

Article

An Assessment Model for Winter Wheat Crop Water Status Fusing Hyperspectral and Environmental Data

Nana Han ^{1,2}, Minmin Wang ^{1,3}, Qingyun Zhou ^{1,2,*}, Xin Han ^{1,3}, Xiaomao Liu ¹, Zhigong Peng ³ and Songmin Li ^{1,2}

¹ College of Water Conservancy Engineering, Tianjin Agricultural University, Tianjin 300392, China; hannana@tjau.edu.cn (N.H.); wangminmin1007@163.com (M.W.); xinhan@tjau.edu.cn (X.H.); 15222655078@163.com (X.L.); lisongmin228@126.com (S.L.)

² Tianjin Agricultural University-China Agricultural University Joint Smart Water Conservancy Research Center, Tianjin 300392, China

³ China Institute of Water Resources and Hydropower Research, Beijing 100038, China; pengzhg@iwhr.com

* Correspondence: zhouqingyun@tjau.edu.cn; Tel.: +86-159-2208-7501

Abstract

Accurate monitoring of the crop water status is of great significance for agricultural water management. To address the limitations of traditional spectral models that neglect the synergistic effects of environmental factors, this study aimed to improve the prediction ability of winter wheat water status by integrating multi-source data and machine learning algorithms. The results demonstrated significant improvements in prediction accuracy when environmental factors were integrated with hyperspectral data. During the jointing, heading, and filling stages, the prediction accuracy of the winter wheat plant water content model based on canopy hyperspectral fusion environmental factors (temperature and soil water content) was significantly higher than that based on the canopy spectral data model. The model performance (R^2) increased from 0.74, 0.59, and 0.70 to 0.82, 0.69, and 0.76, respectively. The SVM-based full-growth-stage fusion model exhibited superior performance ($R^2 = 0.85$, RMSE = 5.10%, RE = 7.79%), achieving accuracy improvements of 3.53%, 23.19%, and 11.84% compared to three key growth-period models. This study confirms that integrating canopy hyperspectral data with environmental factors systematically enhances the generalization capability and accuracy of winter wheat water content prediction, providing a reliable technical solution for precision irrigation and innovative agricultural development in the future.

Keywords: winter wheat; hyperspectral index; environmental factor; synergy model; plant water status; machine learning



Academic Editor: Haijun Liu

Received: 14 July 2025

Revised: 17 August 2025

Accepted: 26 August 2025

Published: 31 August 2025

Citation: Han, N.; Wang, M.; Zhou, Q.; Han, X.; Liu, X.; Peng, Z.; Li, S. An Assessment Model for Winter Wheat Crop Water Status Fusing Hyperspectral and Environmental Data. *Water* **2025**, *17*, 2574. <https://doi.org/10.3390/w17172574>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

As a globally pivotal cereal crop, winter wheat has an irreplaceable strategic position in ensuring food security and maintaining agricultural economic stability [1,2]. In China, winter wheat is the ballast stone of food security. The main producing areas cover core agricultural areas, such as the North China Plain and the Huang-Huai-Hai River Basin. The annual output is stable at more than 130 million tons, accounting for nearly a quarter of the country's total grain output. As the core environmental factor for the growth and development of winter wheat, water not only regulates key physiological processes such as photosynthesis and nutrient absorption, but also directly determines the formation of yield potential and grain quality [3–6]. As the world's largest wheat producer and consumer,

particularly in the context of current global climate change, the rise in drought frequency and alterations in precipitation regimes have led to heterogeneous water resource allocation across geographical areas and periods. The stable and high-yielding capacity of winter wheat is directly related to the national strategy of “holding the rice bowl firmly in your own hands.” Therefore, the accurate estimation of winter wheat plants’ water content is important for irrigation scheduling improvement decisions and improving water-use efficiency, and is a key technical for achieving precision agriculture [7,8].

