Wheat biomass estimation in different growth stage based on color and texture features of UAV images

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Abstract: In order to realize rapid and nondestructive monitoring of wheat biomass in field, field experiments based on different densities, nitrogen fertilizer and variety treatments were studied. RGB images of wheat in the main growth stage were obtained by UAV, and wheat color and texture feature indices were obtained by image processing, and wheat biomass was obtained by field sampling in the same period. Then the relationship between different color and texture feature indices and wheat biomass was analyzed to select the color and texture feature index suitable for wheat biomass estimation. The results showed that there was a high correlation between image color index and wheat biomass in different stages, and most of them reached a very significant correlation level. However, the correlation between image texture feature index and wheat biomass was poor, only a few indexes reached significant or extremely significant correlation level. Based on the above results, the color indices with the highest correlation to wheat biomass or the combining indices of color and texture feature in different growth stage were used to construct estimation model of wheat biomass. The models were validated using independently measured biomass data, and the correlation between simulated and measured values reached the significant level, RMSE were smaller. This indicated that the estimated results by the models were reliable and accurate. It also showed that the estimation models of wheat biomass combined with color and texture feature indices of UAV image were better than the single color index models. The results would provide a new method for real-time monitoring of wheat field growth and biomass estimation.

Keywords: wheat; UAV image; color index; texture feature index; biomass

1. Introduction

Biomass is one important physical and chemical parameter in ecosystems and is a significant index for assessing the life activities of vegetation and for monitoring growth and estimating crop yield[1-3]. Traditional biomass estimation methods are not only time-consuming and labor-intensive, but also fail to achieve large-scale biomass monitoring[4]. The rapid development of remote sensing technology in recent years has resulted in its wide application in crop biomass estimation, as it is fast, accurate, and non-destructive[2].

Based on the spectral features of vegetation, previous studies have made some progress in using vegetation indices to estimate biomass. Shibayama et al[5] constructed an effective rice biomass estimation model based on the difference and ratio vegetation indices. Hou et al[6] produced a biomass estimation model based on multiple vegetation indices, of which the index model of red edge location was used to estimate the wheat biomass model, achieving high accuracy. Liu et al[7] used arbor as an object to analyze the correlation between biomass and biomass factors, and constructed a highly accurate forest biomass estimation model using the partial least-squares method. However, the vegetation index is not sensitive to canopy biomass changes in high density scenarios and deviates easily when inverting physical and chemical parameters or even agronomic parameters, thus affecting the accuracy of the estimation model[8]. In response, some scientists have added texture feature information to the spectral features to improve saturation when only spectral information is available, as well as to improve the spatial and temporal discrimination of image information and the estimation potential of agronomic parameters[9].

Many scholars have quantitatively analyzed the application of texture features in agronomic parameters. Gu et al[10] studied vegetation coverage and found that the combination of vegetation indices and texture feature indices could improve the accuracy of vegetation coverage estimation. Sarker et al[11] assessed the biomass of arbor forest and found that the combination of vegetation indices and texture features is better at biomass estimation. Cao et al[12] extracted the texture features and spectral features of thematic mapper (TM) images and established a biomass regression estimation model, which could effectively estimate the biomass of mangrove wetlands. Muqier et al[13] constructed a multivariate regression model of vegetation indices, texture features, and vegetation biomass using four typical vegetation indices, achieving good results. Based on the above research, it was found that the accuracy of the model for estimating biomass in combination with texture features is higher than the accuracy of the model for estimating biomass using a single vegetation index[14].

In terms of monitoring crop growth based on Unmanned Aerial Vehicle (UAV) images, Lee et al[15] used RGB (red green blue) cameras to obtain rice canopy images and showed that the absolute value of green light depth (G) simulated by the exponential equation is well correlated with the aboveground biomass and leaf area index (LAI). Wang et al[16] demonstrated that the G-R value of rice RGB images has a good relationship with biomass and LAI, which can be used to construct an estimation model. Li et al[17] extracted wheat plants from wheat canopy images using image threshold segmentation and established the LAI inversion model to estimate the wheat LAI. Hunt et al[18] constructed the normalized green-red difference index (NGRDI) from the G vector and the R vector and the number of pixels in the RGB image and used this index to estimate the biomass of corn and soybean. Shan et al[19] used digital image processing technology to explore the vertical distribution of wheat biomass and found that a linear regression relationship could be better obtained with a single row of wheat images. The estimation accuracy was also higher.

In this study, UAVs were used to obtain RGB images of wheat in different reproduction periods, and simultaneous sampling was conducted in the field to determine wheat biomass. The best color and texture feature indices were determined through correlation analysis, and these indices were used to construct the estimation models of wheat biomass in different reproduction periods based on a UAV platform in order to provide a new means for biomass estimation and real-time monitoring of wheat growth in the field.

2. Materials and Methods

2.1. Field experiment design

There were two experiments in this study, of which the data from experiment 1 were used to construct a wheat biomass estimation model and the data from experiment 2 were used for model validation. Study sites were located in Yizheng and Zhangjiagang, Jiangsu Province (Figure 1).

