprehensive growth indicator of winter wheat. A variety of algorithms was used to construct the inverse model of the comprehensive growth indicator by combining the vegetation index and texture parameters. The results of this study can provide a valuable reference for monitoring the growth of winter wheat and other field crops.

Author Contributions: Conceptualization, J.Y. and S.Z.; methodology, J.Y., R.H. and S.Z.; software, J.Y. and R.H.; validation, J.Y., S.Z. and Y.Z.; formal analysis, J.Y. and A.S.L.; investigation, J.Y., R.H. and S.Z.; resources, J.Y. and A.S.L.; data curation, J.Y. and Y.Z.; writing—original draft preparation, J.Y. and S.Z.; writing—review and editing, J.Y. and A.S.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Huaibei Mining Group Technology Research and Development Project (No.2022-103 and No.2023-209), Land development and Agricultural Resources Investigation in the Tarim River Basin (No. 2021xjkk0200), the Graduate Innovation Fund Project of Anhui University of Science and Technology (No. 2022CX2166).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Mahlayeye, M.; Darvishzadeh, R.; Nelson, A. Cropping patterns of annual crops: A remote sensing review. *Remote Sens.* **2022**, *14*, 2404. [\[CrossRef\]](#)
2. Liu, Y.; Feng, H.K.; Yue, J.B.; Li, Z.H.; Yang, G.J.; Song, X.Y.; Yang, X.D.; Zhao, Y. Remote-sensing estimation of potato above-ground biomass based on spectral and spatial features extracted from high-definition digital camera images. *Comput. Electron. Agric.* **2022**, *198*, 107089. [\[CrossRef\]](#)
3. Zhu, W.X.; Rezaei, E.E.; Nouri, H.; Sun, Z.; Li, J.; Yu, D.; Siebert, S. UAV-based indicators of crop growth are robust for distinct water and nutrient management but vary between crop development phases. *Field Crops Res.* **2022**, *284*, 108582. [\[CrossRef\]](#)
4. Guo, Y.; He, J.; Huang, J.; Jing, Y.; Xu, S.; Wang, L.; Li, S.; Zheng, G. Effects of the spatial resolution of UAV images on the prediction and transferability of nitrogen content model for winter wheat. *Drones.* **2022**, *6*, 299. [\[CrossRef\]](#)
5. Hasan, U.; Sawut, M.; Chen, S. Estimating the leaf area index of winter wheat based on unmanned aerial vehicle RGB-image parameters. *Sustainability* **2019**, *11*, 6829. [\[CrossRef\]](#)
6. Wang, W.; Zheng, H.; Wu, Y.; Yao, X.; Zhu, Y.; Cao, W.; Cheng, T. An assessment of background removal approaches for improved estimation of rice leaf nitrogen concentration with unmanned aerial vehicle multispectral imagery at various observation times. *Field Crops Res.* **2022**, *283*, 108543. [\[CrossRef\]](#)
7. Zhu, W.; Sun, Z.G.; Yang, T.; Li, J.; Peng, J.B.; Zhu, K.Y.; Li, S.J.; Gong, H.T.; Lyu, Y.; Li, B.B.; et al. Estimating leaf chlorophyll content of crops via optimal unmanned aerial vehicle hyperspectral data at multi-scales. *Comput. Electron. Agric.* **2020**, *178*, 105786. [\[CrossRef\]](#)
8. Devia, C.A.; Rojas, J.P.; Petro, E.; Martinez, C.; Mondragon, I.F.; Patino, D.; Rebolledo, M.C.; Colorado, J. High-Throughput Biomass Estimation in Rice Crops Using UAV Multispectral Imagery. *J. Intell. Robot. Syst.* **2019**, *96*, 573–589. [\[CrossRef\]](#)
9. Sapkota, S.; Paudyal, D.R. Growth monitoring and yield estimation of maize plant using unmanned aerial vehicle (UAV) in a hilly region. *Sensors* **2023**, *23*, 5432. [\[CrossRef\]](#)
10. Dilmurat, K.; Sagan, V.; Moose, S. AI-driven maize yield forecasting using unmanned aerial vehicle-based hyperspectral and lidar data fusion. *ISPRS Annals of the Photogrammetry. Remote Sens. Spat. Inf. Sci.* **2022**, *3*, 193–199.