Traditional winter wheat water monitoring mainly depends on field sampling combined with laboratory analysis methods (e.g., drying and pressure chamber techniques). Although these methods can provide more accurate data, they have inherent limitations, such as destructive sampling and poor timeliness. These issues severely limit the efficiency of precision irrigation decision-making [9–11]. In contrast, hyperspectral remote sensing technology can non-contactly monitor key parameters, such as leaf water content, and quantitatively analyze crop canopy water dynamics by capturing continuous narrow-band spectral information in the range of 400–2500 nm, which provides efficient technical support for building precision irrigation systems [12,13]. The theoretical foundation for using hyperspectral remote sensing to monitor crop moisture lies in the fact that changes in the energy levels of O–H bonds in water molecules produce significant spectral responses in specific wavelength bands, such as 970, 1200, 1450, 1950, and 2500 nm. The spectral characteristics related to crop moisture are primarily found in the near-infrared (750–1300 nm) and shortwave-infrared (1300–2500 nm) regions [14]. Therefore, when crops are subjected to drought stress, changes in their morphological and physiological indices, as well as leaf texture, lead to significant differences in the reflectance spectral curve. These changes can be effectively monitored using remote sensing [15].

In the construction of a water monitoring model, previous studies have confirmed a significant correlation between leaf water content and various spectral indices (such as the normalized difference water index, NDWI, simple ratio, SR, and shortwave infrared vertical water stress index, SPSI) [16]. Furthermore, the introduction of machine learning algorithms in recent years has significantly enhanced the accuracy and efficiency of water monitoring methods. For example, Unmanned Aerial Vehicle (UAV) multispectral thermal imaging data are combined with machine learning models to predict the crop water stress index (CWSI), which provides a more timely and reliable basis for decision-making in precision irrigation [17]. Based on the machine learning language, the researchers developed an estimation model of wheat leaf water content using the hyperspectral reflectance data of the 750–1300 nm band. Its accuracy is significantly better than that of the traditional vegetation index model [18]. Further validation using hyperspectral data from 10 wheat varieties confirmed the strong potential of combining hyperspectral remote sensing with machine learning for crop water monitoring [19].

Current research primarily constructs estimation models based on the direct correlation between spectral data and plant water content, while overlooking the effects of environmental factors, such as temperature and soil moisture, on crop water regulation. These environmental factors directly affect crop growth and yield formation by altering their physiological processes and water-use efficiency. In terms of temperature, crop water status is primarily regulated through two key physiological processes: stomatal conductance and the activity of photosynthetic enzymes. This regulation exhibits a significant threshold effect [20]. Based on this physiological mechanism, canopy temperature (T_c) has become an effective indicator of crop water stress because of its close correlation with plant water status [21], and the temperature difference between canopy and atmosphere is used to calculate crop water stress index (CWSI) and guide irrigation practice [22]. In terms of soil moisture, some studies have found that soil water content directly determines

root water uptake capacity, and its influence shows threshold characteristics. When soil moisture is insufficient, crops will reduce water loss by reducing stomatal conductance and transpiration rate. Farmers can determine the optimal irrigation time and quantity by evaluating the water status of their crops and soil moisture levels [23]. On the other hand, some researchers have found a certain relationship between soil moisture and canopy temperature. Under sufficient irrigation, moderate irrigation, and deficit irrigation, the canopy temperature of maize changes. It was found that with a decrease in irrigation amount, when soil moisture is deficient, the leaves of the plant curl and the stomata close, increasing crop canopy temperature [24]. However, it is worth noting that there are notable distinctions in the effects of environmental factors on crop physiological indicators at different growth stages, and this dynamic change feature is often neglected in current research [25]. On this basis, this study constructed a winter wheat plant water inversion model based on hyperspectral-environmental factor coupling at different growth stages and the entire growth period, and compared and analyzed the accuracy of the plant water content inversion model at various growth stages and the entire growth period.

In summary, spectral data and environmental factors, such as temperature and soil water content, play an important role in indicating crop water status. Although numerous studies have proposed various spectral indices for water status monitoring across different crops, species, and growth stages, and extensive research has been conducted on winter wheat, several critical research gaps have remained. First, few studies have integrated ground-based hyperspectral technology with environmental factors. Second, most research has focused on only one or several key growth stages, lacking comprehensive water status diagnostics covering winter wheat's entire lifecycle. This study has addressed these gaps; therefore, This study conducted the following analyses: (i) based on near-ground hyperspectral data from 2023 to 2024, an estimation model of plant water content in different life cycles of winter wheat was constructed and evaluated; (ii) the near-ground hyperspectral index combined with environmental factors (canopy temperature, ground temperature, and soil moisture content) was used to optimize the diagnostic model of winter wheat plant moisture content at different growth stages; (iii) based on the optimized plant water content estimation model at different growth stages, a winter wheat plant water content estimation model based on the hyperspectral index combined with environmental factors at the whole growth stage was constructed. This study addresses the limitations of traditional spectral models in terms of adaptability to environmental heterogeneity, and its results can provide more reliable technical support for precision agriculture and sustainable water resource management.

