HYPERSPECTRAL MONITORING OF PLANT WATER CONTENT IN WINTER WHEAT (*TRITICUM AESTIVUM* L.) AFTER DROUGHT STRESS

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Abstract. Winter wheat (*Triticum aestivum* L.) is an important food crop with high economic and social value. Frequent drought disasters in northern China, have a negative influence on the growth and development of winter wheat, thus the risk of diseases and pests is increased, and yield and quality are reduced. We took winter wheat treated with different water stress as the research object, collected the plant water content (PWC) at different growth stages and hyperspectral remote sensing data, and carried out logarithmic (Lg R), first derivative (R') and logarithmic first derivative (Lg R') transformation of the raw spectrum (R) of winter wheat. We established the spectral prediction model of PWC by analyzing the quantitative relationship between the spectral data of winter wheat under different mathematical transformations and the PWC in the range of 350 - 2500 nm. The results showed that the prediction model of PWC based on lg R' had the highest accuracy, which can provide an effective basis for rapid and non-destructive monitoring of winter wheat moisture.
Keywords: *winter wheat, drought, hyperspectral, water content, preprocessing, PLSR*

Introduction

Water is an indispensable resource for crop growth. Changes in global climate, directly or indirectly, caused the frequent occurrence of meteorological disasters such as drought, which will have a certain impact on the natural ecosystem as well as human production and life (Zhang et al., 2022). The current climate is warm and dry (Lai and Xu, 2024), and in recent years, the increase in intensity and frequency of drought has slowed down the increasing trend of food production, with a significant negative effect on the yields of crops (summer maize and winter wheat (*Triticum aestivum* L.)) in northern China (Zhang et al., 2023). There are significant differences in the impact of dry weather on grain yields at different growth stages (Miao et al., 2023).

Wheat is the main food crop in China, accounting for a large amount of agricultural water consumption in the north of China. With global climate change and growing population, drought has become a major meteorological disaster in China's wheat-growing areas, and water resources for wheat irrigation has become a key issue (Wang et al., 2022). It is of great importance to understand the patterns of drought occurrence in winter wheat, especially its characteristics at different stages, so as to enable government departments at all levels to make corresponding decisions and take active and effective measures to prevent and relieve drought (Ren et al., 2023).

Water is an important component of crops and a vehicle for crop nutrient absorption and transportation. It can maintain the turgor pressure of crop cells, keep the crop cells

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plump and round, maintain the morphological structure of crops, and promote the growth and development of crops (Li et al., 2023). In the initial stage of crop water deficiency, it will cause the leaf cells to droop due to water loss, lose their luster, and the edges of the leaves will show characteristics such as curling and yellowing. This is closely related to the change in chlorophyll content. When crops are short of water, the synthesis and stability of chlorophyll will be affected. The chlorophyll content begins to decline, which directly weakens the plants' ability to capture light energy. This situation will have a certain impact on the crop growth process. For example, photosynthesis is blocked. Timely watering at this time can effectively improve the water deficiency status of crops (Sah et al., 2020). However, winter wheat is sensitive to water response (Zhang et al., 2023). If watering is carried out after the leaves show wilting symptoms, it often cannot achieve a remedial effect and will cause irreversible consequences to the growth and development of winter wheat. Therefore, by monitoring the water content of winter wheat plants, the water status of winter wheat can be judged in a timely manner (Huang et al., 2023). According to the water demand of winter wheat, a reasonable irrigation plan can be formulated to effectively guarantee the normal growth and yield increase of winter wheat.

Since the twenty-first century, under the continuous progress and development of science and technology, the use of hyperspectral sensor equipment in agriculture is becoming more and more mature, and is gradually moving towards the direction of low-cost, high-efficiency, flexible access to large-area, high spatial resolution crop information, further promoting the progress of modern agriculture. It plays an important role in the development of precision agriculture (Qi, 2022; Xiong et al., 2023).

Hyperspectral technology has been widely used for crop monitoring and has achieved successful research results for many years (Cheng et al., 2024). REN (2018) integrated the MSC algorithm, the chi-square test feature selection algorithm and different modelling methods for the purpose of non-destructive detection of Dimethoate pesticides in spinach. The experimental results showed that the combination of chi-square test and LDA is the best construction method for this model, and the accuracy of prediction reaches 99.7% with a standard deviation of 0.008. The identification accuracy of the prediction model is high, and therefore, the method is suitable for non-destructive detection of botanical pesticides in spinach. It provides experience for the implementation of rapid non-destructive monitoring of crops using hyperspectral remote sensing technology.