2.1.1. Experiment 1

The experiment was conducted in Yizheng from 2017 to 2018. Two varieties of Yangmai 23 and Yangfumai 4 were selected as the research objects. In the field trial, three planting density were respectively set: 1 million plants·ha^{-1}, 1.5 million plants·ha^{-1}, and 2 million plants·ha^{-1}; and four nitrogen fertilizer levels were respectively set: 0 kg·ha^{-1} , 120 kg·ha^{-1} , 160 kg·ha^{-1} , 200 kg·ha^{-1}. Nitrogen fertilizers were applied according to the ratio of base fertilizer: new shoots boosting fertilizer: jointing fertilizer: booting fertilizer = 5:1:2:2, and the phosphorus and potassium fertilizers were applied according to the ratio of base fertilizer: jointing fertilizer=5:5, and the application amounts all were 120 kg·ha^{-1}. Wheat was planted on November 2, 2016, with a plot area of 16.65 m^2. Each treatment was repeated twice for a total of 48 experimental plots.

2.1.2. Experiment 2

The experiment was conducted in Zhangjiagang from 2016 to 2017. The tested variety, density, and fertilizer were the same as trial 1. Wheat was planted on November 10, 2017, with a plot area of 30 m^2. Each treatment was repeated twice for a total of 48 experimental plots.

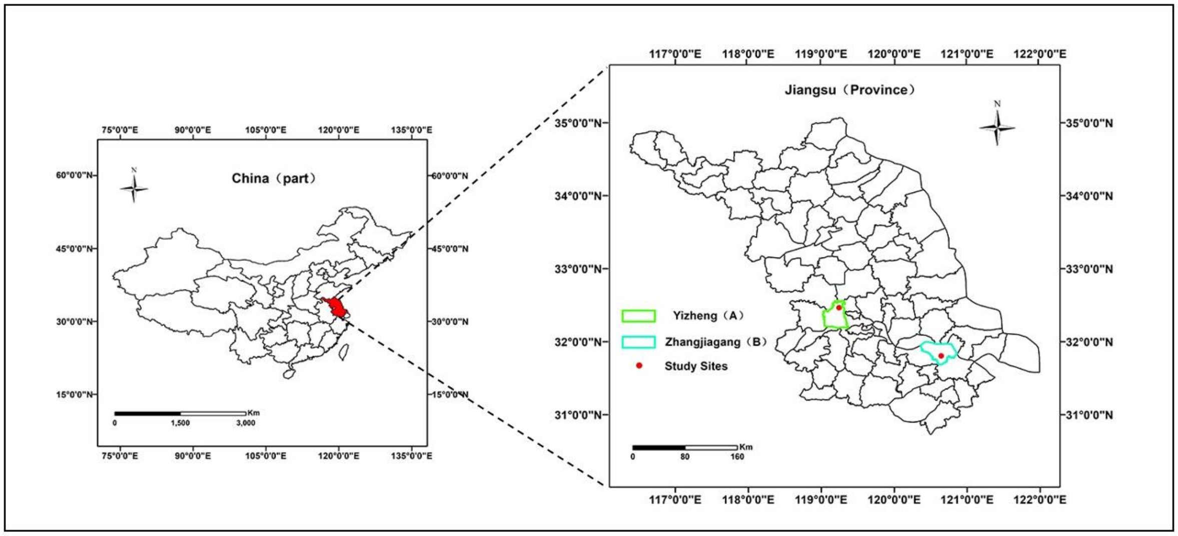

Figure 1.Study sites: (A) Yizheng city, rice and wheat rotation field; (B) Zhangjiagang city, rice and wheat rotation field

2.2. Data acquisition method

2.2.1. Image acquisition device

We used the DJI Inspire 1 RAW UAV for image data acquisition. UAVs are small, heavy, powerful, and convenient and easy to operate. A UAV is able to fly for about 15–20 min depending on the load and battery. The remote control was connected to the wireless follower to extend the control distance to 5 km.

2.2.2. Image acquisition process

The periods of UAV image acquisition included the pre-winter period, jointing period, booting period, and flowering period. In order to ensure the safety of aircraft flight and the availability of data, the aircraft was set for the waypoints, routes, flight heights, and image repetition rates after installation[20].

2.2.3. Determination of aboveground biomass

In the pre-winter period, jointing period, booting period, and flowering period of wheat growth, we selected 15 wheat plants from each plot, removed the upper part, transported the material back to the laboratory, dried it in an oven for half an hour at 105°C and then at 80°C until constant weight, and then weighed and converted to biomass per unit area.

2.3. Data analysis and utilization

2.3.1. UAV image preprocessing method

MATLAB2014a software was used for UAV image preprocessing. Image preprocessing includes image cropping, denoising, smoothing, and sharpening. Image cropping stitches the images into uniform images according to different cells. Denoising eliminates the noise in digital images. Smoothing and sharpening reduce the slope of the image, improve the quality, and reduce the loss of pixel extraction from the target.

2.3.2. Introduction to color indices

There are many types of image color indices. In this study, eight commonly used color indices were selected for UAV image data analysis, including Visual Atmospheric Resistance Vegetation Index (VARI), Excess Red Vegetation Index (ExR), Excess Green Vegetation Index (ExG), Green Leaf Vegetation Index (GLI), Green Red Difference Index (ExGR), Normalized Difference Index (NDI), Modified Green Red Vegetation Index (MGRVI) and Red Green Blue Vegetation Index (RGBVI).

