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Wheat Biomass Estimation Based on Neural Network and Hyperspectral Vegetation Index

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Abstract: Wheat biomass is an important indicator reflecting the growth status of wheat. Wheat biomass management is one of the most important links in wheat breeding and plant production management in agro-ecosystems, and it is also one of the key factors affecting wheat growth. Wheat production and income. The purpose of this work is to study wheat biomass estimation based on neural network and hyperspectral vegetation index, and to study and establish a biomass prediction model based on hyperspectral vegetation index. Corresponding characteristic parameters (spectral reflectance, spectral index, red edge width, characteristic wavelength) were extracted by analyzing the canopy spectrum, the correlation between characteristic parameters and biomass was analyzed, and a biomass prediction model based on neural network was established. The comparison results of vegetation index and traditional multiple regression model show that the total sample prediction R2 of the multiple linear regression model is 0.869, which is smaller than the total sample prediction R2 of the BP neural network. The biomass estimation model is higher than the wheat biomass estimation model of BP neural network.

1. Introduction

Wheat has been cultivated in China for thousands of years, and it is one of the main food crops in my country. The production of food crops is not only one of the most important issues closely related to people's lives, but also the relevant policies issued by the food sector and the proposed price control measures affected to some extent [1]. The emergence of crop remote sensing monitoring technology not only makes non-destructive monitoring possible, but also helps to understand the growing status of crops in real time, implement reasonable supervision and provide good technical methods for good yield estimation. Therefore, the ability to accurately and quickly estimate wheat yield will be a major development in agriculture [2].

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The study of wheat biomass estimation has always been one of the research hotspots of scholars at home and abroad. Prey L simulates multispectral satellite data by reconstructing the hyperspectral spectrum of the Earth's atmosphere (400-1000 nm). Spectral data were collected at high temporal frequency at 3 nm resolution during growth stages 5-14 of three winter wheat growing seasons to study the effects of year and season. Field trials were carried out for 24 genotypes with different morphology and phenology under different nitrogen application conditions, different planting time and third-season fungicide intensity. Ground reflectance data was resampled to match the spectral resolution of Landsat-8, Quickbird, RapidEye, WorldView-2, and Sentinel-2 satellite sensors. The resulting collection of spectra was used to calculate all possible indices of normal vegetation related to grain yield, nitrogen uptake and nitrogen concentration. Index performance is highly dependent on developmental stage and age [3]. Mert studied the relationship between the FAO Soil Productivity Rating (SPR) and different vegetation indices. Sentinel-2A images use NDVI, RE-OSAVI and REMCARI indices. Wheat was chosen as the reference plant for yield estimation, as wheat was the most abundant crop in the field (27.47%). The study was conducted at Kalakabi State Farm, 87 km (2) in Bursa Province, Turkey. Research shows that SPR correlates with returns in 2018 (r (2) = 0.616). When dividing, RE-OSAVI has r(2) of 0.629. At the header level, NDVI has an r(2) of 0.577. The REMCARI index provided low precision (0.216 <= r(2) <= 0.258) yield estimates across all vegetation cycles. These findings can be interpreted as land quality monitoring using multi-satellite imagery through NDVI and RE-OSAVI. In this way, we can use soil surveys to determine when soil properties have recovered to determine soil productivity, while we can use measurements to detect declines in certain growing seasons [4]. Joerg H Understanding the impact of changes in agricultural soil and plant parameters on synthetic cavity radar (SAR) measurements is important when using SAR to monitor the temporal evolution of crops. In this regard, it is based on multipole multibaseline SAR data and includes position measurements. Data was collected for 6 days from May 2014 to July 2014 as part of the DLR CROPEX project. The reported experiments address the sensitivity of zones X, C, and L to phenological changes by examining multiple groups. On a per acquisition day basis. The application of tomography enables the calculation of three-dimensional (3-D) backscatter distributions and separation of ground and volume scattering materials. The tomography parameters are at different frequencies, i.e. the center of the 3D backscatter curve, which summarizes only the volume and power of the ground and volume. Their sensitivity and ability to detect land and vegetation changes have been evaluated, focusing on the added value of 3-D analysis at different frequencies and polarizations [5]. From this point of view, foreign scholars have a lot of valuable research results in wheat research, especially the use of hyperspectral vegetation index to estimate wheat biomass.