In the 1980s, Chinese government has stepped up investment in the research and development of hyperspectral remote sensing technology, began the path of independent research, and achieved a large amount of research results, and at present, China is in an important stage of modern agricultural development (Tong et al., 2016). Through the use of hyperspectral remote sensing technology can quickly and accurately obtain crop growth information without doing harm to crops, and thus hyperspectral technology is being widely used in crop growth data monitoring (Fan et al., 2022). For example, the reflectance and transmittance coefficients of winter wheat under different wavelength bands were determined using a ground spectrometer, and the spectral information of winter wheat was measured using a canopy analyser to obtain its spectral curve; a remote sensing inversion model was established by analysing the measured data, and the overall accuracy of the remote sensing inversion model was significantly improved (Li, 2021). Sun (2018) analyzed the responses of growth physiological parameters and canopy spectra of winter wheat under different irrigation conditions, the results showed that there were great differences in growth physiological parameters of winter wheat under different irrigation conditions, moreover, all these parameters decreased with the decrease of

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irrigation water. Xiao (2019) pointed out that the spectral characteristics of winter wheat canopy changed differently at different growth stages and under drought stress, and water was an important factor affecting the spectral characteristics of winter wheat canopy, and the water status of winter wheat canopy at different growth stages would have an important impact on the spectral characteristics of winter wheat canopy. Xie (2020, 2023) found that under water stress, winter wheat Pro content appeared to accumulate to some extent, and the canopy spectral reflectance changed regularly in the range of different bands, indicating that the Pro content of winter wheat has a sensitive response to water stress. Therefore, real-time monitoring of the canopy spectral characteristics of winter wheat during the reproductive period and under drought stress can be realized by remote sensing technology, which can provide guidance for the field production of winter wheat.

Spectral analysis is widely used in agriculture because of its advantages such as fast speed, low cost and non-destructive, but the spectral data is easily disturbed by noise, which affects the modeling accuracy (Otsuka et al., 2003; Roggo et al., 2004). The pretreatment of the original spectrum can effectively eliminate the interference of background noise and specific physical factors, and improve the accuracy of the model (Diwu et al., 2019). Guo (2021) treated the hyperspectral data with reciprocal logarithm, which weakened the influence of light variation and soil surface unevenness on the experimental results. Gao (2024) utilized the continuous wavelet transform (CWT) and the successive projection algorithm (SPA) to identify the hyperspectral sensitive spectral bands of winter wheat. In comparison to the single-sensor model, the fusion model based on the GRA algorithm demonstrates higher accuracy. The first derivative of spectrum is a common preprocessing method in NIR spectral analysis. Derivative spectrum can effectively eliminate the interference of baseline and other background, and improve the resolution and sensitivity (Chu et al., 2004). Li (2019) performed SG smoothing, first derivative and second derivative processing on the original spectrum, and conducted correlation analysis between the spectrum and plant water content (PWC) of winter wheat. The results showed that the correlation between the spectrum and PWC could be significantly improved based on the first derivative processing.

In this study, winter wheat under drought stress treatment was taken as the research object. The drought conditions of winter wheat were simulated to obtain the information of plant water content and hyperspectral reflectance at different growth stages. Based on the quantitative study of spectral reflectance and plant water content, a monitoring model of winter wheat PWC was constructed with different mathematical transformations.

The aim of our study was to measure the PWC in winter wheat after drought stress, and then to realize precise irrigation according to the water demand of winter wheat, so as to provide a guarantee for the increase of winter wheat yield.

Materials and methods

Overview of the study area

The experimental area of this study is located in the central part of Shanxi Province, in the northeast edge of Jinzhong Basin, within the agricultural station of Shanxi Agricultural University, which has a mild climate and abundant resources, and is suitable for a variety of crop cultivation experiments (*Figure 1*). The four seasons are distinct, with hot and rainy summers and cold and dry winters, with an average annual temperature of 9.7 °C, a frost-free period of about 175 days, an annual precipitation of about 460 mm (Yao et al., 2024).

