GRAIN STARCH ESTIMATION USING HYPERSPECTRAL DATA AND ITS RELATIONSHIP WITH LEAF WATER CONTENTS FOR BROOMCORN MILLET (*PANICUM MILIACEUM* L.)

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Abstract. The analysis of grain starch content is one of the main indices to determine crop quality. The experiment was performed using two broomcorn millet varieties (Neimi 2 and Ningmi 14) in northern China, having 5 different sowing dates. The prediction models for grain starch fraction were constructed by integrating the spectral models and grain starch content with leaf water content using the intersection approach. We have identified 468, 630, 806, and 1488 nm as characteristic bands of the first derivative spectrum having a positive correlation. The correlation coefficient between the vegetation index of 608 nm and 1488 nm was significantly higher than other characteristic bands regarding leaf water contents. It is therefore identified that RDVI (1488, 806) could be used effectively to monitor leaf water content of broomcorn millet under different sowing date treatments, $R^2 = 0.7075$, RMSE = 0.073, RPD = 1.430 in the calibration set, $R^2 = 0.8458$, RMSE = 0.042, RPD = 2.546 in the validation set. In addition, the monitoring models of RVI (1488, 806), RDVI (1488, 806), and PVI (1488, 806) were superior to other models, and RPD was 0.020, 1.978, and 1.904, respectively. Overall, the RDVI (1488, 806) monitoring model, due to its stability and higher accuracy provided precise data on the grain starch fraction of broomcorn millet.
Keywords: *sowing dates, vegetation index, crop, agronomic parameters, remote sensing*

Introduction

Prolonged or transient water stress negatively affects crop growth and development, leading to crop yield and quality reductions (Jackson et al., 1982; Gupta et al., 2020; Hunter et al., 2021; García-León et al., 2021). It has been reported that cereal crops under water stress conditions tend to accumulate compatible solutes of osmolytes to counter osmotic imbalance and reduce water potential (Shafiq et al., 2018). A significant part of photosynthates is diverted towards roots to counter water imbalance and to tolerate drought stress. The ultimate result is a reduction in starch accumulation and its composition due to imbalanced photoassimilate transport (Prathap et al., 2019). Therefore, the analysis of grain starch content is one of the important indexes to evaluate its quality. The grain starch content directly affects its taste quality and processing quality, such as flavor, gelatinization temperature, etc. With the improvement of people's living standards, people have higher and higher requirements for quality, so it is particularly important to study the starch content of broomcorn millet.

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Broomcorn millet also called proso millet, is a minor cereal crop mainly cultivated in dry and nutrient-poor soils by poor farmers. It is essential to mention here that millets are small-seeded annual cereals. About 20 different species are cultivated globally for food, forage, and fuel purposes, feeding about one-third of the global population (Fuller, 2006; Amadou et al., 2013; Changmei and Dorothy, 2014). Millets can grow on relatively less productive soils and serve as an essential food source to counter food insecurity. The broomcorn millet (*Panicum miliaceum*) has a somewhat shorter growing season of about 60-100 days (Habiyaremye et al., 2017) and was a warm-season grass member from the PACCAD (Panicoideae, Arundinoideae, Chloridoideae, Centothecoideae, Aristidoideae, Danthonioiseae) clade (GPWG, 2001) and is domesticated in China sometime around 10,000 BP (Before Present). Because of its strong drought resistance, barren tolerance, and shorter life cycle, some growers tend to cultivate this crop to compensate for the economic losses (Ravi, 2004; Brahmachari et al., 2019). Besides, the sowing time range for broomcorn millet is relatively broad; it has become an increasing trend to quickly and accurately obtain the starch content of the broomcorn millet for commercial harvests.

Different physiological plant indices, including leaf water contents, can be determined using hyperspectral data or a remote sensing approach (Miao et al., 2015; Han et al., 2018; Wang et al., 2019). The use of spectral features allows a non-destructive approach (Ding et al., 2004). to determine quality parameters possibly in less time and through eco-friendly method without using toxic dyes and chemicals. Numerous reports reported remote sensing of leaf water contents and grain protein contents from different crops (Wang et al., 2012, 2018; Hansen et al., 2002; Li et al., 2005; Feng et al., 2007; Caporaso et al., 2008; Onoyama et al., 2017; Marek et al., 2019). The research of spectral monitoring of leaf water content and grain quality by scholars at home and abroad is mainly focused on staple crops, but less research on broomcorn millet. Of different spectral studies of leaf water content, Ndlovu et al. (2021) reported that EWT (equivalent water thickness) and FMC (fuel moisture content) yielded the highest predictive performance and were the most optimal indicators of maize leaf water content. CAO et al. (2015) studied the normalized ratio (ND) type index dND (1415, 1530) and the simple ratio (SR) type index dSR (1530, 1895) based on the first derivative, which were the best for monitoring the relative water content (RWC) of all species. R^2 values are 0.95 and 0.97, respectively. Zhang et al. (2021) showed extreme random trees-x-loading weight (ERT-x-Lw) and difference vegetation index (DVI) (R1185, R1307) can effectively predict wheat leaf water content.

Of different spectral studies of grain starch, Kjær et al. (2016) sampled 60 potatoes from 10 varieties and used the hyperspectral reflectance to predict the starch content of potatoes. Similarly, Lu et al. (2017) found reported that the support vector regression principal component analysis (SVR-PCA) model can accurately detect grain starch content of rice, and the predicted coefficient of Determination (R^2) and root mean square error (RMSEP) were 0.991 and 0.669%, respectively. Likewise, Tian et al. (2004) suggested that the SPAD value, ratio index R(1500,610) and R(1220,560) of wheat leaves could predict the accumulation of grain starch during different growth stages of wheat. A linear discriminant analysis (LDA) normalized by the short-wave infrared spectrum was used to determine starch contents in rice (SEO et al., 2020). Other methods and validation techniques include the use of remote sensing images NDVI and climate environment data (Li et al., 2007), use of near-infrared spectral data (Zhao et al., 2011), and through model of support vector machine (SVM), stepwise

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multiple linear regression (SMLR) and partial least squares method (PLS), R-SVM models (Wang et al., 2019).