11. Adeluyi, O.; Harris, A.; Foster, T.; Clay, G.D. Exploiting centimetre resolution of drone-mounted sensors for estimating mid-late season above ground biomass in rice. *Eur. J. Agron.* **2022**, *132*, 126411. [\[CrossRef\]](#)
12. Liu, Y.N.; Liu, S.S.; Li, J.; Guo, X.Y.; Wang, S.Q.; Lu, J.W. Estimating biomass of winter oilseed rape using vegetation indices and texture metrics derived from UAV multispectral images. *Comput. Electron. Agric.* **2019**, *166*, 105026. [\[CrossRef\]](#)
13. Yue, J.B.; Yang, G.J.; Tian, Q.J.; Feng, H.K.; Xu, K.J.; Zhou, C.Q. Estimate of winter-wheat above-ground biomass based on UAV ultrahigh-ground-resolution image textures and vegetation indices. *Isprs J. Photogramm.* **2019**, *150*, 226–244. [\[CrossRef\]](#)
14. Yue, J.B.; Zhou, C.Q.; Guo, W.; Feng, H.K.; Xu, K.J. Estimation of winter-wheat above-ground biomass using the wavelet analysis of unmanned aerial vehicle-based digital images and hyperspectral crop canopy images. *Int. J. Remote Sens.* **2021**, *42*, 1602–1622. [\[CrossRef\]](#)

15. Huang, Y.Y.; Ma, Q.M.; Wu, X.M.; Li, H.; Xu, K.; Ji, G.X.; Qian, F.; Li, L.X.; Huang, Q.; Long, Y.; et al. Estimation of chlorophyll content in *Brassica napus* based on unmanned aerial vehicle images. *Oil Crop Sci.* **2022**, *7*, 149–155. [\[CrossRef\]](#)
16. Ndlovu, H.S.; Odindi, J.; Sibanda, M.; Mutanga, O.; Clulow, A.; Chimonyo, V.G.P.; Mabhaudhi, T. A comparative estimation of maize leaf water content using machine learning techniques and unmanned aerial vehicle (UAV)-based proximal and remotely sensed data. *Remote Sens.* **2021**, *13*, 4091. [\[CrossRef\]](#)
17. Feng, H.; Tao, H.; Li, Z.; Yang, G.; Zhao, C. Comparison of UAV RGB imagery and hyperspectral remote-sensing data for monitoring winter wheat growth. *Remote Sens.* **2022**, *14*, 3811. [\[CrossRef\]](#)
18. Sun, Q.; Chen, L.P.; Xu, X.B.; Gu, X.H.; Hu, X.Q. A new comprehensive index for monitoring maize lodging severity using UAV-based multi-spectral imagery. *Comput. Electron. Agric.* **2022**, *202*, 107362. [\[CrossRef\]](#)
19. Wang, H.D.; Cheng, M.H.; Zhang, S.H.; Fan, J.L.; Feng, H.; Zhang, F.C.; Wang, X.K.; Sun, L.J.; Xiang, Y.Z. Optimization of irrigation amount and fertilization rate of drip-fertigated potato based on Analytic Hierarchy Process and Fuzzy Comprehensive Evaluation methods. *Agric. Water Manag.* **2021**, *256*, 107130. [\[CrossRef\]](#)
20. Yang, C.B.; Xu, J.; Feng, M.C.; Bai, J.; Sun, H.; Song, L.F.; Wang, C.; Yang, W.D.; Xiao, L.J.; Zhang, M.J.; et al. Evaluation of hyperspectral monitoring model for aboveground dry biomass of winter wheat by using multiple factors. *Agronomy* **2023**, *13*, 983. [\[CrossRef\]](#)
21. Xu, Y.F.; Cheng, Q.; Wei, X.P.; Yang, B.; Xia, S.S.; Rui, T.T.; Zhang, S.W. Monitoring of winter wheat growth under UAV using variation coefficient method and optimized neural network. *T. Chin. Soc. Agric. Eng.* **2021**, *37*, 71–80.