2.3.3. Introduction to texture indices

We used MATLAB software to extract texture features based on a gray level co-occurrence matrix[21]. We extracted four common texture features from the UAV image: energy(ASM), contrast(CON), correlation(COR) and entropy(ENT).

2.4. Model construction and evaluation

Based on the correlation between image color and texture feature indices and wheat biomass, the color and texture feature index with the largest correlation coefficient was selected to construct a single or multiple regression model for biomass estimation (trial 1 data). The independent measured biomass data were then used to validate and evaluate the model based on the coefficient of determination (R^2), root mean square error (RMSE), and 1:1 map (trial 2 data).

3. Results

3.1. Correlation between wheat biomass and image color/texture feature indices in different reproduction periods

Wheat biomass experiences various changes throughout the reproduction period and undergoes a process of continuous increase. In this study, we used the data in trial 1 to quantitatively analyze the correlation between eight color indices as well as four texture feature indices in the main reproduction periods of wheat and biomass to determine the optimal color index and texture feature index for estimating biomass. The correlation between the different color indices as well as the texture feature indices and biomass based on the UAV image is shown in Tables 1 and 2.

Table 1. Correlations between different color indices and wheat biomass based on UAV image(n=24)

Growth stage	ExG	VDI	ExR	ExGR	VARI	GLI	MGRVI	RGBVI
Pre-wintering stage	0.594**	0.458*	-0.619**	0.678**	0.743**	0.657**	0.706**	0.598**
Jointing stage	0.813**	0.823**	-0.824**	0.911**	0.817**	0.809**	0.687**	0.625**
Booting stage	0.493*	0.793**	-0.779**	0.607**	0.734**	0.483*	0.817**	0.351
Flowering stage	0.367	0.540**	-0.652**	0.463*	0.679**	0.369	0.540**	0.316

Note: * P < 0.05, ** P < 0.01 (r0.05=0.396, r0.01=0.505).

Table 2. Correlations between different Texture feature indices and wheat biomass based on UAV image

Growth stage	ASM	CON	COR	ENT
Pre-wintering stage	0.573**	0.195	-0.132	-0.564**
Jointing stage	0.271	0.511**	-0.574**	-0.072
Booting stage	-0.200	0.417*	-0.351	0.260
Flowering stage	-0.222	0.123	-0.167	0.126

3.2. Biomass estimation models for wheat growth in different reproduction periods based on color indices

3.2.1. Model construction

3.2.1.1. Estimation model of wheat biomass in the pre-winter period

It can be seen from Table 1 that the correlation between the color indices of the UAV image and biomass was good during this period. Except for NDI, the correlation between the other seven indices and biomass was extremely significant, among which the correlation of VARI and biomass was the highest, with the correlation coefficient r reaching 0.743. Therefore, the color index VARI was chosen as the independent variable. The wheat biomass estimation model B=535.9×VARI+87.9 was constructed by regression analysis, and the coefficient of determination

R^2 was 0.553. The results are shown in Table 3, where B represents the biomass (kg·ha^{-1}) of wheat in this period.

3.2.1.2. Estimation model of wheat biomass in the jointing period

The correlation between the color indices and biomass of the UAV image in the jointing period was the best, and eight color indices reached a highly significant correlation level (Table 1). Among them, ExGR had the highest correlation with biomass, and the correlation coefficient r reached 0.911. Therefore, the color index ExGR was selected as the independent variable, and the wheat biomass estimation model B=9054.6×ExGR+1915.5 was constructed by regression analysis, with a coefficient of determination R^2 of 0.804.

3.2.1.3. Estimation model of wheat biomass in the booting period

With the gradual advancement of wheat growth and the increasing biomass, the color of the UAV image will become saturated, and its correlation with biomass will be correspondingly weakened. The correlation between UAV image color indices and biomass in the booting period was significantly lower than that in the jointing period. Only six indices were significantly correlated (Table 1). Among them, MGRVI had the highest correlation with biomass, and the correlation coefficient r was 0.817. Therefore, the color index MGRVI was chosen as the independent variable, and the wheat biomass estimation model B=20024.1×MGRVI−543.2 was constructed by regression analysis, with an R^2 of 0.670.

3.2.1.4. Estimation model of wheat biomass in the flowering period

The canopy image in the flowering period contains different types of objects such as the ear and leaf, and the correlation between image color indices and biomass is further reduced. During this period, the correlation between the UAV image color indices and biomass was the lowest among the four periods, three of which being non-significant, one being significantly correlated, and the other four reaching extremely significant levels (Table 1), of which the correlation of VARI and biomass was the highest and the correlation coefficient r was 0.679. Therefore, the color index VARI was selected as the independent variable, and the wheat biomass estimation model B=42623.1×VARI+7115.3 was constructed by regression analysis, and the R^2 was 0.461. The results were shown in table 3.