2. Materials and Methods

2.1. Study Site

The experimental site was located in the Daxing Water-Saving Irrigation Experimental Research Base of the China Institute of Water Resources and Hydropower Research (39° 37.25' N, 116° 25.51' E, 30 m above sea level). It belongs to the semi-humid continental monsoon climate zone, and the abundant light and heat conditions are suitable for the growth of winter wheat, corn, and other crops. The field soil type and the soil type in the lysimeter were sandy loam. During the test period, the average annual precipitation in the study area was approximately 540 mm, the average annual temperature was 12.1 °C, the average yearly water surface evaporation exceeded 1800 mm, and the annual sunshine hours were approximately 2600 h (Figure 1).

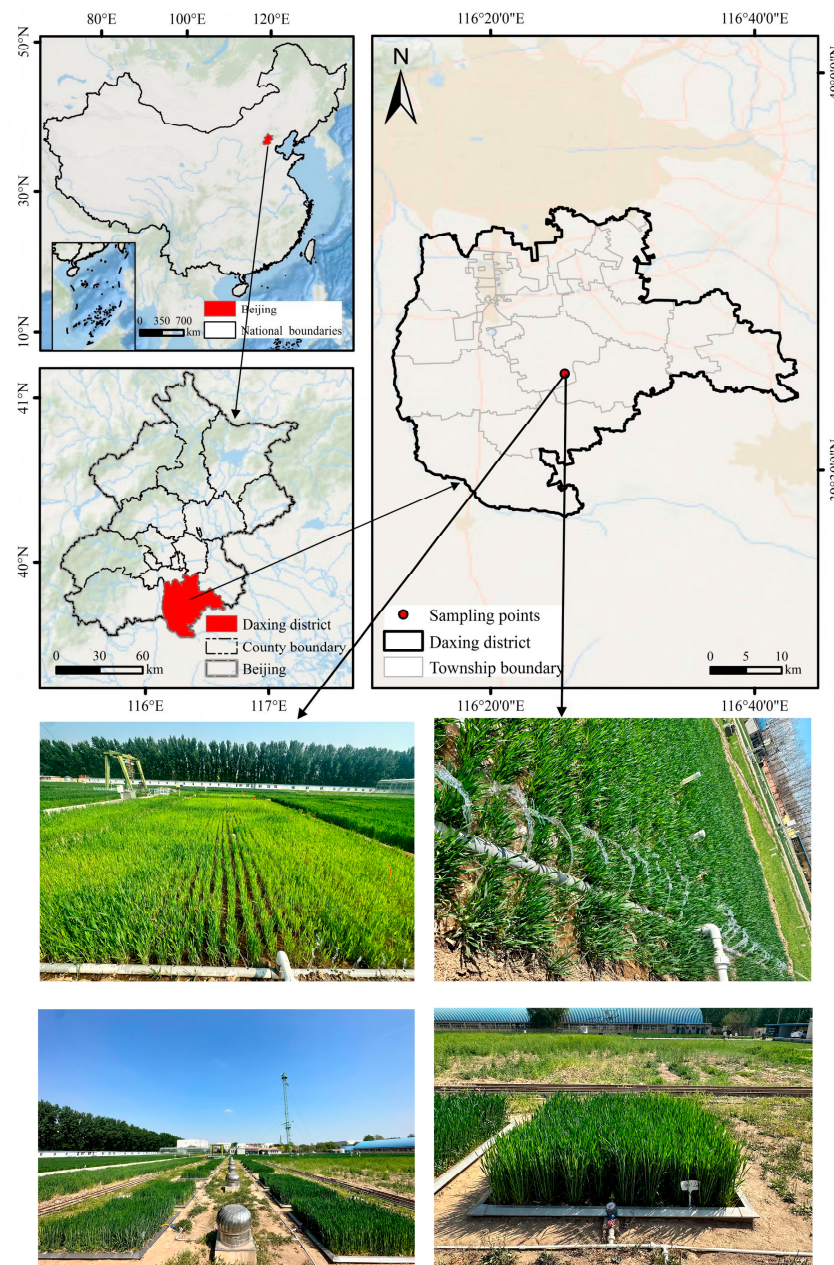


Figure 1. Distribution map of study areas.