In this paper, wheat biomass is estimated based on neural network and hyperspectral vegetation index. Large-scale wheat biomass estimation has always been a hot and difficult point in agricultural research. Mastering regional and global wheat biomass and carbon storage is important for understanding changes in the entire ecosystem. It is of great help and can provide reliable support and basis for the macro-setting of global climate change mitigation policies and wheat resource management. In recent years, with the maturity and wide application of geographic information system and remote sensing technology, the models for studying wheat biomass on a large scale have been enriched. Integrating ground data and multi-source remote sensing data is of great significance to carry out research on wheat biological parentage.

2. Research on Neural Network, Hyperspectral Vegetation Index and Wheat Biomass Estimation

2.1. BP Neural Network

BP (Back Propagation) neural network is back propagation neural network. With the development of theory and application, people are more and more aware of the powerful ability of BP neural network. At present, deep learning methods are brilliant in the fields of artificial intelligence, image recognition, speech recognition, etc. Every breakthrough in deep learning will profoundly change people's lives, and BP neural network is the cornerstone of deep learning. The importance of BP neural network It goes without saying [6-7]. Regression is a method used in artificial neural networks to estimate the error contribution of each neuron after processing a batch of data (in image recognition, multiple images). This is a special case of an older, more general technique called automatic differentiation. In the case of learning, gradient descent optimization algorithms often use regression to adjust the weights of neurons by computing a loss function. This process is also sometimes referred to as error propagation, since errors are computed at the output layer and propagated through the network layers [8-9]. The back-propagation algorithm is generated iteratively, which is equivalent to automatic changes in back-loading mode. Trajectory requires a known desired output for each input value, so it is a supervised learning method (although it has been used in some unsupervised networks, such as automated simulations). The principle is also an extension of the delta rule to a multilayer feed network, constructed by iteratively computing the slope at each level using the chain rule. It is closely related to the Gauss-Newton algorithm and is part of neural background research. Regression can be used with any gradient-based optimization, such as the L-BFGS method or the truncated Newton method. Convolution is often used to train deep neural networks [10-11].

2.2. Vegetation Spectral Vegetation Index

The visible light band and the near-infrared band can be combined according to the spectral characteristics of vegetation. They are combined to form a vegetation index. The effective, real-time and empirical index of the surface vegetation is the vegetation index. Vegetation index can quantitatively measure vegetation growth. The sensitivity of vegetation index is better than that of single band [12-13]. With the development of hyperspectral remote sensing technology, vegetation index has been widely used in different fields such as ecological environment, agriculture and vegetation. Vegetation index is most widely used in the field of vegetation application: 1. Monitoring vegetation distribution and growth. 2. Monitoring yield estimation, nutrient elements, and regional environmental assessment. 3. Extract various biological parameters. In this paper, the vegetation spectral index analysis will be used to process the data [14-15].

2.3. Basic Principles of Remote Sensing Monitoring of Crops

Remote sensing (Remote Sensing), in a broad sense, refers to the technology of detecting and perceiving objects or things from a distance, that is, it does not require direct contact with the target object itself, but only needs to rely on some equipment such as sensors to receive the detected object. The generated spectrum, such as electric field, magnetic field, electromagnetic wave, seismic wave and other information, is processed through radiation correction and other related technologies, and finally the relevant signs of the target object are identified through visual interpretation or image recognition technology [16-17]. Crop remote sensing monitoring is to use the spatial information technology of remote sensing technology to carry out systematic monitoring of all aspects of the agricultural production process. And the temporal and spatial distribution characteristics of related disasters (including meteorological disasters and biological disasters), monitor the sown area of crops and their changes. Crop remote sensing monitoring is closely related to my country's food security. It can collect information resources related to agriculture in a large-scale, real-time and accurate manner, which helps agricultural production ministries and governments at all levels to make agricultural decisions based on this information [18].

3. Experiment and Research on Wheat Biomass Estimation

3.1. Experimental Design

The test was conducted in Test Kitchen A in 2019-2020. Two concentration levels were set in the field experiment: three nitrogen fertilizer levels were set, 50 kg ha-1 (N1), 100 kg ha-1 (N2) and 150 kg ha-1 (N3) . . Compost The operating system is: nitrogen fertilizer is applied according to the ratio of base fertilizer: solid strip fertilizer: compound fertilizer: starting fertilizer = 4:2:1:3. Sowing on October 30, 2019, the area test area is 50 ㎡.