Table 3. Estimation models of wheat biomass at different growth stages based on color indices

Growth stage	Models	R^2
Pre-wintering stage	B=535.9×VARI+87.9	0.553
Jointing stage	B=9054.6×ExGR+1915.5	0.804

Booting stage	B=20024.1×MGRVI-543.2	0.670
Flowering stage	B=42623.1×VARI+7115.3	0.461

3.2.2. Model validation

3.2.2.1. Validation of the wheat biomass estimation model in the pre-winter period

The independently measured data were used to validate the wheat biomass estimation model in the pre-winter period and plot the 1:1 relationship between the measured values and the model predictions (Figure 2-A). It is evident from the figure that there was good agreement between the predicted and measured values of wheat biomass in the pre-winter period, and the predicted R^2 of the model was 0.538. Correlation analysis showed that the correlation between the predicted value and the measured value reached a highly significant level, indicating that the estimation model is feasible. In addition, the simulated RMSE was 27.88 $kg \cdot ha^{-1}$, which is relatively small, indicating that the simulation results of the model are relatively reliable.

3.2.2.2. Validation of the wheat biomass estimation model in the jointing period

The validation results of the estimation model in the jointing period are shown in Figure 2-B. The predicted value of wheat biomass in the jointing period was close to the measured value, and there was good consistency between the two. The predicted R^2 of the model was 0.631, and the effect was better than the pre-winter period. Correlation analysis indicated that the correlation between the predicted value and the measured value reached a highly significant level, indicating that the estimation model is feasible. In addition, the simulated RMSE was 516.99 $kg \cdot ha^{-1}$, which is relatively small, indicating that the simulation results of the model are relatively reliable.

3.2.2.3. Validation of the wheat biomass estimation model in the booting period

The results of the estimation model in the booting period are shown in Figure 2-C. It can be seen from the figure that the predicted value of wheat biomass in the booting period was close to the measured value, and there was good consistency between the two. The predicted R^2 of the model was 0.708, and the effect was better than the jointing period. Correlation analysis indicated that the correlation between the predicted value and the measured value was significant, indicating that the estimation model is feasible. In addition, the simulated RMSE was 868.26 $kg \cdot ha^{-1}$, which is relatively small, indicating that the simulation results of the model are relatively reliable.

3.2.2.4. Validation of the wheat biomass estimation model in the flowering period

The validation results of the estimation model in the flowering period are shown in Figure 2-D. The predicted value of wheat biomass in the flowering period was close to the measured value, and there was good agreement between the two. The model predicted an R^2 of 0.464, and the effect was the worst among the four periods. However, the correlation analysis demonstrated a correlation between the predicted value and the measured value, indicating that the estimation model is feasible. In addition, the simulated RMSE was 1539.81 kg·ha^{-1}, which is relatively small, indicating that the simulation results of the model are relatively reliable.

In summary, the UAV image color indices could be used to estimate wheat biomass in different reproduction periods, and the effects in the different periods also differed. However, wheat biomass estimation using a single color index did not achieve the best results.