22. Shen, L.; Gao, M.; Yan, J.; Wang, Q.; Shen, H. Winter wheat SPAD value inversion based on multiple pretreatment methods. *Remote Sens.* **2022**, *14*, 4660. [\[CrossRef\]](#)
23. Pan, H.Z.; Chen, Z.X.; Ren, J.Q.; Li, H.; Wu, S.R. Modeling winter wheat leaf area index and canopy water content with three different approaches using Sentinel-2 multispectral instrument data. *IEEE J.-STARS* **2018**, *12*, 482–492. [\[CrossRef\]](#)
24. El-Hendawy, S.; Al-Suhaibani, N.; Al-Ashkar, I.; Alotaibi, M.; Tahir, M.U.; Solieman, T.; Hassan, W.M. Combining genetic analysis and multivariate modeling to evaluate spectral reflectance indices as indirect selection tools in wheat breeding under water deficit stress conditions. *Remote Sens.* **2020**, *12*, 1480. [\[CrossRef\]](#)
25. Liu, H.; Zhang, F.; Zhang, L.; Lin, Y.; Wang, S.; Xie, Y. UNVI-Based time series for vegetation discrimination using separability analysis and random forest classification. *Remote Sens.* **2020**, *12*, 529. [\[CrossRef\]](#)
26. Ouadi, N.; Jarlan, L.; Ezzahar, J.; Zribi, M.; Khabba, S.; Bouras, E.; Bousbih, S.; Frison, P.L. Monitoring of wheat crops using the backscattering coefficient and the interferometric coherence derived from Sentinel-1 in semi-arid areas. *Remote Sens. Environ.* **2020**, *251*, 112050. [\[CrossRef\]](#)
27. Li, X.; Yang, C.; Huang, W.; Tang, J.; Tian, Y.; Zhang, Q. Identification of cotton root rot by multifeature selection from sentinel-2 images using random forest. *Remote Sens.* **2020**, *12*, 3504. [\[CrossRef\]](#)
28. Feng, L.; Wu, W.; Wang, J.; Zhang, C.; Zhao, Y.; Zhu, S.; He, Y. Wind field distribution of multi-rotor UAV and its influence on spectral information acquisition of rice canopies. *Remote Sens.* **2019**, *11*, 602. [\[CrossRef\]](#)
29. Aburas, M.M.; Abdullah, S.H.; Ramli, M.F.; Ash'aari, Z.H. Measuring land cover change in Seremban, Malaysia using NDVI index. *Procedia Environ. Sci.* **2015**, *30*, 238–243. [\[CrossRef\]](#)
30. Issa, S.; Dahy, B.; Saleous, N.; Ksiksi, T. Carbon stock assessment of date palm using remote sensing coupled with field-based measurements in Abu Dhabi (United Arab Emirates). *Int. J. Remote Sens.* **2019**, *40*, 7561–7580. [\[CrossRef\]](#)
31. Ferreira, L.G.; Huete, A.R. Assessing the seasonal dynamics of the Brazilian Cerrado vegetation through the use of spectral vegetation indices. *Int. J. Remote Sens.* **2004**, *25*, 1837–1860. [\[CrossRef\]](#)
32. Radočaj, D.; Šiljeg, A.; Marinović, R.; Jurišić, M. State of Major Vegetation Indices in Precision Agriculture Studies Indexed in Web of Science: A Review. *Agriculture* **2023**, *13*, 707. [\[CrossRef\]](#)
33. Zhao, Y.L.; Zheng, W.X.; Xiao, W.; Zhang, S.; Lv, X.J.; Zhang, J.Y. Rapid monitoring of reclaimed farmland effects in coal mining subsidence area using a multi-spectral UAV platform. *Environ. Monit. Assess.* **2020**, *192*, 474. [\[CrossRef\]](#) [\[PubMed\]](#)
34. Upendar, K.; Agrawal, K.N.; Chandel, N.S.; Singh, K. Greenness identification using visible spectral colour indices for site specific weed management. *Plant Physiol. Rep.* **2021**, *26*, 179–187. [\[CrossRef\]](#)
35. Qiao, L.; Zhao, R.M.; Tang, W.J.; An, L.L.; Sun, H.; Li, M.Z.; Wang, N.; Liu, Y.; Liu, G.H. Estimating maize LAI by exploring deep features of vegetation index map from UAV multispectral images. *Field Crops Res.* **2022**, *289*, 108739. [\[CrossRef\]](#)
36. Hatfield, J.L.; Prueger, J.H. Value of using different vegetative indices to quantify agricultural crop characteristics at different growth stages under varying management practices. *Remote Sens.* **2010**, *2*, 562–578. [\[CrossRef\]](#)
37. Xiao, W.; Chen, J.L.; Da, H.Z.; Reng, H.; Zhang, J.Y.; Zhang, L. Inversion and Analysis of Maize Biomass in Coal Mining Sub-sidence Area Based on UAV Images. *Trans. Chin. Soc. Agric. Mach.* **2018**, *49*, 169–180.