The sowing dates and un-even quality of starch grains are two significant aspects of this study that will facilitate agronomic practices regarding broomcorn millet cultivation and harvest. Grain starch contents were determined using a non-destructive remote sensing approach. The quantitative relationship between leaf water content with canopy spectral parameters and grain starch content of broomcorn millet at each growth period under different sowing is presented here. Hence, the study provides the theoretical basis and technical support for remote sensing technology in broomcorn millet quality monitoring, management, and regulation of production. These findings are valuable and provide the technical basis for the utilization of hyperspectral technology towards precision agriculture.

Materials and methods

Experimental conditions

This study is a two-year study conducted from July 2019 to October 2019 and from July 2020 to October 2020. The experiment was carried out in Dingxiang County, Xinzhou (38°33′N, 112°54′E), Shanxi Province, China. The area was situated at an altitude of 780 m. During the experimental span, the annual rainfall was approx. 430 mm, the annual average temperature was 8.7 °C, the frost-free period was about 158 days, the annual sunshine hours was up to 2 734.6 h, and the temperature, light and heat resources were suitable for the growth and development of broomcorn millet. The mineral nutrient composition of the experimental soil is as follows; N (0.080%), P (12.4 mg kg^{-1}), K (114 mg kg^{-1}), organic matter percentage (13.7 g kg^{-1}), and soil pH of 8.09.

Introduction of broomcorn millet

Broomcorn millet is a short-day crop with strong photoperiod sensitivity, which can mature when the active accumulated temperature of ≥ 10°C is about 1000 °C, but the plant is short and yield is extremely low. In ancient times, broomcorn millet was often used as a disaster relief crop, when other crops could not be sown due to natural disasters, broomcorn millet was finally selected to sow. In northern China, the sowing period of broomcorn millet is relatively wide, usually from May to July, Therefore, the research results obtained by setting different sowing periods are more widely representative.

Experimental design

Through continuous cultivation experiment of broomcorn millet in Dingxiang County for many years, it was concluded that 10th June was the best sowing date, because its yield was the highest. Therefore, the experiment took June 10 as the central point and set four sowing dates before and after it. The experimental treatments included five sowing dates (Factor-1) viz. B1 (10th May 2019), B2 (25th May 2019), B3 (10th June 2019), B4 (25th June 2019), and B5 (15th July 2019); and the second source of variation (Factor-2) included two broomcorn millet varieties P1 (Neimi 2) and P2 (Ningmi 14) respectively. The planting density was 60×10^4 seedlings hm^{-2} with a plot area of 30 m^2 (5 × 6 m) with row spacing of 30 cm. The experiment conducted using a randomized complete block design (RCBD) with three replications per treatment. The amount of fertilization is 120 kg hm^{-2} for pure N, 120 kg hm^{-2} for pure P_2O_5, and

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90 kg hm^{-2} as pure K_2O. The soil type is loam, which has good aeration, water permeability, water and fertilizer conservation, water and fertilizer supply, and cultivation performance. This experiment is mainly used for the establishment of the model. Under the B1 and B2 planting conditions, the height of the millet plant is high due to early sowing, which leads to partial lodging during the dough period of the grain. Spectral measurement and sampling cannot be performed in 5 plots. P1 lodging was more serious than P2. Therefore, 145 spectral data, 145 leaf water content data and 30 grain starch content data were obtained in 3 repetitions, 128 spectral data and 30 grain starch content data were obtained by removing abnormal values.

From June 2020 to October 2020, the experimental design is the same as those of the experiment in 2019. This experiment is mainly used for the validation of the model, the repeated data were measured at jointing stage, booting stage, heading stage and maturity stage, a total of 40 spectral data and 40 leaf water content data were obtained, and 25 spectral data and corresponding leaf water content data were obtained by removing abnormal values to verify the monitoring model. 20 spectral data, 20 leaf water content data and 20 grain starch content data of corresponding maturity stage were obtained by measuring 2 repeated data at filling stage. 15 spectral data and corresponding leaf water content and grain starch content data were obtained by removing abnormal values, which were used to verify the monitoring model of grain starch content.

Canopy spectral reflectance

The canopy spectral reflectance of broomcorn millet was measured at the jointing stage, booting stage, heading stage, filling stage, and maturity stage of 5 sowing dates. Five points were measured from each plot. The measurements from each plot repeated five times, and the leaf water contents were determined simultaneously.

Determination of spectral reflectance and eco-physiological indices

Canopy spectrum

Canopy reflectance spectra were recorded at the jointing stage, booting stage, heading stage, filling stage, and maturity stages. The FieldSpec-4 back-mounted field hyperspectral radiometer was used for this purpose (American Analytical Spectral Device (ASD), USA). The band range used was 350-2500 nm, and the field of view angle was 25°; 350-1000 nm with a spectral sampling interval of 1.4 nm. The spectral resolution is 3 nm; the 1000-2500 nm spectral sampling interval is 2 nm, and the spectral resolution is 10 nm. The instrument was calibrated using a white standard white plate once every quarter. The canopy spectral of broomcorn millet was recorded from 10:00 AM to 2:00 PM; the sensor probe was vertically downward, and the vertical height from the top of the canopy is about 1.0 m. The standard whiteboard correction was carried out before and after the observation of each group of targets. A total of five points were measured from each plot. In addition, the measurement of each point was repeated five times, and average values were processed. It is pertinent to mention here that this experiment was used for the establishment of the model. Under the B1 and B2 planting conditions, the height of the millet plant was higher due to early sowing, which caused partial lodging during the dough period of the grain. Spectral measurement and sampling could not be performed in 5 plots. P1 lodging was more severe than P2. In the determination of spectral data, the spectral data sometimes become abnormal due to the environment, the instrument itself, and lodging in the late stage of broomcorn millet

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plant. Because the anomalous spectral values differ greatly from the standard spectral values, these data are removed. Therefore, 145 spectral data, 145 leaf water content data, and 30-grain starch content data were obtained in 3 repetitions, 128 spectral data and 30-grain starch content data were obtained by removing abnormal values.

Determination of leaf water content

Leaf water contents were calculated using the methodology of González and González-Vilar (2001). Fresh leaves from each treatment were selected, and fresh weight was recorded (FW). Afterward, the leaves were oven-dried at 105 °C for 30 min and dried at 75 °C for 24 h to constant weight. The leaf water contents were then calculated using this formula:

$$\text{Leaf water content} = (\text{leaf fresh weight} - \text{leaf dry weight}) / \text{leaf fresh weight} \times 100$$

Quantitative determination of grain starch using anthrone reagent

The soluble sugar and starch were separated by using 80% ethanol. After that, the starch was further decomposed into glucose by acid hydrolysis. The glucose content was determined using an anthrone reagent (Dubois et al., 1956) at 560 nm using a SP-756P UV-Vis spectrophotometer (Shanghai Spectrometer Co., Ltd).