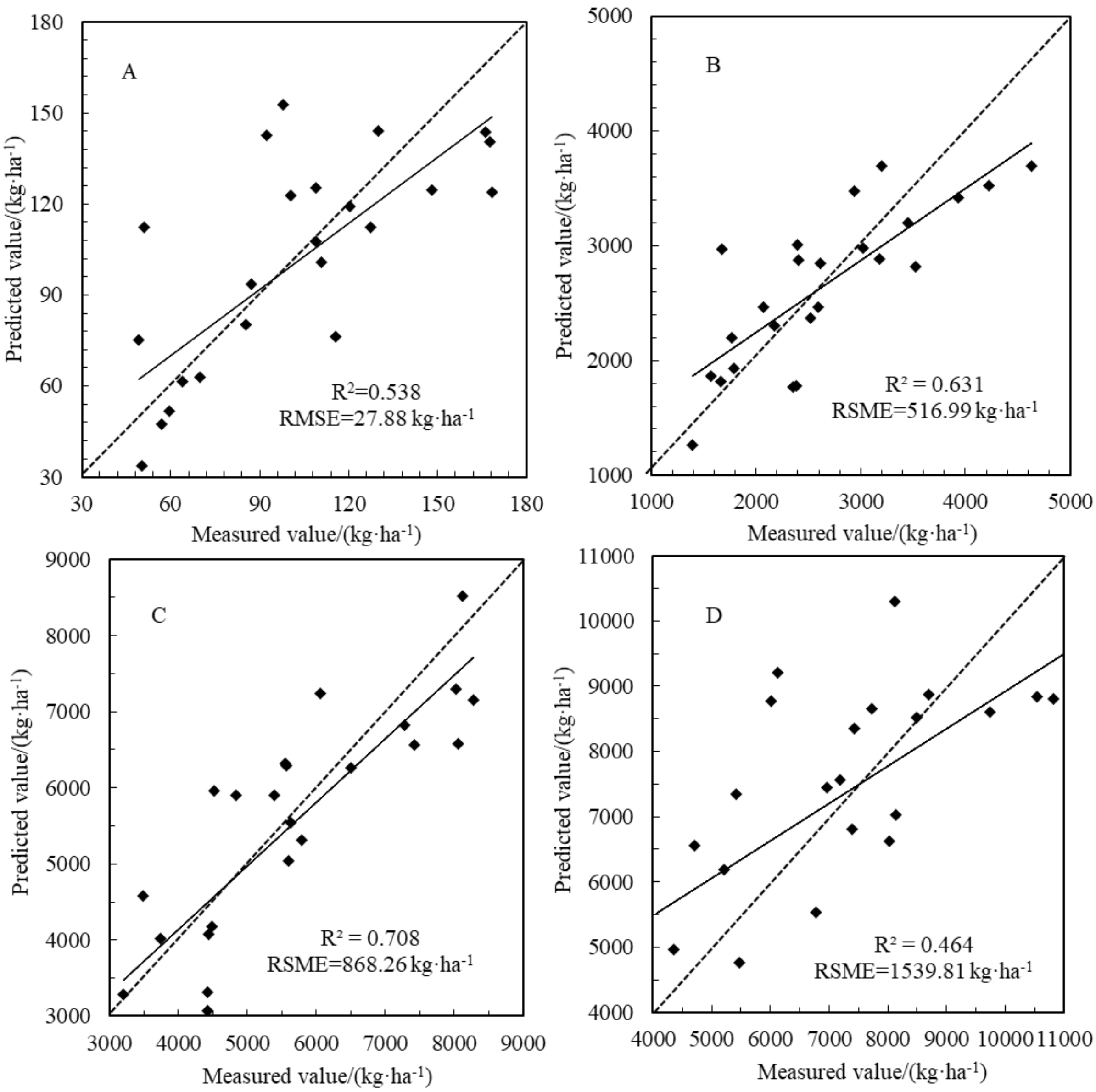

Figure 2. Verification of wheat biomass estimation models based on color indices (A: pre-wintering stage; B: jointing stage; C: booting stage; D: flowering stage)

3.3. Wheat biomass estimation models in different reproduction periods based on color and texture feature indices

3.3.1. Model construction

3.3.1.1. Estimation model of wheat biomass in the pre-winter period

It can be seen from Table 2 that the correlation between UAV image texture indices and biomass in the pre-winter period was good, but was worse than the color indices. Among the four texture feature indices, two were not significantly correlated, whereas the other two were significantly correlated, of which ASM had the highest correlation with biomass, with a correlation coefficient of 0.573. Therefore, the texture feature index ASM was combined with the color index VARI, and the wheat biomass estimation model B=547.9×VARI−35.9×ASM+97.2 was constructed by multiple regression analysis. The R^2 was 0.565, and the accuracy was slightly improved compared with the single color index model (2.17% increase). The results are shown in Table 4.

3.3.1.2. Estimation model of wheat biomass in the jointing period

From the pre-winter period to the jointing period, the UAV image texture indices did not improve significantly. Among the four texture feature indices, only two had a significant correlation with biomass, with COR exhibiting the highest correlation with an r of 0.574 (Table 2). Therefore, the texture feature index COR was combined with the color index ExGR. The wheat biomass estimation model B=8762.5×ExGR−259.4×COR+2075.8 was constructed by multiple regression analysis. The R^2 was 0.833, and the accuracy was improved compared with the single color index model (3.61% increase).

3.3.1.3. Estimation model of wheat biomass in the booting period

The colors of the wheat UAV images in the booting period showed a certain saturation phenomenon, and the texture feature indices were also affected. Among the four texture feature indices, only one (CON) was significantly correlated with biomass, with an r of 0.417 (Table 2). Therefore, the texture feature index CON was combined with the color index MGRVI, and the wheat biomass estimation model B=24027.4×MGRVI−3098.6×CON+2252.3 was constructed by multiple regression analysis. The R^2 was 0.762, and the accuracy was significantly improved compared with the single color index model (13.73% increase).

3.3.1.4. Estimation model of wheat biomass in the flowering period

The correlation between UAV image texture feature indices and wheat biomass in the flowering period was relatively poor, and the correlation between the four feature indices and wheat biomass did not reach a significant correlation level(Table 2). Therefore, the index ASM with the largest correlation coefficient was selected and combined with the color index VARI. The wheat biomass estimation model B=42654.9×VARI−5595.3×ASM+8507.9 was constructed by multiple regression analysis, and the R^2 was 0.485. The accuracy was much higher than the single color index model (5.21.% increase). The results were shown in table 4.

Table 4. Estimation models of wheat biomass at different growth stages based on color and texture feature indices

Growth stage	Models	R^2
Pre-wintering stage	B=547.9×VARI-35.9×ASM+97.2	0.565
Jointing stage	B=8762.5×ExGR-259.4×COR+2075.8	0.833
Booting stage	B=24027.4×MGRVI-3098.6×CON+2252.3	0.762
Flowering stage	B=42654.9×VARI-5595.3×ASM+8507.9	0.485

3.3.2. Model validation

3.3.2.1. Validation of the wheat biomass estimation model in the pre-winter period

The independently measured data were used to validate the wheat biomass estimation model in the pre-winter period, and the 1:1 relationship between the measured values and the model predictions was plotted (Figure 3-A). There was good agreement between the predicted value of wheat biomass and the measured value in the pre-winter period. The predicted R^2 of the model was 0.571, which was much better than the single color index model (6.13% increase). Correlation analysis showed that the correlation between the predicted value and the measured value was significant, indicating that the estimation model is feasible. In addition, the simulated RMSE was 25.49 $kg \cdot ha^{-1}$, which was smaller than the RMSE of the single color index model (reduced by 8.57%), indicating that the reliability of the model had been further improved.