38. Luo, P.L.; Liao, J.J.; Shen, G.Z. Combining spectral and texture features for estimating leaf area index and biomass of maize using Sentinel-1/2, and Landsat-8 data. *IEEE Access* **2020**, *8*, 53614–53626. [\[CrossRef\]](#)
39. Girolamo-Neto, C.D.; Sanches, I.D.; Neves, A.K.; Prudente, V.H.R.; Körting, T.S.; Picoli, M.C.A.; Aragão, L.E.O.e.C.d. Assessment of Texture Features for Bermudagrass (*Cynodon dactylon*) Detection in Sugarcane Plantations. *Drones* **2019**, *3*, 36. [\[CrossRef\]](#)
40. Li, Z.; Luo, Z.J.; Wang, Y.; Fan, G.Y.; Zhang, J.M. Suitability evaluation system for the shallow geothermal energy implementation in region by Entropy Weight Method and TOPSIS method. *Renew. Energy* **2022**, *184*, 564–576. [\[CrossRef\]](#)
41. Zhe, W.; Xigang, X.; Feng, Y. An abnormal phenomenon in entropy weight method in the dynamic evaluation of water quality index. *Ecol. Indic.* **2021**, *131*, 108137. [\[CrossRef\]](#)

42. Wu, Y.N.; Zhang, T. Risk assessment of offshore wave-wind-solar-compressed air energy storage power plant through fuzzy comprehensive evaluation model. *Energy* **2021**, *223*, 120057. [[CrossRef](#)]
43. Xiao, B.; Zeng, Y.; Zou, Y.; Hu, W. Hydropower Unit State Evaluation Model Based on AHP and Gaussian Threshold Improved Fuzzy Comprehensive Evaluation. *Energies* **2023**, *16*, 5592. [[CrossRef](#)]
44. Burnett, A.C.; Anderson, J.; Davidson, K.J.; Ely, K.S.; Lamour, J.; Li, Q.Y.; Morrison, B.D.; Yang, D.D.; Rogers, A.; Serbin, S.P. A best-practice guide to predicting plant traits from leaf-level hyperspectral data using partial least squares regression. *J. Exp. Bot.* **2021**, *72*, 6175–6189. [[CrossRef](#)]
45. Desai, S.; Ouarda, T.B.M.J. Regional hydrological frequency analysis at ungauged sites with random forest regression. *J. Hydrol.* **2021**, *594*, 125861. [[CrossRef](#)]
46. Sulaiman, S.M.; Jeyanthi, P.A.; Devaraj, D.; Shihabudheen, K.V. A novel hybrid short-term electricity forecasting technique for residential loads using Empirical Mode Decomposition and Extreme Learning Machines. *Comput. Electr. Eng.* **2022**, *98*, 107663. [[CrossRef](#)]
47. Haq, Z.U.; Ullah, H.; Khan, M.N.A.; Naqvi, S.R.; Ahad, A.; Amin, N.A.S. Comparative study of machine learning methods integrated with genetic algorithm and particle swarm optimization for bio-char yield prediction. *Bioresour. Technol.* **2022**, *363*, 128008. [[CrossRef](#)]
48. Barzegar, R.; Adamowski, J.; Moghaddam, A.A. Application of wavelet-artificial intelligence hybrid models for water quality prediction: A case study in Aji-Chay River, Iran. *Stoch. Environ. Res. Risk Assess.* **2016**, *30*, 1797–1819. [[CrossRef](#)]
49. Zhou, C.; Gong, Y.; Fang, S.H.; Yang, K.L.; Peng, Y.; Wu, X.T.; Zhu, R.S. Combining spectral and wavelet texture features for unmanned aerial vehicles remote estimation of rice leaf area index. *Front. Plant Sci.* **2022**, *13*, 957870. [[CrossRef](#)]