3.2. Data Collection

(1) Hyperspectral data collection

Hyperspectral data acquisition: The American ASD Fieldspec FR spectrometer was used. On a sunny day with no wind and no clouds, the population spectrum test was performed at the bud stage, early flowering stage, full bloom stage, boll stage and boll opening stage of wheat from 12:00 to 16:00 Beijing time. Before the measurement, a whiteboard was used for calibration. The test set the field of view angle of 30°, the sensor probe was vertically downward, about 1.1m from the top of the canopy, and 15 curves were measured for each treatment (the average value was taken as the spectral reflectance value of the plot).), and the scanning time of each spectral curve was set to 0.1 s.

(2) Determination of biomass

In the wheat spectral test sample area, sample plants were taken, and then the stems, leaves, and bellflowers of wheat were collected in the room for classification, and their fresh weights were weighed. 100 ℃ oven for 25 minutes, then adjusted to 70 ℃ constant temperature drying, weighed after 36 hours, weighed again after 2 hours, the weight difference between the two times before and after ≤ 1%, no longer bake, and then calculate the total of these parts to calculate the wheat ground. Department of dry biomass weight.

3.3. Model Checking and Accuracy Evaluation Criteria

The functional relationship between spectral variables and agronomic parameter estimation models should be judged not only by the significance test of the coefficient of determination, but also by the RMSE (Root Mean Square Error) and the correlation coefficient r between the measured value and the predicted value and accuracy evaluation.

In the correlation and regression analysis of spectral data and physiological parameters, the square value of the correlation coefficient (r) (determination coefficient R2) can be used to evaluate the correlation of the two types of data and the pros and cons of the prediction results. Generally speaking, the higher the level of prediction accuracy of the model.

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

Among them, xi and yi are the measured value and the simulated value, respectively; n is the number of measurements.

The accuracy of parameters estimated by univariate and multivariate regression models can be evaluated by the root mean square difference.

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

In the formula: yi and y^i are the measured value and the theoretical value calculated by the model, respectively, and n is the number of samples (including training samples and test samples).

4. Analysis and Research on Wheat Biomass Estimation Based on Neural Network

4.1. Estimation of Wheat Biomass by Height Index

Lidar can obtain high-precision vegetation spatial structure and topographic information at the bottom of the canopy by emitting laser light and receiving return signals, and can quickly estimate wheat biomass. In previous studies, most of them used different height indicators H to invert biomass, including Hmax, H95, H90, H85, H80, Hmean, Hstd, Hev, etc.

Table 1. Height indicators to estimate wheat biomass

Parameter	Modeling	Modeling Verification		
	R2	R2	RMSE	RRMSE
Tillering stage	0.66	0.61	0.67	0.59
Jointing period	0.67	0.66	0.87	0.37
Heading date	0.54	0.48	0.76	0.38

As shown in Table 1, the model was constructed by using the height index H,95 and the measured biomass. The R2 of the tillering stage model was 0.66, the R2 of the model test was 0.61, the RMSE=0.67t/ha, and the RRMSE=59%; The inversion accuracy of the heading date is the highest (model R2=0.67, in the model test, R2=0.66, RMSE=0.87t/ha, RRMSE=37%), and the inversion accuracy of the heading date is the lowest (model R2=0.54, in the model test, R2= 0.48,RMSE=0.76t/ha,RRMSE=38%).

4.2. Estimation of Wheat Biomass by Volume Index

This paper estimates the biomass of wheat based on the volume index V, and the data has a good monitoring effect in the whole growth period and single growth period of wheat. The results are shown in Table 2.