Vegetation index

To enhance the sensitivity to biophysical parameters, biochemical parameters, and other ecological function parameters, many dual-channel or multi-channel spectral indices have been developed and successfully used for biomass, leaf area index, chlorophyll and nitrogen. We used previous analytical data/research results in the present study, combined with the instrument characteristics and the research focus to summarize several characteristic spectral parameters reported (*Table 1*).

Table 1. *Algorithm and references of different spectral parameters*

Spectral parameter	Abbreviation	Algorithm	Reference
Reflectance	R_λ	–	Cropscan (2000)
Ratio vegetation index	RVI	R_{NIR}/R_{Red}	Pearson et al (1972)
Difference vegetation index	DVI	$R_{NIR}-R_{Red}$	Jordan (1969)
Normalized difference vegetation index	NDVI	$R_{NIR}-R_{Red}/R_{NIR}+R_{Red}$	Rouse et al. (1974)
Perpendicular vegetation index	PVI	$(R_{NIR}-aR_{Red}-b)/\sqrt{1+a^2}$ a=10.489, b=6.604	Richardson et al. (1977)
Enhanced vegetation Index	EVI	$2.5\times(R_{NIR}-R_{Red})/(R_{NIR}+6.0R_{Red}-7.5R_{Blue}+1)$	Chen et al. (2005)
Soil adjusted vegetation index	SAVI	$(1+L)(R_{NIR}-R_{Red})/(R_{NIR}+R_{Red}+L)$ L=0.5	Huete et al. (1988)
Optimized soil-adjusted vegetation index	OSAVI	$(1+0.16)(R_{800}-R_{670})/(R_{800}-R_{670}+0.16)$	Ronddeaux et al. (1996)
Renormalized difference vegetation index	RDVI	$\sqrt{NDVI \times DVI}$	Roujean et al. (1995)

R is reflectance

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Derivation and validation of statistical models

This experiment used 2019 test data to construct a monitoring model and used 2020 test data to test and verify the above monitoring models. The accuracy and applicability of the model were evaluated by the statistical parameters such as coefficient of Determination (R^2), root mean squared error (RMSE), and residual prediction difference (RPD) of the predicted and measured values. If the R^2 is closer to 1, the RMSE is smaller, indicating that the model has better prediction accuracy. When RPD > 2, the model has good prediction ability. When 1.4 < RPD < 2, the model has medium prediction ability, when RPD < 1.4, the model has poor prediction ability and vice versa. A 1:1 relationship diagram is drawn between the predicted value and the measured value to show the fit and reliability of the monitoring model visually.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - Y_i')/(n-p-1)}{\sum_{i=1}^{n}(Y_i - Y_i')^2/(n-1)}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - Y_i')^2}$$

$$\mathrm{RPD} = \frac{\mathrm{SD}}{\mathrm{RMSE}}$$

where *n* is the number of samples, *p* is the number of variables entering the model, Y_i' and Y_i are the predicted values and the measured values, respectively, SD (standard deviation) is the standard deviation of the measured values.

Statistical analyses

The collected data was initially processed to remove abnormal values and then analyzed using SPSS 19.0 software. The Matlab (7.0) software was used to analyze the correlation between the original and first-order differential bands and their relationship with the leaf water contents. Finally, the spectral data were processed by first-order differential and Savitsky Golay smoothing by unscrambler 9.7, and data for various figures was processed using MS Excel and Origin8.

Results

Spectral characteristic analysis

As the spectral vegetation index calculated by visible light and near-infrared light, the spectral band of 400-1500 nm was selected for data analysis. The sensitive area of the original spectrum was mainly concentrated in 400-500 nm, and the range is relatively narrow; the sensitive area of the first derivative is concentrated in the whole range of 400-1500 nm (*Fig. 1*). So the spectral band of the first derivative is selected to construct the vegetation index, and the bands with good correlation with leaf water content (LWC) were selected for data analysis. Following bands at 468, 630, 806, and 1488 nm were identified as the characteristic bands of the first derivative spectrum, the correlation coefficients were -0.548, - 0.518, - 0.724, and -0.5581, respectively.

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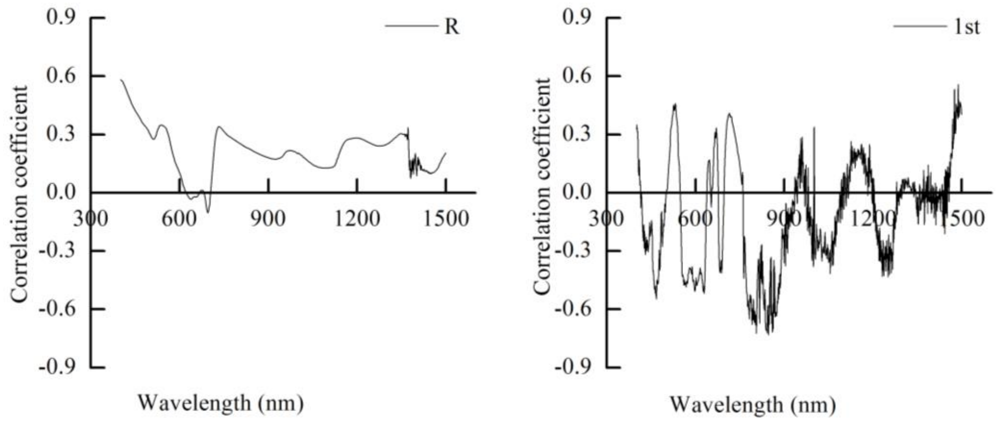

Figure 1. *Relationship between leaf water content and canopy spectral reflectance of broomcorn millet - First derivative spectral*

Canopy spectral variation patterns of broomcorn millet

It can be seen from *Figure 2* that under different sowing dates (B1-B5), the comparative canopy spectral reflectance of both the two kinds of broomcorn millet varieties was the same. It varied significantly among different growth stages. *Figure 2A* shows the spectral reflectance of P1B3 in different growth periods. The canopy spectral reflectance of P1B3 indicated an absorption valley (lower reflectance) near 680 nm in the red light band, which is the absorption valley of photosynthetic pigments (*Fig. 2A*). A decrease in the absorption in this range would be an indicator of broomcorn millet reaching maturity. However, a smaller reflection peak near 540 nm could be evident due to the relatively small chlorophyll absorption. The canopy spectral reflectance at the heading stage was significantly higher than other growth stages (*Fig. 2A*). Besides, the canopy spectral reflectance of P1 and P2 varieties shows the same phenomenon. The canopy spectral reflectance of B2 was the highest and the B3 was the second, while the least values were recorded in B5 (*Fig. 2B, C*).