2.2. Field Experiment Design

The crop in the study area was winter wheat. The tested wheat variety is Jimai 21, which is sown in mid-October of each year and harvested in mid-June of the following year. The experimental observation period occurred during the main growth period of winter wheat (March–June) in 2018–2019 and 2023–2024. The experiment was unavoidably suspended between 2020 and 2022 due to COVID-19 pandemic restrictions. The change in irrigation amount between the different treatment groups in this experiment refers to the local irrigation experience and a previous field experiment on winter wheat [26,27]. Following winter wheat's green-up stage, three irrigation treatments were established during the 2018–2019 trials: W1 treatment (irrigation once after regreening, representing severe water stress) with a 165 mm quota; W2 treatment (irrigation two times after regreening, mild water stress) with a 225 mm quota; and W3 treatment (irrigation three times after regreening normal water conditions) with a 285 mm quota, with six replicates for each treatment. In the field experiment from 2018 to 2019, there were a total of 18

plots, with an area of approximately 60 m² per plot. This study established five irrigation gradients in the 2023–2024 experiment (The irrigation quotas are 245 mm, 200 mm, 155 mm, 105 mm, and 285 mm, labeled as a, b, c, d, and e, respectively). Treatments a, b, and c were conducted in the buried small lysimeter observation system, whereas treatments d and e were performed in the field. The winter wheat in the soil column of the small lysimeter had an environment similar to that of the field. The irrigation water source was groundwater, and the irrigation method was flood irrigation. Each irrigation was measured using a water meter. Each irrigation treatment set in the 2023–2024 field test and small lysimeter tests had six replicates. The field test consisted of a total of 12 plots, with an approximate area of 60 m² for each plot. There were eighteen small lysimeter tests buried, and the single lysimeter size was 2 m × 2 m × 2.4 m. Other management measures follow local winter wheat field management standards (Table 1).

Table 1. Winter wheat irrigation test treatment.

Year	Treatment		Irrigating Quota on Each Application/mm					Irrigation Quota/mm
			Pre-Sowing Irrigation	Winter Irrigation	Reviving-Jointing 5 April 2019 3 April 2024	Jointing-Heading 26 April 2019 23 April 2024	Heading-Filling 21 May 2019 17 May 2024	
2018–2019	field test	W1	45	60		60		165
		W2	45	60	60	60		225
		W3	45	60	60	60	60	285
2023–2024	small lysimeter test	a	45	60	45	45	50	245
		b	45	60	45		50	200
		c	45	60	50			155
	field test	d	45	60				105
		e	45	60	60	60	60	285

Before sowing winter wheat, apply compound fertilizer (15% N, 15% P₂O₅, 15% K₂O) as base fertilizer, Urea as top dressing after irrigation or rainfall during the jointing-heading stages in 2018–2019 and 2023–2024, respectively. Each application of fertilizer was applied at a rate of 225 kg/ha, with uniform levels maintained across all plots. Field management, including seeding, herbicide application, foliar spraying, and other agricultural operations, was consistent with the routine practices of local farmers.

2.3. Data Measurements

This study collected canopy hyperspectral data and ground-based measurements (canopy temperature, ground surface temperature, soil moisture content) during the jointing stage (22 April 2019, and 18 April 2024), heading stage (13 May 2019, and 18 May 2024), and filling stage (28 May 2019, and 28 May 2024).