3.3.2.2. Validation of the wheat biomass estimation model in the jointing period

The validation results of the jointing estimation model are shown in Figure 3-B. It can be seen from the figure that the predicted value of wheat biomass in the jointing period was close to the measured value, and there was good agreement between the two. The predicted R^2 of the model was 0.658, which is better than the pre-winter period, and the prediction accuracy was improved compared to the single color index model (4.28% increase). Correlation analysis indicated that there was a correlation between the predicted value and the measured value, indicating that the estimation model is feasible. The simulated RMSE was 443.20 $kg \cdot ha^{-1}$, which was significantly smaller than the RMSE of the single color index model (14.27% decrease), indicating that the reliability of the model had been greatly improved.

3.3.2.3. Validation of the wheat biomass estimation model in the booting period

The validation results of the booting period estimation model are shown in Figure 3-C. The predicted value of wheat biomass in the booting period was close to the measured value, and there was good consistency between the two. The model predicted an R^2 of 0.753, which was better than the jointing period, and the prediction accuracy was greatly improved compared to the single color index model (6.36% increase). Correlation analysis indicated that the correlation between the predicted value and the measured value was significant, indicating that the estimation model is feasible. In addition, the simulated RMSE was 816.25 $kg \cdot ha^{-1}$, which was smaller than the RMSE of the single color index model (5.99% decrease), indicating that the reliability of the model had been improved.

3.3.2.4. Validation of the wheat biomass estimation model in the flowering period

The validation results of the flowering period estimation model are shown in Figure 3-D. The predicted value of wheat biomass in the booting period was close to the measured value, and there was good agreement between the two. The predicted R^2 of the model was 0.515, and the prediction accuracy was greatly improved compared to the single color index model (10.99% increase). Correlation analysis indicated that the correlation between the predicted value and the measured value was significant, indicating that the estimation model is feasible. In addition, the simulated RMSE was 1396.97 $kg \cdot ha^{-1}$, which was smaller than the RMSE of the single color index model (reduced by 9.28%), indicating that the reliability of the model had been improved.

Based on the above results, the biomass estimation model of wheat in different reproduction periods based on the combination of UAV image color and texture feature indices was significantly improved over the single color index model and can be used to estimate the biomass of wheat in different reproduction periods.