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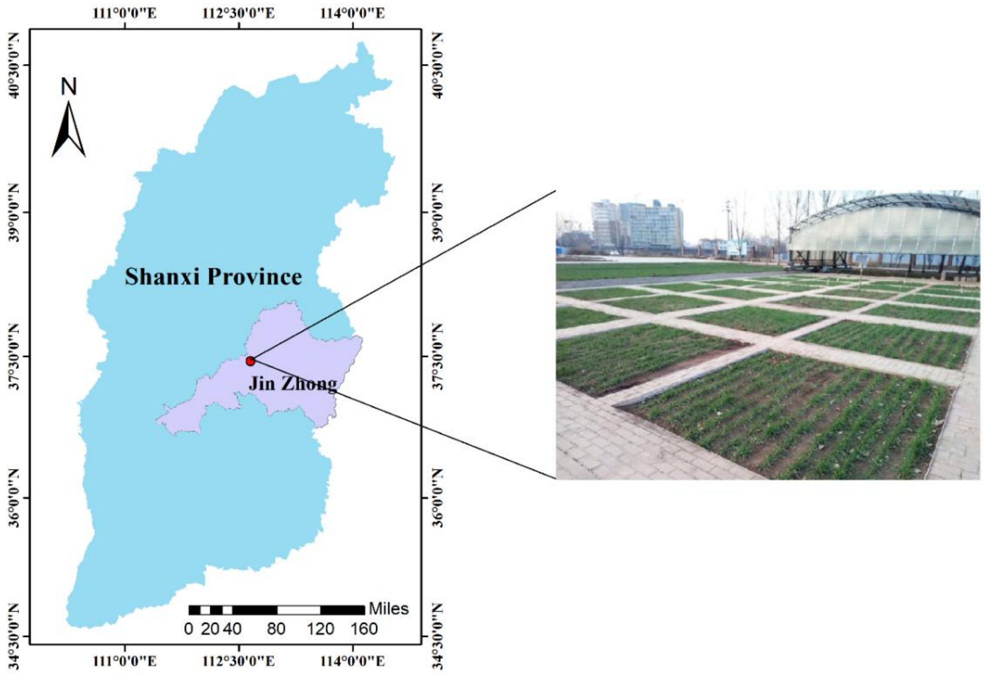

Figure 1. *Overview of the study area*

At the same time, the land in the area is fertile and suitable for agricultural production. The soil is calcareous yellow-brown soil developed from loess parent material with a medium soil fertility (Alfisols in U.S. taxonomy). The basic soil properties (0–20 cm) collected from experiment field were measured by using method of Lu (1999): the alkaline nitrogen content was 53.8 mg/ kg, the effective phosphorus content was 18.43 mg/ kg, the rapidly available potassium content was 236.9 mg/ kg, organic matter content was 22.01 g/ kg, the bulk density was 1.41 g/ cm^3, and field capacity was 21.88% (Xie et al., 2020). The supporting facilities are well developed. For example, we are equipped with a soil moisture meter manufactured by Spectrum of the United States and an electrically controlled mobile fiberglass-reinforced dry shed, which can accurately control the plant moisture content. The government attaches great importance to agricultural development, which provides convenient conditions and makes it an ideal place for conducting experiments on planting a variety of crops.

Experimental design

This experiment was carried out in an electronically controlled mobile glass fiber reinforced dry shed at the Agricultural Crop Station of Shanxi Agricultural University from October 2017 to June 2018. Five different irrigation conditions (*Table 1*) were set by random grouping, and each condition was repeated three times. A total of 15 plots were set up, and the area of each plot was 3 m×3 m=9 m^2. Drought stress treatment was initiated at the regreening stage, and water control was carried out throughout the whole growth period by an electrically controlled rain shelter. In the process of water control treatment, in order to ensure as much as possible that the soil moisture condition in each treatment plot is in the target water treatment condition, for each treatment level, the soil moisture content from 0 to 20 cm in the treatment is measured every 3-5 d and converted

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to the current soil moisture as a percentage of the field water holding capacity, and then the amount of water that needs to be irrigated under the current condition of the treatment is calculated according to the target field water holding capacity of the treatment. To ensure the accuracy of the experimental results, the moisture pool cells were separated from each other by impermeable water panels 2 m deep to prevent interpenetration between the cells. And used bird nets to cover after the flowering period.

Table 1. *Settings of water stress treatments*

Treatment	Degree	Representations
W1	Control Check	80% of field water capacity
W2	Mild Drought	60% of field water capacity
W3	Drought	45% of field water capacity
W4	Severe Drought	35% of field water capacity
W5	Extreme Drought	30% of field water capacity

Note: The actual measured field water capacity of the test soil is 21.880%

The tested variety was Chinese Wheat 175 (National Certification No. 2011018), planted in rows spaced 20 cm apart, the planting density experiment was 6×10^6 plants/hm^2. N (Nitrogen), P (Phosphorus), and K (Kalium)were used as bottom fertilizers and were applied at one time before sowing to ensure that the elements of N, P, and K were at the same level in all plots. The level of N was 150 kg/hm^2, P was 120 kg/hm^2 and K was 150 kg/hm^2. In order to reduce the error of the experimental results, the plots were managed in a uniform way.