2.3.1. Canopy Spectral Data Acquisition

Throughout the winter wheat growing season, this study utilized the FieldSpec 4 Hi-Res NG back-mounted ground object spectrometer (field angle: 25°, band range: 350–2500 nm), produced by ASD in the United States, to monitor the spectral reflectance of the plant canopy. The monitoring work was conducted under sunny, windless, or breezy weather conditions, with a specific time frame of 10:00–12:00 every day. The wavelength range of the instrument was 350–2500 nm. The sampling interval was 1.4 nm (350–1000 nm) and 1.1 nm (1001–2500 nm), respectively. The spectral resolution was 3 nm (700 nm) and 6 nm (1400/2100 nm), respectively.

During monitoring, the operator maintained the field spectrometer probe in a vertical downward position at a consistent 15 cm distance above the wheat canopy. To ensure data quality, the operator performed instrument calibration before each monitoring session

using a standard white reference panel (reflectivity = 1), repeating this calibration every 15 min. At each sampling point, the operator recorded 10 spectral curves and calculated their average as the representative spectral data for that location. For each experimental plot, the operator selected two representative monitoring points and used their averaged measurements as the final canopy spectral reflectance value for that winter wheat plot.

2.3.2. Determination of Water Content of Winter Wheat Plant

In this experiment, the researchers measured the water content of winter wheat plants and collected spectral data on the same day. After obtaining the canopy spectral data of winter wheat, 20–30 winter wheat plants at the corresponding points were collected and brought back to the laboratory to determine their fresh weight. They were then placed in an oven at 105 °C for 30 min and subsequently adjusted to 75 °C for drying to a constant weight. The dry weight was measured, and the plant water content (PWC) was calculated.

$$PWC = (M1 - M2)/M1 \times 100\% \quad (1)$$

M1 and M2 are the fresh and dry weights of the plant, respectively.

2.3.3. Determination of Soil Moisture Content of Winter Wheat

The soil moisture content was measured using a German TDR (Time Domain Reflectometer, IMKO Micromodultechnik GmbH, Ettlingen, Germany). There were two measuring points in each plot, and the estimated value of soil moisture content in the plot was the average value of the two points. We measured five soil depths (0.2, 0.4, 0.6, 0.8, and 1 m) at each measuring point in the plot.

2.3.4. Determination of Canopy Temperature and Ground Temperature of Winter Wheat

The measurement time of the winter wheat canopy and ground temperatures corresponded to the spectral acquisition time. Using a handheld infrared thermometer, A vertical distance of 15–20 cm was maintained between the instrument and the top of the winter wheat canopy during measurement. The crop canopy and surface temperatures were recorded simultaneously.

2.4. Hyperspectral Data Preprocessing and Spectral Index Calculation

The original spectral data collected in this experiment were pre-processed using ViewSpecPro5.6.8 software. Based on previous research results, 10 hyperspectral indices related to plant water status were selected. The specific index names and calculation methods are listed in Table 2.

Table 2. Computational approach and citation for vegetation water-related spectral indices.

Spectral Index	Definition or Equation	References
Water index, WI	$R900/R970$	Peñuelas et al. [28]
Normalized differential water index, NDWI	$(R860 - R1640)/(R860 + R1640)$	Eitel et al. [29]
Ratio Index, RI	$R810/R460$	Elvidge et al. [30]
Moisture stress index, MSI	$R1600/R820$	Hunt et al. [31]
Normalized Difference Infrared Index, NDII	$(R820 - R1649)/(R820 + R1679)$	Hardisky et al. [32]
Simple Ratio Water Index, SRWI	$R820/R1200$	Zarco et al. [33]
$R(810,460)$	$R810/R460$	Bai et al. [34]
Vegetative and Reproductive Index, VARI	$(R700 - 1.7 \cdot R670 + 0.7 \cdot R450)/(R700 + 2.3 \cdot R670 - 1.3 \cdot R450)$	Bai et al. [34]
Pigment Specific Simple Ratio, PSSRa	$R800/R680$	Bai et al. [34]
Normalized Difference Vegetation Index, NDVI	$(R820 - 1240)/(R820 + 1240)$	Gao et al. [35]

2.5. Modeling Method

In this study, three algorithms of univariate regression, random forest (RF), and support vector machine (SVM) were used to construct the estimation model of winter wheat plant water content with the selected hyperspectral index as the input variable. The univariate regression model was constructed using Excel 2021, and the random forest and support vector machine models were constructed using R 4.1.3 software.