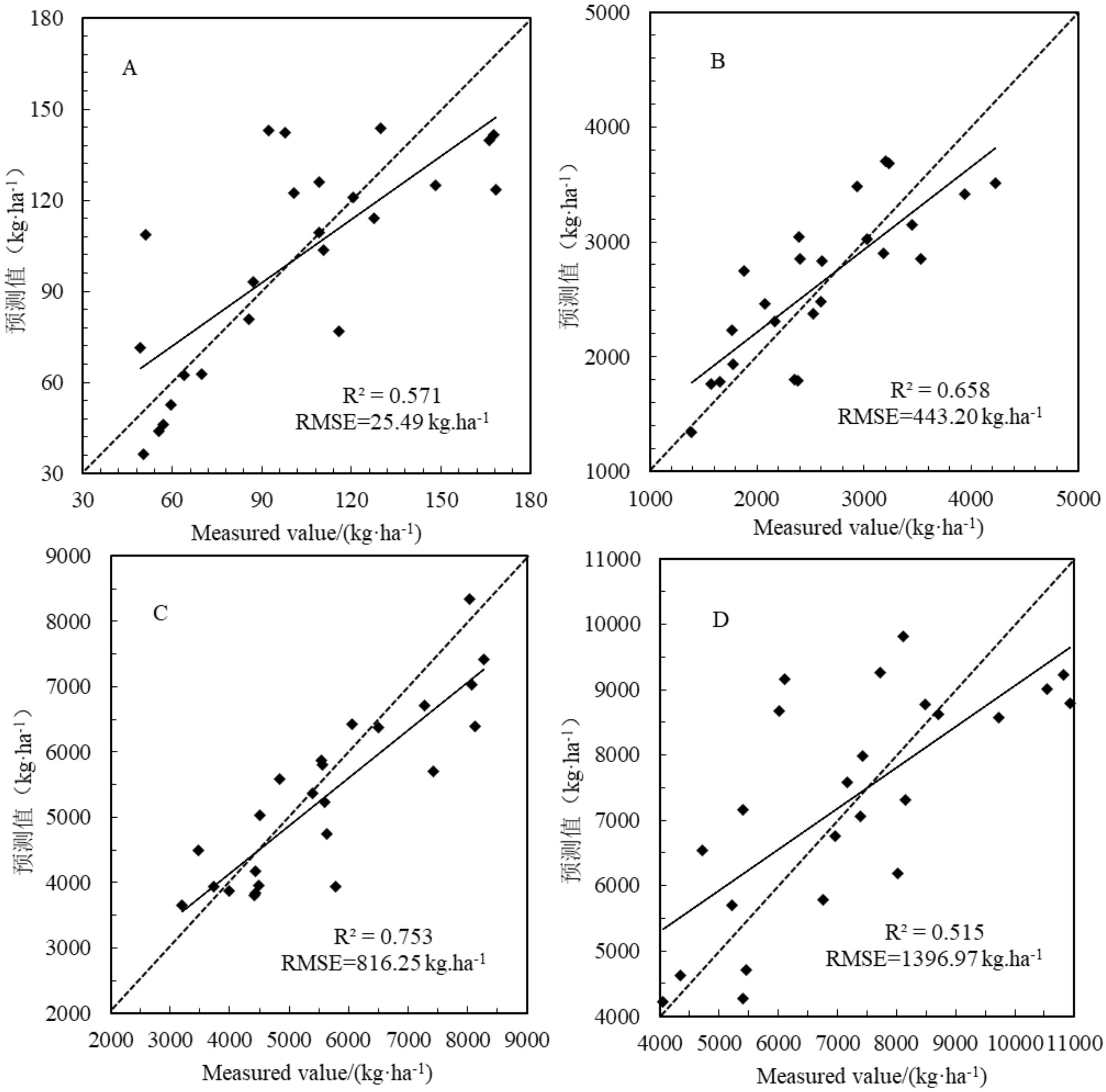

Figure 3. Verification of wheat biomass estimation models based on color and texture feature indices (A: pre-wintering stage; B: jointing stage; C: booting stage; D: flowering stage)

4. Discussion

At present, few studies have monitored growth indices such as wheat biomass using the RGB image data of UAVs. Hunt et al[22] obtained wheat canopy images using UAVs and used the vegetation indices NDVI and GNDVI to monitor wheat growth in order to validate the use of UAV images in wheat growth monitoring. However, this approach was hindered by great insensitivity. In this study, the RGB images collected in the four key reproduction periods of wheat were systematically analyzed. The image information was extracted, and eight common color indices and four texture feature indices were calculated. The best performing color index and texture feature index were selected by correlation analysis. The results showed that the biomass estimation model constructed using a single color index reduced the estimation effect due to the saturation of the image in the late reproduction period of wheat. In order to solve the above problems, the UAV image color and texture feature indices were combined to establish a multivariate model of wheat biomass estimation based on two types of indices, and the model was tested using independent measured biomass data, achieving an overall better performance than a single color index model.

Other studies have combined image color indices with other indices to estimate crop yield or biomass. For example, Lu et al. used UAV image data and point cloud data to estimate the aboveground biomass of wheat. Compared to the use of single color data, the model with combined indices improved the estimation accuracy[23]. Duan et al established a new method combining the vegetation indices based on UAV images and the abundance information obtained from spectral mixture analysis (SMA). The results showed that the vegetation index with abundance information exhibited better predictive ability for rice yield than the vegetation index alone[24]. Li et al used a combination of spectral and morphological features of UAV images to monitor the biomass and nitrogen and chlorophyll content of sorghum. The results showed that the biomass obtained from the image color, plant height, and canopy coverage of the UAV image was strongly correlated with fresh stem/leaf biomass and dry stem/leaf biomass[25]. The above results demonstrate that combining the color indices of UAV images with different indices, such as shape, texture, and coverage, can improve the estimation effect of the model.

In addition, previous studies often only monitored the biomass in a certain reproduction period of the crop due to image availability or other constraints, and thus the results are difficult to extrapolate. In this study, UAV images of the four key reproduction periods of wheat were analyzed, and the dynamic monitoring model of wheat biomass based on the UAV platform was established. The model was tested using independent measured data, and the results were all reliable, indicating that it is feasible to dynamically monitor wheat biomass using an UAV platform equipped with a digital camera, which is suitable for small and medium area applications. However, in the future, UAVs will be equipped with many types of cameras. Therefore, in future research, information such as the spectrum, color, and texture of the image could be comprehensively used to improve the monitoring accuracy and range.

5. Conclusion

We first identified the color index and texture feature index that were optimally correlated with wheat biomass. Among the eight color indices, most of the correlations with wheat biomass were significant, and the correlation of VARI in the pre-winter period was the strongest at r=0.743**; the correlation of ExGR in the jointing period was the strongest at r= 0.911**; the correlation of MGRVI in the booting period was strong at r=0.817**; and the correlation of VARI in the flowering period was strong at r=0.679**. The correlation between the four image texture feature indices and wheat biomass was poor, and only a few indices reached significant correlation levels. Using the color indices VARI, ExGR, MGRVI, and VARI, the biomass estimation models of wheat in the pre-winter, jointing, booting, and flowering periods were constructed, and the wheat biomass estimation multivariate models were constructed by combining the texture feature indices with the highest correlation with wheat biomass. Finally, the models were validated using independently measured biomass data. The results showed that both types of estimation models passed the significance test, with the correlation reaching a very significant level and the RMSE being small. We also found that the wheat biomass estimation model combined with the UAV image color and texture feature indices was better than the single color index model.

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References

1. Li, J.J. Monitoring bio-physical and bio-chemical parameters of wheat by hyper-spectral remote sensing. Nanjing: Nanjing University of Information Science & Technology, 2015.
2. Zhang, K., Wang, R.Y., Wang, X.P., Zhao, H., Han, H.T. Hyperspectral remote sensing estimation models for aboveground fresh biomass of spring wheat on Loess Plateau. Chinese Journal of Ecology, 2009, 28(6), 1155-1161.
3. Shang, Y. Wheat canopy spectral features and its research relationship with agronomy parameter under different nitrogen levels.Shanxi: Northwest A&F University, 2015.