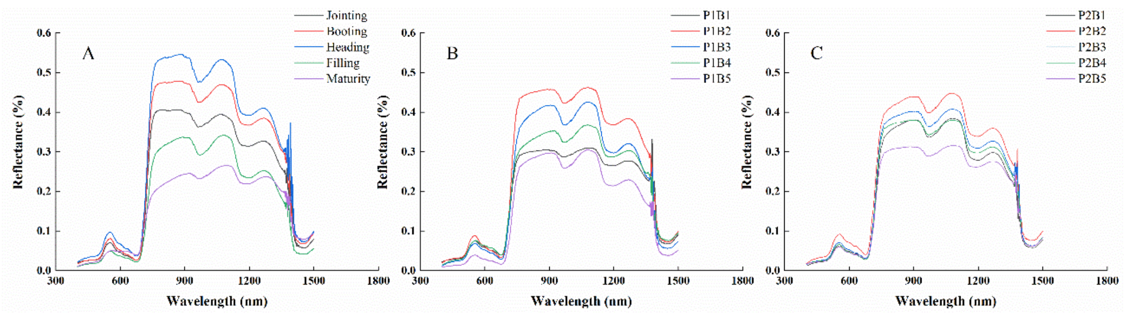

Figure 2. *Spectral characteristics of broomcorn millet at different sowing date and growing stage combinations*

Relationship between leaf water contents and canopy spectral parameters

Based on the calculation of leaf water content and corresponding different spectral indexes at the filling stage under five sowing dates, the RVI, DVI, NDVI, and some common vegetation indexes were used as the variable x. The leaf water content was

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used as the variable y for correlation analysis. The results showed that the vegetation index composed of 806 and 1488 nm characteristic bands was better than other band combinations. The vegetation index composed of RVI, NDVI, SAVI, DVI, OSAVI, RDVI, EVI, and PVI significantly positively correlated with leaf water contents to sowing dates. The above spectral index and leaf water content were correlated and fitted; the spectral index, regression equation, R^2, RMSE, and RPD indicated good correlation (*Table 2*). Except for EVI and PVI, the vegetation index of RPD in the modeling set was higher than 1.4, indicating good prediction ability. The SAVI model was the best based on the R^2 value, which was higher than other models (the RMSE model exhibited lease value). The evaluation index parameters of RDVI model accuracy were not significantly different from SAVI. The RPD of SAVI, OSAVI, DVI, and RDVI were higher than 2.0, indicating that the model has good prediction ability, the RDVI model is the best, R^2 was 0.8458 and RMSE was the best 0.042. The results also depicted that RDVI (1488,806) could predict leaf water contents.

Table 2. *Fitting (n = 128) and validation (n = 25) models of hyperspectral in leaf water content*

Model type	Calibration set				Validation set			
	Equation	R^2	RMSE	RPD	Equation	R^2	RMSE	RPD
NDVI (1488,806)	$y = 0.9331x + 0.0533$	0.702	0.074	1.415	$y = 1.0042x + 0.0002$	0.7203	0.056	1.888
SAVI (1488,806)	$y = 0.9161x + 0.0653$	0.7121	0.073	1.434	$y = 1x - 4E - 05$	0.7665	0.051	2.069
OSAVI (1488,806)	$y = 0.929x + 0.0555$	0.7017	0.074	1.415	$y = 1x + 9E - 06$	0.7661	0.052	2.068
DVI (1488,806)	$y = 0.939x + 0.0491$	0.6984	0.074	1.408	$y = 1x + 5E - 05$	0.7664	0.051	2.069
RDVI (1488,806)	$y = 0.9347x + 0.0514$	0.7075	0.073	1.430	$y = 1x + 6E - 06$	0.8458	0.042	2.546
RVI (1488,806)	$y = 0.9077x + 0.0736$	0.7114	0.074	1.422	$y = 0.9805x + 0.0195$	0.7521	0.053	1.996
EVI (1488,806,468)	$y = 0.9431x + 0.0476$	0.6612	0.079	1.328	$y = 1.0624x - 0.0471$	0.7291	0.056	1.911
PVI (1488,806)	$y = 0.9511x - 0.038$	0.6506	0.080	1.316	$y = 1x + 0.007$	0.6843	0.060	1.768

Quantitative relationship between leaf water content and grain starch content of broomcorn millet

The delay in the sowing date caused a reduction in grain starch contents of the broomcorn millet (*Fig. 3*). The grain starch contents of P1B1 were 15.8% higher than P1B5, and of P2B1 were 13.6% higher than that of P2B5, respectively. A regression model is established that suggested a strong correlation between leaf water contents and grain starch contents at the grain filling stage (R^2 = 0.8125; *Table 3*).