Simple regression (SR) includes linear regression, power functions, and logarithmic functions. The RF algorithm is an ensemble learning algorithm composed of many randomly generated decision trees. The RF algorithm can enhance model performance by mitigating overfitting and reducing overlearning [36–38]. The SVM maps the input vector data from the original space to a higher space (HS) by either linear or nonlinear mapping, and constructs the optimal regression function in HS [39,40].

The coefficient of determination (R^2), root mean square error (RMSE), and relative error (RE) were used to evaluate the model's accuracy. The closer R^2 is to 1, the better the model's fitting effect. The closer the RMSE is to 0, the higher the accuracy of the model and the better its effect. The RE value was less than 10%, and the model's stability was good. When the RE was between 10% and 30%, the model's stability was good. The RE is greater than 30%, and the model's stability is poor [40,41]. The calculation formula is as follows:

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

$$RE = \frac{RMSE}{\bar{y}} \times 100\% \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (x_i - y_i)^2}{n}} \quad (4)$$

y_i is the observed value, x_i is the predicted value, $\bar{y}$ is the mean value, and n is the sample size.

2.6. Technology Roadmap

This study was conducted at the Daxing Water-Saving Irrigation Experimental Station of the China Institute of Water Resources and Hydropower Research, where we carried out field plot experiments on winter wheat under different irrigation treatments during 2018–2019 and 2023–2024. In this study, we constructed a winter wheat plant water content monitoring model by integrating environmental factors and spectral indices, which effectively overcomes the limitations of traditional spectral indices in evaluating the water status of winter wheat plants. Simultaneously, the correlation analysis method was used to screen the key predictors to avoid the problem of index redundancy. The primary process of this study included the following steps: (a) collect spectral data and ground data; (b) screen vegetation indicators and environmental factors; (c) use different feature selection methods and machine learning algorithms to construct a winter wheat prediction model; (d) validate the stability of the model (R^2 , RMSE, RE). This study improved the accuracy of the water content estimation model of winter wheat plants, to provide a theoretical basis for the identification of water phenotype information of winter wheat and the regulation of efficient irrigation in farmland (Figure 2).