Table 2. Volume metrics to estimate wheat biomass

Parameter	Modeling	Modeling Verification		
	R2	R2	RMSE	RRMSE
Tillering stage	0.63	0.55	0.48	0.37
Jointing period	0.74	0.66	0.68	0.28
Heading date	0.64	0.54	1.14	0.34

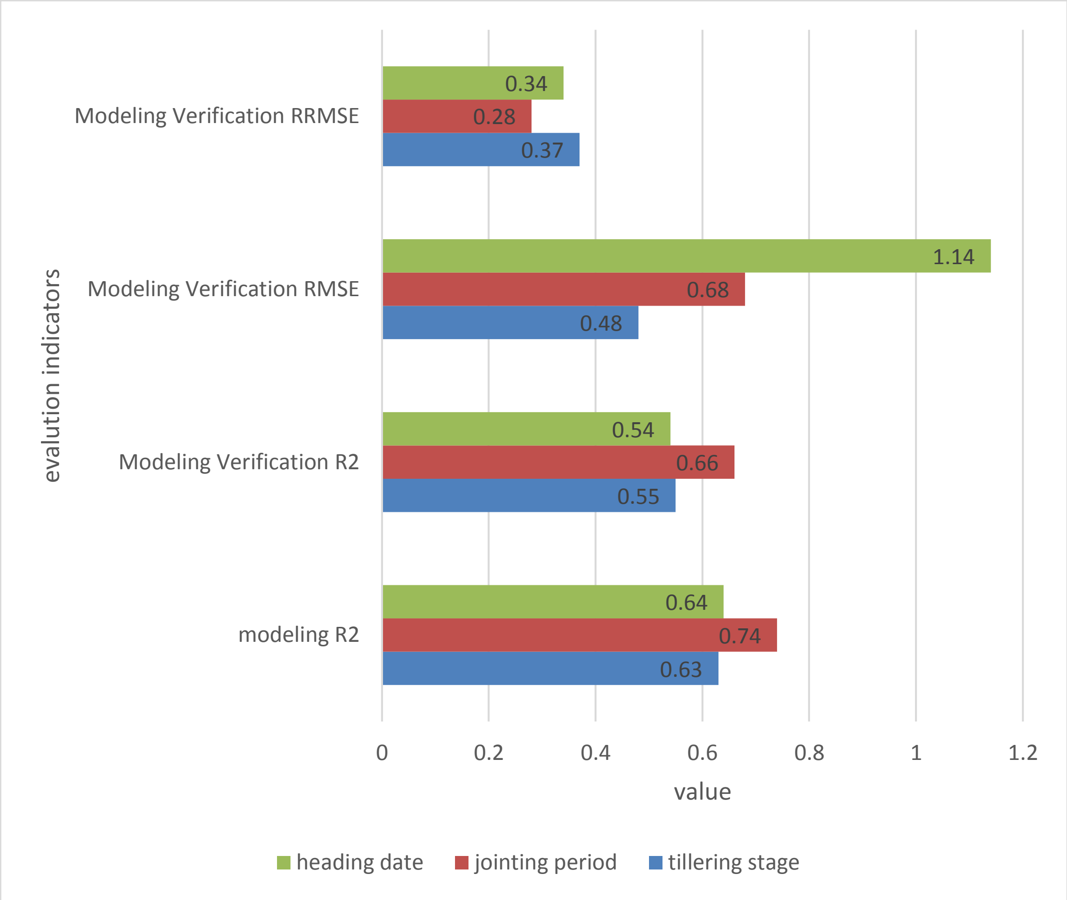

Figure 1. Comparison of wheat biomass estimated by volume indicators

As shown in Figure 1, using the volume index V and the measured biomass to build a model, the model R2 in the tillering stage is 0.63, and the model test, RMSE and RRMSE are 0.48Vha and 37%, respectively; in a single growth period, the jointing stage has the highest accuracy, among which the model The R2 was 0.74, the model test figure, R2 was 0.66, RMSE and RRMSE were 0.68t/ha and 28%. The inversion accuracy of heading date was the lowest, the R2 of the model was 0.64, the R2 of the model was 0.54, and the RMSE and RRMSE were 1.14 t/ha and 34%, respectively.

4.3. Model Comparison

Firstly, the model constructed by multiple linear regression method and BP neural network algorithm is analyzed from the inside of the model. The training sample prediction accuracy, test sample prediction accuracy and overall prediction accuracy of the model are listed in Table 3.