50. Zhai, W.; Li, C.; Cheng, Q.; Mao, B.; Li, Z.; Li, Y.; Ding, F.; Qin, S.; Fei, S.; Chen, Z. Enhancing Wheat Above-Ground Biomass Estimation Using UAV RGB Images and Machine Learning: Multi-Feature Combinations, Flight Height, and Algorithm Implications. *Remote Sens.* **2023**, *15*, 3653. [[CrossRef](#)]
51. Xu, T.; Wang, F.; Xie, L.; Yao, X.; Zheng, J.; Li, J.; Chen, S. Integrating the Textural and Spectral Information of UAV Hyperspectral Images for the Improved Estimation of Rice Aboveground Biomass. *Remote Sens.* **2022**, *14*, 2534. [[CrossRef](#)]
52. Zhang, X.; Zhang, K.; Sun, Y.; Zhao, Y.; Zhuang, H.; Ban, W.; Chen, Y.; Fu, E.; Chen, S.; Liu, J.; et al. Combining Spectral and Texture Features of UAS-Based Multispectral Images for Maize Leaf Area Index Estimation. *Remote Sens.* **2022**, *14*, 331. [[CrossRef](#)]
53. Zhang, J.Y.; Qiu, X.L.; Wu, Y.T.; Zhu, Y.; Cao, Q.; Liu, X.J.; Cao, W.X. Combining texture, color, and vegetation indices from fixed-wing UAS imagery to estimate wheat growth parameters using multivariate regression methods. *Comput. Electron. Agric.* **2021**, *185*, 106138. [[CrossRef](#)]
54. Tian, Y.C.; Huang, H.; Zhou, G.Q.; Zhang, Q.; Tao, J.; Zhang, Y.L.; Lin, J.L. Aboveground mangrove biomass estimation in Beibu Gulf using machine learning and UAV remote sensing. *Sci. Total Environ.* **2021**, *781*, 146816. [[CrossRef](#)]
55. Pei, H.J.; Feng, H.K.; Li, C.C.; Jin, X.L.; Li, Z.H.; Yang, G.J. Remote sensing monitoring of winter wheat growth with UAV based on comprehensive index. *T. Chin. Soc. Agric. Eng.* **2017**, *33*, 74–82.
56. Ding, X.; Chong, X.; Bao, Z.; Xue, Y.; Zhang, S. Fuzzy Comprehensive Assessment Method Based on the Entropy Weight Method and Its Application in the Water Environmental Safety Evaluation of the Heshangshan Drinking Water Source Area, Three Gorges Reservoir Area, China. *Water* **2017**, *9*, 329. [[CrossRef](#)]
57. Maimaitijiang, M.; Ghulam, A.; Sidike, P.; Hartling, S.; Maimaitiyiming, M.; Peterson, K.; Shavers, E.; Fishman, J.; Peterson, P.; Kadam, S.; et al. Unmanned Aerial System (UAS)-based phenotyping of soybean using multi-sensor data fusion and extreme learning machine. *ISPRS J. Photogramm.* **2017**, *134*, 43–58. [[CrossRef](#)]
58. Xu, T.Y.; Guo, Z.H.; Yu, F.H.; Xu, B.; Feng, S. Genetic algorithm combined with extreme learning machine to diagnose nitrogen deficiency in rice in cold region. *T. Agric. Eng.* **2020**, *36*, 209–218.
59. Lima, A.R.; Cannon, A.J.; Hsieh, W.W. Nonlinear regression in environmental sciences using extreme learning machines: A comparative evaluation. *Environ. Model. Softw.* **2015**, *73*, 175–188. [[CrossRef](#)]
60. Ahmad, I.; Bashari, M.; Iqbal, M.J.; Rahim, A. Performance comparison of support vector machine, random forest, and extreme learning machine for intrusion detection. *IEEE Access* **2018**, *6*, 33789–33795. [[CrossRef](#)]
61. Cao, Y.L.; Jiang, K.L.; Wu, J.X.; Yu, F.H.; Du, W.; Xu, T.Y. Inversion modeling of japonica rice canopy chlorophyll content with UAV hyperspectral remote sensing. *PLoS ONE* **2020**, *15*, e0238530. [[CrossRef](#)] [[PubMed](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.