Hyperspectral data measurement

Spectroscopic measurements were performed using a belt mounted Field spectrometer, model number Field-SPEC 3.0, manufactured by American Analytical Instruments (ASD). The effective wavelength range is 350 - 2500 nm, the spectral sampling interval is 1.37 nm and the spectral resolution is 3 nm in the wavelength range of 350 - 1050 nm. In the wavelength range of 1000 - 2500 nm, the spectral sampling interval is 2 nm and the spectral resolution is 10 nm. Spectral measurements are sensitive to weather conditions. Therefore, in order to avoid errors, spectral data determination should be carried out between 10:00 and 14:00, and the weather conditions are clear, cloudless and wind-free. The probe of the spectrometer needs to be fixed vertically 1.0 m above the uniformly growing winter wheat canopy to be measured. In order to ensure the accuracy of data, 3 sample points with uniform representative plants should be selected from the same plot during the collection process, and 10 reflectance spectra should be measured for the selected canopy. When collecting spectral data of winter wheat canopy, standard correction should be performed under a 35 cm×35 cm whiteboard.

Determination of PWC

PWC was measured at 191, 208, 221, 229, and 241 days after sowing. *Table 2* shows the corresponding BBCH codes.

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Table 2. *Days after sowing and corresponding BBCH code*

Days after sowing	BBCH code	General description
191	32	2nd node detectable
208	45	Boots swollen
221	57	3/4 of inflorescence emerged
229	68	Anthesis complete
241	75	Medium milk

Plant collection needs to be synchronized with the determination of spectral data. Winter wheat plants were uprooted with spectral data collected, after which they were quickly placed in airtight bags labeled with the corresponding area to avoid water loss. The collected wheat was quickly transported to the laboratory, where the root system was removed and the weight of the fresh wheat was weighed on an operating table. To ensure the accuracy of the data, the plants in each plot were repeatedly weighed three times, and the average value was taken as the fresh weight of a single wheat plant. The weighed wheat seedlings were put into drying bags labeled with numbers, killed out in a thermostatic oven at 105°C for 30 min, and then baked in a thermostatic oven at 80°C until stable weight. In order to minimize the influence of external moisture on the results, the dried plants were weighed three times quickly and averaged as dry weight, and finally the moisture content of the plants was determined from the fresh weight and dry weight of the plants, here is the formula (Carter, 1991):

$$PWC = \frac{PFW - PDW}{PFW} \times 100\% \qquad \text{(Eq.1)}$$

where, PFW denotes the fresh weight of the plant (g), PDW denotes the dry weight of the plant (g).

Spectral pre-processing methods

The test removed the spectral reflectance bands near 350 - 400 nm, 1350 - 1399 nm, 1800 - 1950 nm and 2400 - 2500 nm, because the spectral range of 350 - 2500 nm is greatly affected by moisture (Yang et al., 2019). By preprocessing the raw spectral data, the removal of spectral noise can be realized, and the effects of environmental background factors (e.g., light) and the instrument's own errors on the test results can be eliminated or reduced as much as possible to ensure the accurate extraction of spectral data on the PWC. On this basis, the raw spectral (R) data were transformed by logarithmic (lg R), first derivative (R'), and logarithmic first derivative (lg R'), and modeled based on this data.

Data analysis methods

The study used View Spec Pro 6.0 to pre-process the spectral data, ArcGIS10.8 to create an overview map of the study area. Origin 2021b to generate the winter wheat PWC line graph and winter wheat canopy spectral image, Excel 2019 and Unscrambler 10.0 to realize the lg R, R’, and lg R’ processing of the R, and finally The partial least squares regression(PLSR) method was used to construct the winter wheat PWC prediction model.

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Model evaluation

Model evaluation uses the coefficient of determination (R^2) and root mean square error (RMSE) as two measures of model accuracy (Li et al., 2022). R^2 is used to measure the ratio between the total variance of the predicted values and the total variance of the actual values, and can indicate the quality of the fit between the predicted and measured values (Ohtani, 2000). RMSE is a metric used to measure the difference between the predicted value and the actual value, the lower the RMSE, the better the quality of the model and the more accurate the prediction (Chai and Draxler, 2014). the closer the R^2 is to 1, the lower the RMSE and the more accurate the model will be.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - Y_i'\right)/(n-p-1)}{\sum_{i=1}^{n}\left(Y_i - Y_i'\right)^2/(n-1)} \qquad \text{(Eq.2)}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - Y_i')^2} \qquad \text{(Eq.3)}$$

where n represents the number of samples, Y_i represents the measured value and Y_i' represents the predicted value.