Table 3. Overall validation results of the two estimation models

	Multiple Linear Regression		BP neural network	
	R^2	RMSE	R^2	RMSE
Training samples	0.892	1.964	0.886	1.576
Test sample	0.814	2.262	0.831	2.345
Overall sample	0.869	2.068	0.868	2.187

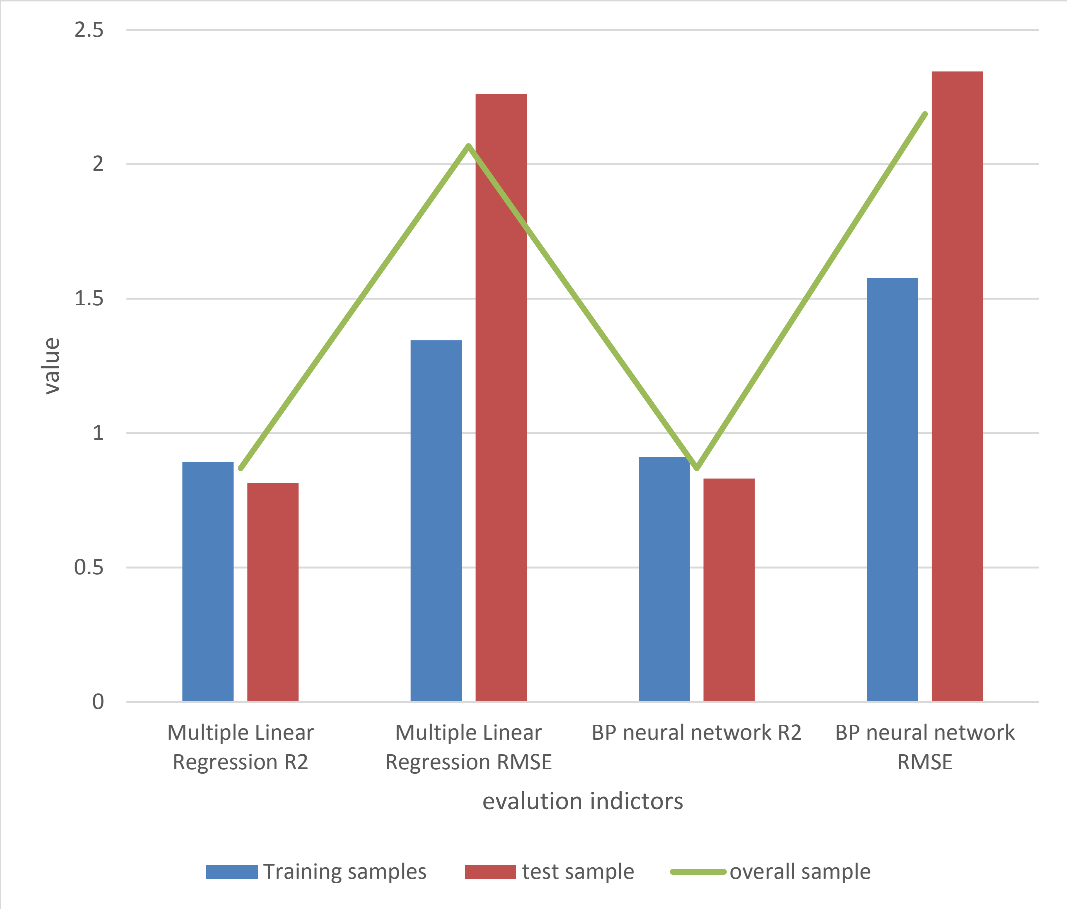

Figure 2. Comparison of the overall validation results of the two estimation models

Figure 2 shows that the overall sample prediction R2 of the multiple linear regression model is 0.869, which is smaller than the BP neural network overall sample prediction R2 of 0.912, indicating that the BP neural network is more stable than the wheat biomass estimation model constructed by the multiple linear regression model. At the same time, the RMSE value of the BP neural network is also 0.231 higher than that of the multiple linear regression model.

5. Conclusion

Based on crop yield estimation by traditional remote sensing monitoring platform, this paper applies neural network and hyperspectral vegetation index to crop monitoring and estimation in small and medium-sized areas, and conducts correlation analysis of UAV RGB image features and agronomic parameters. The feasibility of estimating biomass and yield on the UAV platform, constructing a high-precision dynamic monitoring model for the biomass of wheat in main growth periods based on UAV RGB images, and comprehensively using the image data of multiple growth periods to construct a high-accuracy model. Higher wheat yield estimation model. The expected results can not only provide an effective technical approach for UAV monitoring of farmland growth information, but also provide a theoretical basis for real-time monitoring and quantitative management of wheat biomass, thereby promoting the rapid development and application practice of precision agriculture.

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Data Availability

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

Conflict of Interest

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

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