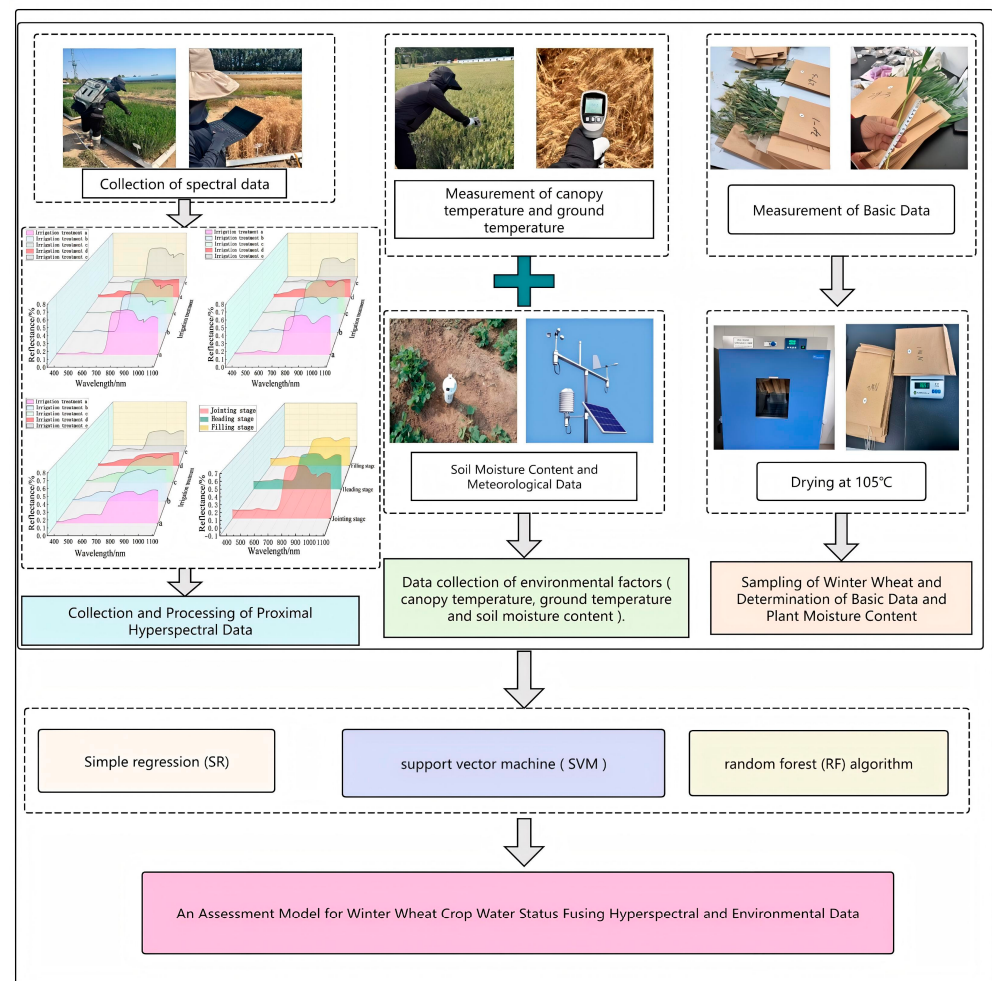


Figure 2. Technical roadmap.

3. Results

3.1. Water Content Variation in Winter Wheat During Growth Stages

According to the water content data collected from field and pit experiments on winter wheat plants from 2023 to 2024, a *t*-test was used to analyze the significant differences in water content of winter wheat plants at different growth stages. The changes in water content of winter wheat plants in the jointing, heading, and filling stages are shown in Figure 3 (the figure indicates that different irrigation treatments have significant differences at the 0.05 level, and the greater the difference). The water content of winter wheat plants under different irrigation treatments during the same growth period was significantly different, and the amount of irrigation was positively correlated with the water content of the plant. As the winter wheat growth period advanced, the water content of plants under different treatments exhibited an overall downward trend.

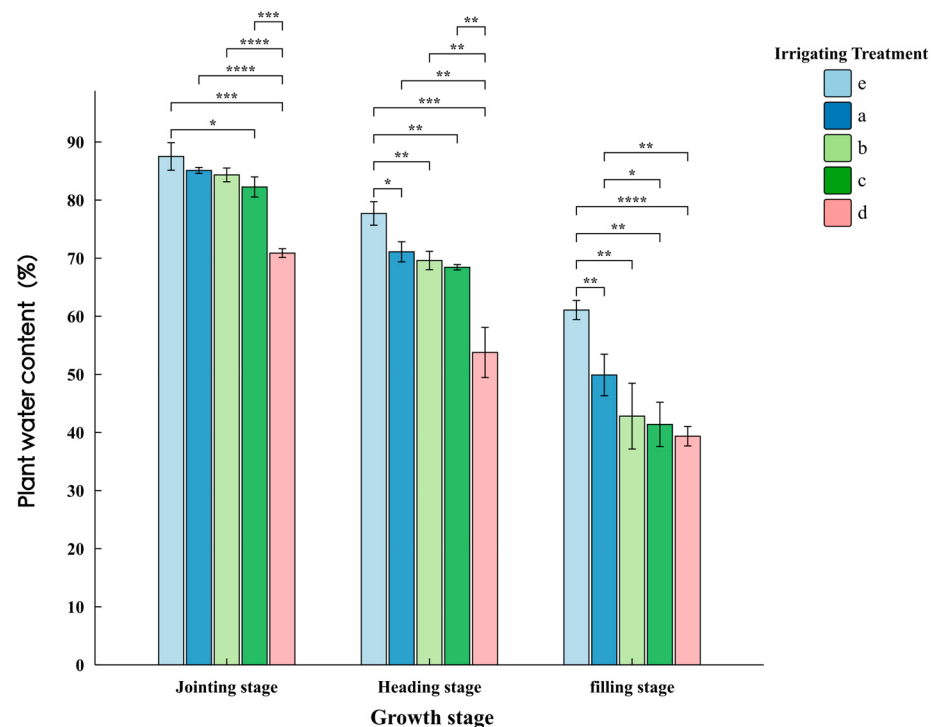


Figure 3. We implemented five irrigation treatments with different water quotas (245 mm, 200 mm, 155 mm, 105 mm, and 285 mm, labeled as a, b, c, d, and e, respectively) during the 2023–2024 growing season. Changes in plant water content during jointing, heading, and the filling stage are indicated by asterisks (* indicates significant differences at the 0.05 level among different irrigation treatments, and ** at the 0.01 level, *** at the 0.001 level, and **** at $p < 0.001$).