4. Fan, Y.B., Gong, Z.N., Zhao, W.J., Zhang, M. Study on vegetation biomass inversion method based on hyperspectral remote sensing. Journal of Hebei Normal University(Natural Science Edition) , 2016, 3, 267-271.
5. Shibayama, M, Akiyama, T. Seasonal visible, near-infrared and mid-infrared spectra of rice canopies in relation to LAI and above-ground dry phytomass. Remote Sensing of Environment, 1989, 27(2), 119-127.
6. Hou, X.H., Niu, Z., Huang, N., Xu, S.G. The hyperspectral remote sensing estimation models of total biomass and true lai of wheat. Remote Sensing for Land & Resources, 2012, 24(4), 30-35.
7. Liu, Q.G., Peng, D.L., Tu, Y.Y., Li, Y.L., Gao, D.Q. Estimating forest biomass by partial least squares regression. Journal of Northeast Forestry University, 2014, 7, 44-47.
8. Chen, P.F., Nicolas, T., Wang, J.H., Philippe, V., Huang, W.J., Li ,B.G. New index for crop canopy fresh biomass estimation. Spectroscopy and Spectral Analysis, 2010, 30(2), 512-517.
9. Li, J.T., Shi, Y.Y., Veeranampalayam-Sivakumar, A., Schachtman, D.P. Elucidating Sorghum Biomass, Nitrogen and Chlorophyll Contents With Spectral and Morphological Traits Derived From Unmanned Aircraft System. Frontiers in Plant Science, 2018, 9, 1-12.
10. Gu, Z.J., Ju, W.M., Li, L., Li, D.Q., Liu, Y.B., Fan, W.L. Using vegetation indices and texture measures to estimate vegetation fractional coverage (VFC) of planted and natural forests in Nanjing city, China. Advances in Space Research, 2013, 51(7), 1186-1194.
11. Sarker, L.R., Nichol, J.E. Improved forest biomass estimates using ALOS AVNIR-2 texture indices. Remote Sensing of Environment, 2011, 115(4), 968-977.
12. Cao, Q.X., Xu, D.P., Ju, H.B. The biomass estimation of mangrove community based on the textural features and spectral information of TM images. Forest Resources Management, 2010, 6, 102-108.
13. Mu, Q.E., Gao, Z.H., Bao, Y.H., Wang, B.Y., Bai, L.N. Estimation of sparse vegetation biomass based on grey-level co-occurrence matrix of vegetation indices. Remote Sensing Information, 2016, 1, 58-63.
14. Liu, C., Yang, G.J., Li, Z.H., Tang, F.Q., Wang, J.W., Zhang, C.L., Zhang, L.Y. Biomass estimation in winter wheat by UAV spectral information and texture information fusion. Scientia Agricultura Sinica, 2018, 51(16), 3060-3073.
15. Lee, K.J., Lee, B.W. Estimation of rice growth and nitrogen nutrition status using color digital camera image analysis. European Journal of Agronomy, 2013, 48(3), 57-65.
16. Wang, Y., Wang, D.J., Zhang, G., Wang, J. Estimating nitrogen status of rice using the image segmentation of G-

R thresholding method. Field Crops Research, 2013, 149(149), 33-39.

17. Li, Y., Chen, D., Walker, C.N., Angus, J.F. Estimating the nitrogen status of crops using a digital camera. Field Crops Research, 2010, 118(3), 221-227.
18. Hunt, E.R., Cavigelli, M., Daughtry, C.S.T., Mcmurtrey III, J.E., Walthall, C.L. Evaluation of digital photography from model aircraft for remote sensing of crop biomass and nitrogen status. Precision Agriculture, 2005, 6(4), 359-378.
19. Shan, C.G., Liao, S.H., Gong, Y., Liang, Z.X., Wang, P. Application of Digital Image Processing for Determination of Vertical Distribution of Biomass in the Canopy of Winter Wheat. Acta Agronomica Sinica, 2007, 33(3), 419-424.
20. Chen, W. Evsluation of seed emergence unifermity of wheat based on UAV image. Yangzhou: Yangzhou Univefrsity, 2018.
21. Haralick, R.M., Shanmugam, K., Dinstein, I. Textural features for image classification. IEEE Transactions on Systems Man & Cybernetics, 1973, 3(6), 610-621.
22. Hunt, E.R., Hively, W.D., Fujikawa, S.J., Linden, D.S., Daughtry, C.S.T, McCarty, G.W. Acquisition of NIR-Green-Blue digital photographs from unmanned aircraft for crop monitoring. Remote Sensing, 2010, 2(1), 290-305.
23. Lu, N., Zhou, J., Han, Z.X., Li, D., Cao, Q., Yao, X., Tian, Y.C., Zhu, Y., Cao, W.X., Cheng, T. Improved estimation ofaboveground biomass in wheat from RGB imagery and point cloud data acquired withalow‑cost unmanned aerial vehicle system. Plant Methods, 2019, 15, 1-16.
24. Duan, B., Fang, S.H., Zhu, R.S., Wu, X.T., Wang, S.Q., Gong, Y., Peng ,Y. Remote Estimation of Rice Yield With Unmanned Aerial Vehicle (UAV) Data and Spectral Mixture Analysis. Frontiers in Plant Science, 2019,10, 1-14.
25. Liu, J., Bi, H.X., Zhu, P.L., Sun, J., Zhu, J.Z., Chen, T. Estimating stand volume of xylosma racemosum forest based on texture parameters and derivative texture indices of ALOS imagery. Transactions of the Chinese Society for Agricultural Machinery, 2014, 45(7), 245-254..