Table 3. *Monitoring models of grain starch content based on leaf water content at different growth stages (n = 95)*

Growth stage	Equation	R^2
Jointing	$Y = -451.59X + 1046.9$	0.1998
Booting	$Y = -349.95X + 951.77$	0.2177
Heading	$Y = -250.73X + 858.07$	0.7472
Filling	$Y = -214.55X + 805.2$	0.8125
Maturity	$Y = -231.14X + 803.47$	0.7535

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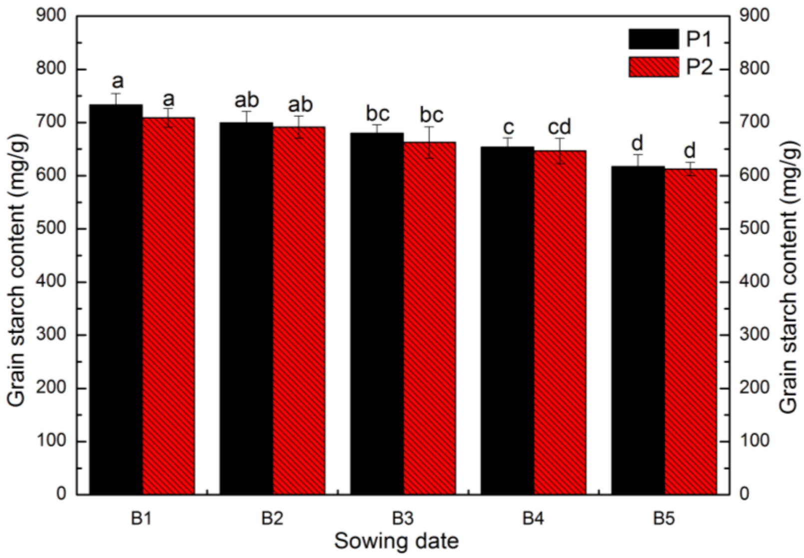

Figure 3. *The effects of different sowing dates on grain starch content of broomcorn millet varieties*

Validation of remote sensing monitoring model

The maximum correlation between leaf water content and grain starch content of broomcorn millet was recorded during the filling stage. In combination with the spectral monitoring model of leaf water content (*Tables 2* and *3*), the hyperspectral data were used to derive monitoring model equations for real-time Determination of grain starch contents (*Table 4*).

Table 4. *Forecasting models of grain starch content (y) to key spectral parameters (x) at leaf water content*

Model type	Equation
NDVI (1488,806)	$y = -214.55 \times (0.9331NDVI + 0.0533) + 805.2$
SAVI (1488,806)	$y = -214.55 \times (0.9161SAVI + 0.0653) + 805.2$
OSAVI (1488,806)	$y = -214.55 \times (0.9290SAVI + 0.0555) + 805.2$
DVI (1488,806)	$y = -214.55 \times (0.939DVI + 0.0491) + 805.2$
RDVI (1488,806)	$y = -214.55 \times (0.9347RDVI + 0.0514) + 805.2$
RVI (1488,806)	$y = -214.55 \times (0.9077RVI + 0.0736) + 805.2$
EVI (1488,806,468)	$y = -214.55 \times (0.9431EVI + 0.0476) + 805.2$
PVI (1488,806)	$y = -214.55 \times (0.9511PVI - 0.038) + 805.2$

The test data of the last growing season-2020 was used to validate the derived above equations using RMSE, $R^{2,}$ and RPD parameters. Finally, a linear relationship between the measured and predicted values was used to determine experimental indices (*Fig. 4*). Only the RPD of RVI (1488, 806) was 2.0, which indicated good predictive ability. The RMSE remained at least 15.656 and $R^2 = 0.8436$; the R^2 value of PVI was the largest, which is 0.8684, but the RPD value remained 1.904, which may be caused by the significant standard deviation between measured and predicted value. The RPD and

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RMSE of RDVI (1488, 806) were 1.978 and 15.988, respectively, second only to RVI (1488 and 806); $R^2 = 0.7694$. Conclusively, the validation of the monitoring model, R^2 and RPD of different treatments were all above 0.65 and 1.4, respectively, which also indicated that it is feasible to predict the grain starch contents of broomcorn millet simply from the canopy spectrum using leaf water contents.

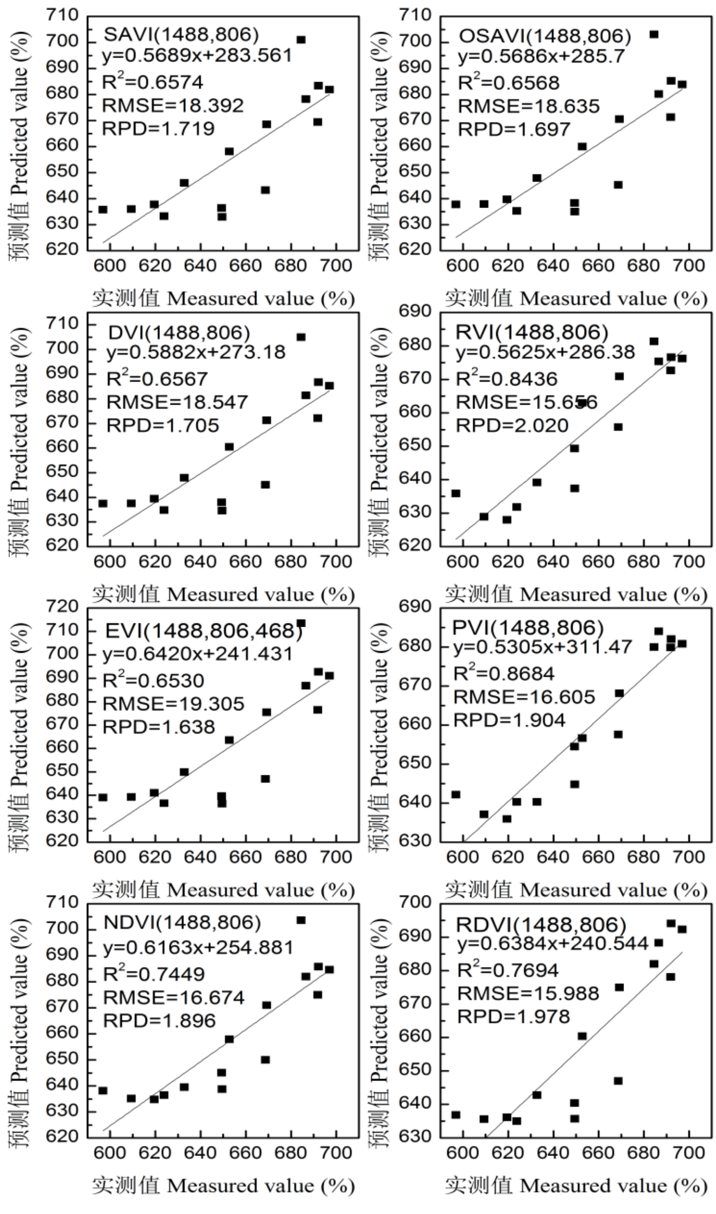

***Figure 4.** The correlation between estimated and measured grain starch content with leaf water content (n = 25)*

Discussion

Remote sensing is an effective technology that enables fast, large-scale, and non-destructive testing with high spectral resolution through continuous wave band and imaging. In this study, the agronomic parameters were used as identification criteria to

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integrate and predict grain starch contents of field-grown broomcorn millet via spectral remote sensing. A prediction model of grain starch content of broomcorn millet was established based on characteristic spectral parameters. The results showed that leaf water content could predict grain starch content accurately. The correlation between the first derivative and leaf water content was better than the original spectral band; the sensitive bands were 455~480 nm, 516~634 nm, 768~890 nm, and 1474~1500 nm. In this context of the recent development in chemometrics, accurately mining and correct extraction of spectral parameters is an important area in spectroscopy research. The derivative, least square method, normalization, baseline correction, and multivariate scattering correction methods are commonly used to correct the original spectral data. To a certain extent, the first derivative spectral band is better than the original spectral band, which is similar to previous results (Liang et al., 2013; Xie et al., 2020).