Results and analysis

Changes in PWC

Figure 2 shows the trend of winter wheat PWC with growth process under different drought stresses. The error bars in the figure indicate that the sample data under all treatment conditions have a low degree of dispersion, which can accurately reflect the real situation of the PWC of winter wheat under these treatment conditions. The PWC data of winter wheat after water stress can be further subjected to statistical analysis. From the figure, it can be seen that the PWC under different water stress conditions showed a decreasing trend. This is because during the development process of winter wheat, water gradually migrates to the leaves and ears, which in turn causes the PWC to continuously decline. At the same period, the overall PWC shows W1 > W2 > W3 > W4 > W5, which is negatively correlated with the degree of drought stress. Under W1 conditions, PWC declined more slowly until 229 days after sowing and more significantly after 229 days after sowing. Under W2 and W3 conditions, PWC decreased slowly until 208 days after sowing, and the decline was pronounced after 208 days of sowing. Under W4 and W5 conditions, winter wheat PWC decreased the most, and the downward trend slowed down after the PWC was below 58%. The difference of water content in winter wheat plants under different treatment conditions was the largest at 229 days after sowing.

Changing law of winter wheat canopy spectral reflectance under different water stress conditions

Under different water conditions, the canopy reflectance spectra of winter wheat showed remarkable commonality (*Figure 3*). Due to the strong absorption of red light by chlorophyll and the reflection of green light, the reflectivity peak appears in the visible light zone (400 - 680 nm), a "green peak" appears between 540 - 560 nm, and a "red valley" appears around 660 - 680 nm. The spectral reflectance of 680 - 780 nm increased sharply, and a high reflectance platform was formed in the NIR region (700-1300 nm),

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and the reflectance regularity was W1 > W2 > W3 > W4 > W5, because the spectral reflectance of the NIR was sensitive to the PWC. 1400nm, 2000nm and 2400nm were water vapor absorption bands, so the spectral reflectance was low.

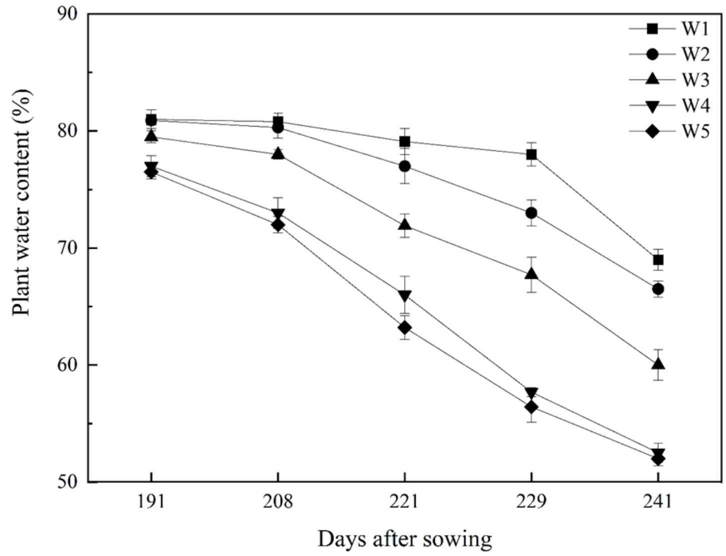

Figure 2. *Changing pattern of water content in winter wheat plants under different water stress conditions*

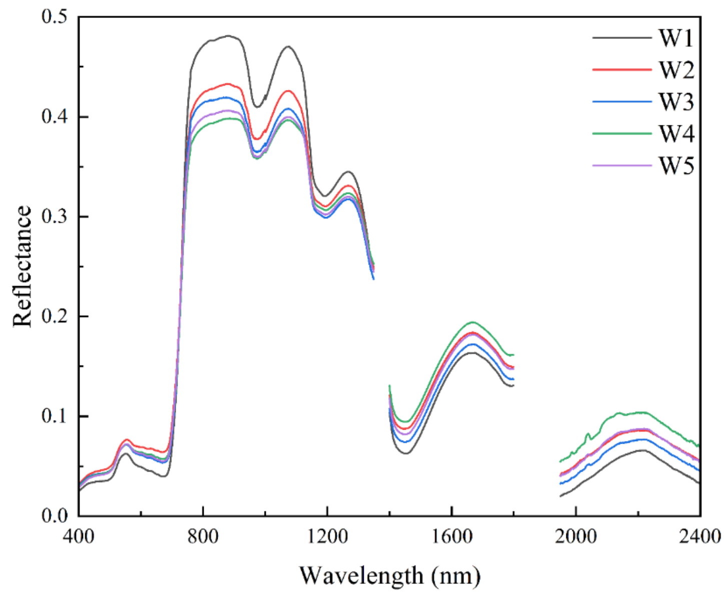

Figure 3. *Spectral reflectance of winter wheat canopy under different water stress conditions*