Leaf water content is an agronomic index to characterize the average growth and drought monitoring of plants. Among the spectral parameters related to leaf water content, the vegetation index constructed by visible light (400~780 nm) and near-infrared light (780~1350 nm) is used to monitor the leaf water content of plants. Recently, the DVI model used for the estimation of winter wheat leaf water content with an R^2 value of 0.886 was best compared with NDVI and RVI (Jin et al., 2020). Chen et al. (2020) also reported that the water content of leaf could be predicted using normalized difference (NDSI), ratio spectral index (RSI), partial least square regression (PLSR), and competitive adaptive reweighted sampling partial least square regression (CARS-PLSR). It was concluded that the accuracy and modeling accuracy of CARS-PLSR was highest, which quickly and accurately predicted leaf water contents of winter wheat. Various other studies used hyperspectral reflectance coupled with a modeling approach to predict leaf water contents (Xu et al., 2018; Hasan et al., 2018) using partial least squares regression (PLSR), BP neural network (ANN), RMSE, and RPD, respectively.

Xu et al. (2018) pointed out that the difference vegetation index DDV (833 and 236 nm) constructed by the first derivative could better predict the leaf water content of rice. Hasan et al. (2018) used the partial least squares regression (PLSR) model and BP neural network (ANN) model to monitor spring wheat leaf water content, partial least squares regression (PLSR) model. Based on the first derivative, could accurately monitor spring wheat leaf water content, and R^2, RMSE and RPD were 0.80, 0.55, and 2.01. It can be seen that the prediction accuracy of leaf water content in response to the vegetation index of the same crop or different crops under different treatment conditions is different. The results also depicted that the vegetation index RDVI (1488, 806) composed of 608 nm and 1488 nm could better predict the leaf water content of broomcorn millet under different sowing dates.

Nonetheless, the inconsistency of crop leaf water content monitoring models may be caused by different crop-specific leaf spectral reflectance, cultivation pattern measures, and edaphic factors. Therefore, different crop spectral monitoring models can be is crop and environment-specific. Here in this study, canopy spectral reflectance at the heading stage was significantly higher than that at other growth stages mainly because the population of broomcorn millet grew well at the flowering stage and was in the critical period of transformation from vegetative to reproductive growth. While the leaves at the maturity stage turned yellow and did not have the spectral characteristics of green vegetation, the reflectance was the lowest. Furthermore, the R^2 value of only 0.1998 at the jointing stage was recorded. In the early growth stage of broomcorn millet, obtained

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nutrients only accumulate in the leaves and stem sheaths and cannot form an apparent relationship with the grain nutrients. With the continuous progress of the growth period, the vegetative growth is gradually transformed into reproductive growth, which gradually enhanced the correlation between the leaves and grain nutrients.

The vegetation index composed of 806 and 1488 nm characteristic bands was better than that of other band combinations, and there was a very significant positive correlation with leaf water content. RDVI (1488, 806) can better predict broomcorn millet leaf water content under different sowing dates. R^2 of the calibration set is 0.7075, RMSE = 0.073, RPD = 1.430; R^2 of the validation set is 0.8458, RMSE = 0.042, RPD = 2.546. The correlation between leaf water content and grain starch content was the best, $R^2 = 0.8125$, which could be used as a bridge to establish a hyperspectral monitoring model of grain starch content. Among the established models, the monitoring models of RVI (1488, 806), RDVI (1488, 806), and PVI (1488, 806) are better than other models, and the RPD were 0.020, 1.978, and 1.904, respectively.

In agreement with this study, amylase contents from rice can be accurately predicted using the difference vegetation index DVI and the ratio vegetation index RVI (Xie et al., 2012, 2020). Similarly, Wang et al. (2013) showed that NDVI (670,1200) accurately predicted starch accumulation in winter wheat ($R^2 = 0.9542$). Li et al. (2007) also showed that NDVI of satellite remote sensing images could accurately predict winter wheat grain starch content. It is essential to mention here that NDVI and DVI can indicate grain starch content of different crops than other vegetation plants, consistent with the optimal vegetation plant for monitoring grain starch content in this study. Our results showed that RDVI (1488, 806) monitoring model had strong stability and high accuracy, which quickly and non-destructively monitored grain starch content of broomcorn millet. The RDVI was calculated from the formula of NDVI and DVI, which represented the differences among all information data to a certain extent. Above all, the spectral vegetation indexes comprised of visible light and near-infrared light, NDVI, DVI, and RDVI can accurately, quickly, and non-destructively monitor grain starch content of different crops than other vegetation indexes.

Conclusions

The R^2, RMSE, and RPD of the hyperspectral monitoring model for leaf water content and grain starch content of broomcorn millet were positively connected. We conclude that the monitoring model of RDVI (1488, 806) had strong stability and high accuracy and could quickly and non-destructively monitor the leaf water content and grain starch content of broomcorn millet. This study mainly considered the effects of different sowing dates and varieties on broomcorn millet grain content but did not fully consider other elements such as fertilizers and water. So more comprehensive and more research is needed. Therefore, the monitoring model needs to be further tested and improved by multi-point experiments and large-scale planting to provide a more accurate theoretical basis for monitoring the leaf water content of broomcorn millet and grain starch content.

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REFERENCES

[1] Amadou, I., Gounga, M. E., Le, G. W. (2013): Millets: nutritional composition, some health benefits and processing. A review. – Emirates Journal of Food & Agriculture 25: 501-508.

[2] Brahmachari, K., Sarkar, S., Santra, D. K., Maitra, S. (2019): Millet for food and nutritional security in drought prone and red laterite region of Eastern India. – Int J Plant Soil Sci 26(6): 1-7.

[3] Cao, Z. X., Wang, Q., Zheng, C. L. (2015): Best hyperspectral indices for tracing leaf water status as determined from leaf dehydration experiments. – Ecological Indicators 54: 96-107.

[4] Caporaso, N., Whitworth, M. B., Fisk, I. D. (2008): Protein content prediction in single wheat kernels using hyperspectral imaging. – Food Chemistry 240: 32-42.

[5] Changmei, S., and Dorothy, J. (2014): Millet - the frugal grain. – International Journal of Scientific Research and Reviews 3(4): 75-90.

[6] Chen, D., Huang, J. F., Jackson, T. J. (2005): Vegetation water content estimation for corn and soybeans using spectral indices derived from MODIS near and short wave infrared bands. – Remote Sensing of Environment 98(2/3): 225-236.

[7] Chen, X. Q., Yang, Q., Han, J. Y., Lin, L., Shi, L. S. (2020): Estimation of winter wheat leaf water content based on leaf and canopy hyperspectral date. – Spectroscopy and Spectral Analysis 40(3): 891-897.

[8] Cropscan, Inc. (2000): Data Logger Controller, User’s Guide and Technical Reference. – CROPSCAN Inc, Rochester.

[9] Ding, S. Y., Li, H. M., Qian, L. X. (2004): Research advances in remote sensing techniques in estimation of vegetation biochemical material contents. – Chinese Journal of Ecology 23(4): 109-117.

[10] Dubois, M., Gilles, K. A., Hamilton. J. K., Rebers, P., Smith, F. (1956): Colorimetric method for determination of sugars and related substances. – Analytical Chemistry 28: 350-356.

[11] Feng, W., Yao, X., Tian, Y. C., Zhu, Y., Liu, X. J., Chao, W. X. (2007): predicting grain protein content with canopy hyperspectral remote sensing in wheat. – Acta Agronomica Sinica 33(12): 1935-1942.

[12] Fuller, D. Q. (2006): A Millet Atlas: Some Identification Guidance. – University College London, London.

[13] García-León, D., Standardi, G., Staccione, A. (2021): An integrated approach for the estimation of agricultural drought costs. – Land Use Policy 100: 104923.

[14] González, L., González-Vilar, M. (2001): Determination of Relative Water Content. – In: Roger, M. J. R. (ed.) Handbook of Plant Ecophysiology Techniques. Springer, Dordrecht, pp. 207-212.

[15] GPWG (Grass Phylogeny Working Group), Barker, N. P., Clark, L. G., Davis, J. I., Duvall, M. R., Guala, G. F., Hsiao, C., Kellogg, E. A., Linder, H. P., Mason-Gamer, R. J., Mathews, S. Y., Simmons, M. P., Soreng, R. J., Spangler, R. E. (2001): Phylogeny and subfamilial classification of the grasses (Poaceae). – Annals of the Missouri Botanical Garden 88(3): 373-457.

[16] Gupta, A., Rico-Medina, A., Caño-Delgado, A. I. (2020): The physiology of plant responses to drought. – Science 368(6488): 266-269.

[17] Habiyaremye, C., Matanguihan, J. B., D’Alpoim Guedes, J., Ganjyal, G. M., Whiteman, M. R., Kidwell, K. K., Murphy, K. M. (2017): Proso millet (Panicum miliaceum L.) and its potential for cultivation in the Pacific Northwest US. A review. – Frontiers in Plant Science 7: 1961.

[18] Han, H. K., Miao, J. Y., Zhang, Y. Y., Zhang, D. Z., Zong, G. H., Gong, X. W., Li, J., Feng, B. L. (2018): Estimating chlorophyll content of proso millet canopy by hyperspectral reflectance. – Agricultural Research in the Arid Areas 36(1): 164-170.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2001_431445

[19] Hansen, P. M., Jorgensen, J. R., Thomsen, A. (2002): Predicting grain yield and protein content in winter wheat and spring barley using repeated canopy reflectance measurements and partial least squares regression. – Journal Agricultural Science 139(3): 307-318.
[20] Hasan, U., Sawut, M., Kasin, N., Taxipulati, N., Wang, J. Z., Ablat, I. (2018): Hyperspectral estimation model of leaf water content in spring wheat based on grey relational analysis. – Spectroscopy and Spectral Analysis 38(12): 3905-3911.
[21] Huete, A. R. (1988): A soil-adjusted vegetation index (SAVI). – Remote Sensing of Environment 25(3): 295-309.
[22] Hunter, M. C., Kemanian, A. R., Mortensen, D. A. (2021): Cover crop effects on maize drought stress and yield. – Agriculture, Ecosystems & Environment 311: 107294.
[23] Jackson, R. D. (1982): Canopy temperature and crop water stress. – Advanced Irrigation 25(1): 43-85.
[24] Jin, N., Zhang, D. Y., Li, Z. H., He, L. (2020): Evaluation of water status of winter wheat based on simulated reflectance of multispectral satellites. – Transactions of the Chinese Society for Agricultural Machinery 51(11): 243-252.
[25] Jordan, C. F. (1969): Derivation of leaf area index from quality of light on the forest floor. – Ecology 50(4): 663-666.
[26] Kjær, A., Nielsen, G., Søren Stærke, S., Clausen, M. R., Edelenbos, M., Jørgensen, B. (2016): Prediction of starch, soluble sugars and amino acids in potatoes using hyperspectral imaging, dielectric and LF-NMR methodologies. – Potato Research 59(4): 357-374.
[27] Li, Y. X., Zhu, Y., Tian, Y. C., You, X. T., Zhou, D. Q., Cao, W. X. (2005): Relationship of grain protein content and relevant quality traits to canopy reflectance spectra in wheat. – Scientia Agricultura Sinica 38(7): 1332-1338.
[28] Li, W. G., Wang, J. H., Zhao, C. J., Liu, L. Y., Guo, W. S. (2007): Study on monitoring starch content in winter wheat grain using land-sat TM image. – Journal of Yunnan Agriculture University 22(3): 365-369.
[29] Liang, L., Zhang, L. P., Li, C. M., Yang, M. H. (2013): Estimating canopy leaf water content in wheat based on derivative spectra. – Scientia Agricultura Sinica 46(1): 18-29.
[30] Lu, X. Z., Sun, J., Mao, H. P., Wu, X. H., Gao, H. Y. (2017): Quantitative determination of rice starch based on hyperspectral imaging technology. – International Journal of Food Properties 20(1): 1037-1044.
[31] Marek, K., Marian, B., Oksana, S., Viliam, B., Pavol, H., Marek, Z. (2019): Evaluation of hyperspectral reflectance parameters to assess the leaf water content in soybean. – Water 11(3): 443.
[32] Miao, J. Y., Zhang, Y. Y., Wang, M., Zhang, P. P., Li, X., Han, H. K., Liu, F. Q., Feng, B. L. (2015): Characteristics of hyper-spectral reflectance of broomcorn millet canopy in semi-arid region. – Journal of Heilongjiang Bayi Agricultural University 27(5): 6-9.
[33] Ndlovu, H. S., John, O., Mbulisi, S., Onisimo, M., Alistair, C., Chimonyo, V. G. P., Tafadzwanashe, M. (2021): A comparative estimation of maize leaf water content using machine learning techniques and unmanned aerial vehicle (UAV)-based proximal and remotely sensed data. – Remote Sensing 13(20): 4091-4091.
[34] Onoyama, H., Ryu, C., Suguri, M., Iida, M. (2017): Estimation of rice protein content before harvest using ground based hyperspectral imaging and region of interest analysis. – Precision Agriculture 19(4): 721-734.
[35] Pearson, R. L., Miller, D. L. (1972): Remote mapping of standing crop biomass for estimation of the productivity of the short grass prairie. – Proceedings of the Eighth International Symposium on Remote Sensing of Environment, Ann Arbor, Michigan, pp. 1357-1381.
[36] Prathap, V., Ali, K., Singh, A., Vishwakarma, C., Krishnan, V., Chinnusamy, V., Tyagi, A. (2019): Starch accumulation in rice grains subjected to drought during grain filling stage. – Plant Physiology and Biochemistry 142: 440-451.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2001_431445