Reflectance variations of different transformed forms of spectra in the canopy

Figure 4 shows the lg R, R', and lg R' transformations of the preprocessed spectral reflectance. The different preprocessed spectra allow a better analysis of the relationship between spectral data and PWC. The lg R curves have the same characteristics as the R curves, and the logarithmic operation stretches the data segments, which can reflect the

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characteristics of the R more obviously. In the plots of the R curves, lg R curves, R’ curves and lg R’ curves, the spectral reflectance curves were sharply elevated at wavelengths from 700 to 800 nm. The spectral reflectance curves decrease at wavelengths from 1100 to 1200 nm. The spectral reflectance curves of the R’ and lg R’ are similar, but the lg R’ curve has a large fluctuation at 2000 nm.

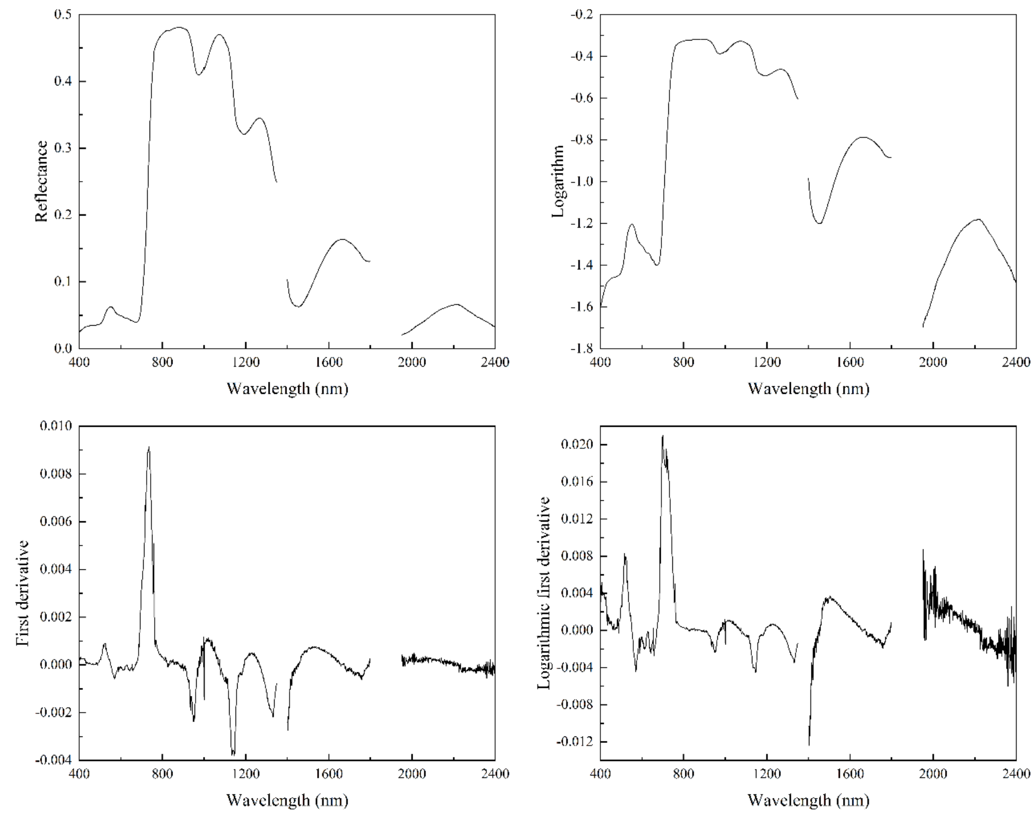

Figure 4. *Reflectance curves of different transformed forms of spectra in the canopy*

Correlation analysis between different pretreatment spectra and PWC

The raw spectral reflectance was highly consistent with the logarithmic spectral image features, and the PWC was negatively correlated with the spectral reflectance (*Figure 5*). In VIS (400-680 nm), the correlation coefficient decreases with the increase of wavelength, and reaches the minimum at 680 nm ($r<-0.55$). Probably due to the strong absorption of chlorophyll, the "red valley". In NIR (800-1400 nm), the correlation between water content and spectral reflectance was low, $r > -0.3$, and reached the lowest at 800 nm (-0.05). In the near infrared band (1400-1800 nm, 2000-2400 nm), the correlation between water content and spectral reflectance was enhanced, and there was a low correlation coefficient near 1400 nm, 1520 nm and 2030 nm, $r<-0.5$. In VIS (400 - 680 nm), the absolute value of correlation coefficients of the R’ spectrum and the lg R’ spectrum is greater than that of the R. The R’ and the lg R’ spectrum can enhance the peak value of the R to a certain extent, reduce the noise, and enhance the correlation between PWC and spectral reflectance of winter wheat.

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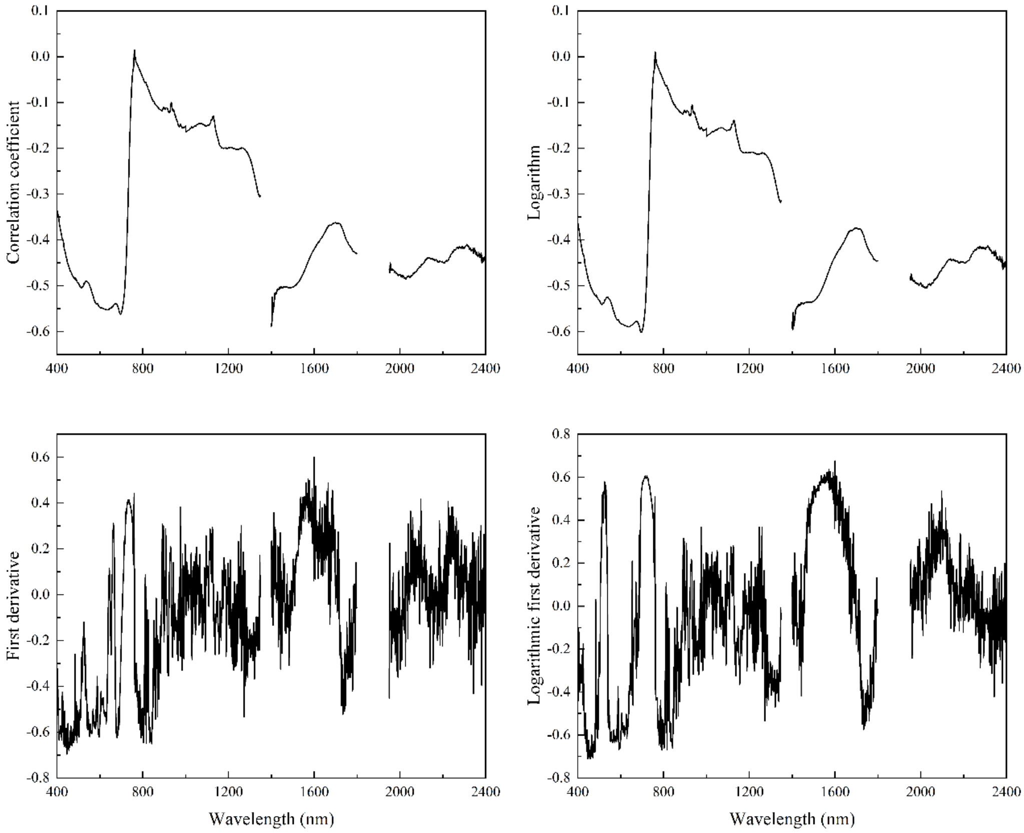

Figure 5. *Correlation coefficients between different pretreatment spectra and PWC*

PWC prediction model based on different pretreatment spectra

The PWC prediction model was constructed by PLSR for the R spectrum, lg R spectrum, R' spectrum and lg R' spectrum (*Table 3*). The lg R' model has the highest correlation with PWC, and the R^2 between the model and the measured value is 0.7259 in the calibration set and 0.8228 in the validation set, and the RMSE is the smallest, which is 6.25 % in the calibration set and 3.63 % in the validation set. Therefore, the PWC prediction model based on lg R' spectroscopy had the highest accuracy. This was followed by the R' spectral model. In the calibration set, the lg R spectral model had the smallest R^2 (0.5065) and the largest RMSE (8.38 %), and this model had the lowest accuracy. In the validation set, the primitive spectral model had the smallest R^2 (0.6784) and the largest RMSE (6.24 %), and this model had the lowest accuracy.