[37] Ravi, S. B. (2004): Neglected millets that save the poor from starvation. – Leisa India 6(1): 1-8.
[38] Richardson, A. J., Wiegand, C. L. (1977): Distinguishing vegetation from soil back ground information. – Photogramm Engineering and Remote Sensing 43(12): 1541-1552.
[39] Rondeaux, G., Steven, M., Baret, F. (1996): Optimization of soil-adjusted vegetation indices. – Remote Sensing of Environment 55(2): 95-107.
[40] Roujean, J. L., Breon, F. M. (1995): Estimating PAR Absorbed by vegetation from bidirectional reflectance measurements. – Remote Sensing of Environment 51(3): 375-384.
[41] Rouse, J. W., Haas, R. H., Schell, J. A., Deering, D. W. (1974): Monitoring the vernal advancement and retro gradation (green wave effect) of natural vegetation. – NASA/GSFCT Type Ⅲ Final Report. Greenbelt, MD, USA, pp. 309-317.
[42] Seo, Y., Lee, A., Kim, B., Lim, J. (2020): Classification of rice and starch flours by using multiple hyperspectral imaging systems and chemometric methods. – Applied Sciences 10(19): 6724.
[43] Shafiq, F., Raza, S. H., Bibi, A., Khan, I., Iqbal, M. (2018): Influence of proline priming on antioxidative potential and ionic distribution and its relationship with salt tolerance of wheat. – Cereal Research Communications 46(2): 287-300.
[44] Tian, Y. C., Zhu, Y., Cao, W. X., Fan, X. M., Liu, X. J. (2004): Monitoring protein and starch accumulation in wheat grains with leaf SPAD and canopy spectral reflectance. – Scientia Agricultura Sinica 37(6): 808-813.
[45] Wang, Y. J., Cheng, J. H. (2018): Rapid and non-destructive prediction of protein content in peanut varieties using near-infrared hyperspectral imaging method. – Grain & Oil Science and Technology 1(1): 40-43.
[46] Wang, Q., Li, P. H. (2012): Identification of robust hyperspectral indices on forest leaf water content using PROSPECT simulated dataset and field reflectance measurements. – Hydrological Processes 26(8): 1230-1241.
[47] Wang, C., Feng, M. C., Wang, J. J., Xiao, L. J., Yang, W. D. (2013): Monitoring grain starch accumulation in winter wheat via spectral remote sensing. – Chinese Journal of Eco-Agriculture 21(4): 440-447.
[48] Wang, J. J., Chen, L., Wang, H. G., Cao, X. N., Liu, S. C., Tian, X., Qin, H. B., Qiao, Z. J. (2019): Effects of hyperspectral prediction on nitrogen content and the grain protein content of broomcorn millet. – Scientia Agricultura Sinica 52(15): 2593-2603.
[49] Xie, X. J., Li, B. B., Zhu, H. X. (2012): Estimating contents of crude protein and amylose content in rice grain by hyper-spectral under different high temperature stress. – Research of Agricultural Modernization 33(4): 481-484.
[50] Xie, L. L., Wang, F. M., Zhang, Y., Huang, J. F., Hu, J. H., Wang, F. L., Yao, X. P. (2020): Monitoring of amylose content in rice based on spectral variables at the multiple growth stages. – Transactions of the Chinese society of agricultural engineering 36(8): 165-173.
[51] Xu, Q., Ma, Y., Jiang, Q., Tong, C. Y., Zhao, Z. Y. (2018): Estimation of rice leaf water content based on hyperspectral remote sensing. – Remote Sensing Information 33(5): 1-8.
[52] Zhao, T. T., Zhang, L. Z., Zheng, S. H., Yang, L. L., Feng, N. H., Liu, G. K. (2011): Analysis of starch of Panicum miliaceum L. seed by near infrared transmittance spectroscopy. – Acta Agriculture Boreali-Sinica 26(1): 234-238.
[53] Zhang, J. J., Zhang, W., Xiong, S. P., Song, Z. X., Tian, W. Z., Shi, L., Ma, X. M. (2021): Comparison of new hyperspectral index and machine learning models for prediction of winter wheat leaf water content. – Plant Methods 17(1): 1-14.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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