Table 3. *Prediction model of PWC after different mathematical transformation*

Mathematical transformation	Calibration model		Validation model	
	R^2c	RMSEc	R^2v	RMSEv
R	0.5689	0.0783	0.6784	0.0624
(lg R)	0.5065	0.0838	0.6919	0.0523
R'	0.6744	0.0681	0.7942	0.0387
(lg R')	0.7259	0.0625	0.8228	0.0363

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Discussion

Rapid monitoring, precise diagnosis and real-time regulation of crop water status have become an important research content and frontier technology of agricultural remote sensing in China and abroad, and one of the most important management measures in crop production (Sahila et al., 2024; Zhao et al., 2024). It was found that the PWC of winter wheat under any water stress condition decreased with the change of fertility process. The spectral reflectance of winter wheat canopy under different water treatments were all different, and PWC and spectral reflectance were roughly negatively correlated.

Chlorophyll is an important pigment in winter wheat leaves and plays a crucial role in photosynthesis (Lotfi et al., 2024). Under water stress conditions, the chlorophyll content in winter wheat may change. Previous studies have shown that in some cases, water stress can lead to a decrease in chlorophyll content (Abdullaev et al., 2024). The reduction in chlorophyll content, in turn, affects the spectral reflectance characteristics of winter wheat. Since chlorophyll has strong absorption in the red and blue regions of the spectrum and relatively high reflection in the green region, changes in chlorophyll content will cause changes in the intensity of the "green peak" and "red valley" in the spectral reflectance curve of the winter wheat canopy. It can be seen from *Figure 3* that under the influence of drought stress, W2, W3, W4, and W5 all show a weakened "green peak" and a shallower "red valley". It can be inferred from this that drought stress leads to a decrease in the chlorophyll content of winter wheat plants. Next, we will deeply explore the correlation between drought stress and chlorophyll content.

Spectral mathematical transformations can greatly eliminate the effects of different backgrounds and noises in spectral determination (Chen et al., 2023). Therefore, in this study, the raw spectral data obtained from the water content of winter wheat plants were transformed by lg R, R’ and lg R’ transformations. By comparing the prediction models under different mathematical transformations, it can be found that the accuracy of the constructed prediction models is greatly improved after applying mathematical transformations to the spectral data. Especially for the validation set, its R^2 is greater than 0.67, which shows that the mathematical transformations such as lg R and R’ processing of the raw spectra can improve the accuracy of the model prediction. This result is consistent with the findings of Wang (2020). The lg R transformation stretches the data segments through logarithmic operation, to some extent highlighting the characteristics of the R, making the variation trend of the spectral reflectance curve in certain bands more obvious, which is helpful for exploring the potential relationship between spectral data and PWC. The R’ transformation, as a common method in near-infrared spectral analysis, has the advantage of effectively eliminating background interferences such as the baseline. By taking the derivative of the spectral data, it highlights the detailed information of spectral changes, thus improving the correlation between the spectrum and PWC. The lg R’ transformation combines the dual effects of logarithm and derivative. While enhancing the spectral characteristics, it further reduces the influence of noise, resulting in the highest accuracy of the constructed PWC prediction model.

The study showed that the logarithmic first derivative transformation has a remarkable effect on improving the model accuracy. It can effectively process the spectral data and enhance the correlation between the data and the water content of winter wheat plants. With this technical means, real-time and accurate monitoring of the water content of winter wheat plants can be achieved, and scientific irrigation can be carried out according to the actual water demand. In this way, not only the waste of water resources can be avoided, but also the maximum effective utilization of water resources can be ensured. It

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provides strong support for the efficient water-saving irrigation of winter wheat planting and promotes the optimization and upgrading of agricultural water resource management.

However, since this experiment did not involve other production conditions such as different wheat varieties, different sowing times, and different soil types, the generalizability of the PWC prediction model constructed in this experiment remains to be further investigated. In conclusion, the results of this study can provide technical support for rapid monitoring, precise diagnosis and implementation of regulation of crop water status.

Conclusion

In this study, winter wheat was subjected to different water stress treatments, and in order to establish a prediction model for winter wheat moisture content, the quantitative relationships between R spectra, R' spectra, lg R spectra, and lg R' spectra in the wavelength range of 350-2500 nm and the moisture content of winter wheat were analyzed. The results showed that the prediction model constructed based on the lg R' spectra was the most accurate, with an R^2 of 0.7259 and an RMSE of 6.25 %; in the validation set, the model had an R^2 of 0.8228 and an RMSE of 3.63 %. It provides the feasibility of non-destructive and rapid monitoring of water content in winter wheat plants. Finally, the prediction of winter wheat yield is our top priority. Yield is the most valuable product of wheat cultivation. The prediction and inversion of winter wheat yield is an important research direction. Next, we will focus on establishing a direct connection between reflectance data and yield as the research emphasis.

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