3.2. Canopy Spectral Reflectance Variations of Winter Wheat Across Growth Stages

As shown in the figure, different irrigation treatments at various growth stages resulted in varying degrees of change in the canopy spectrum; however, the form of the canopy hyperspectral reflectance curve remained essentially unchanged, which plays a significant limiting role in the winter wheat canopy hyperspectral reflectance (Figure 4). Under the same irrigation treatment conditions (Figure 5), the spectral reflectance at the jointing stage was higher than that at other growth stages. With the advancement of the growth period, the hyperspectral reflectance of winter wheat gradually decreased, indicating that the canopy reflectance spectral information can be used to observe water conditions. However, this response characteristic gradually became less pronounced as the growth period advanced, indicating that the water effect on the original reflectance of the winter wheat canopy had a phenological effect.

3.3. Correlation Between Winter Wheat Plant Water Content and Influencing Factors Across Growth Stages

To further understand the relationship between winter wheat plant water content and canopy hyperspectral reflectance, as well as the relationship between winter wheat plant water content and environmental factors, a correlation analysis was conducted on winter wheat test data from 2023 to 2024 in this study. In this experiment, Pearson correlation analysis was employed to calculate the correlation coefficients between hyperspectral indices, environmental factors, and plant water content. Using Origin 2024b software, we generated correlation heatmaps (Figure 6) to illustrate these relationships across the three critical growth stages. The influencing factors with extremely significant correlations were then selected to participate in establishing the model.

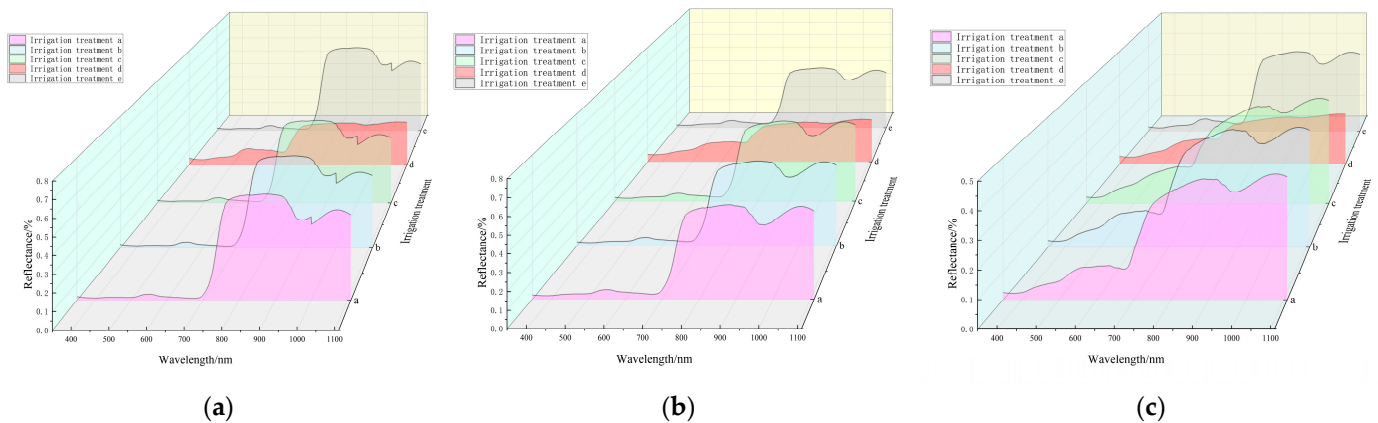


Figure 4. (a) Spectral reflectance of winter wheat canopies under different water treatments during the jointing period. (b) Spectral reflectance of winter wheat canopies under different water treatments during the heading period. (c) Spectral reflectance of winter wheat canopies under different water treatments during the filling period.

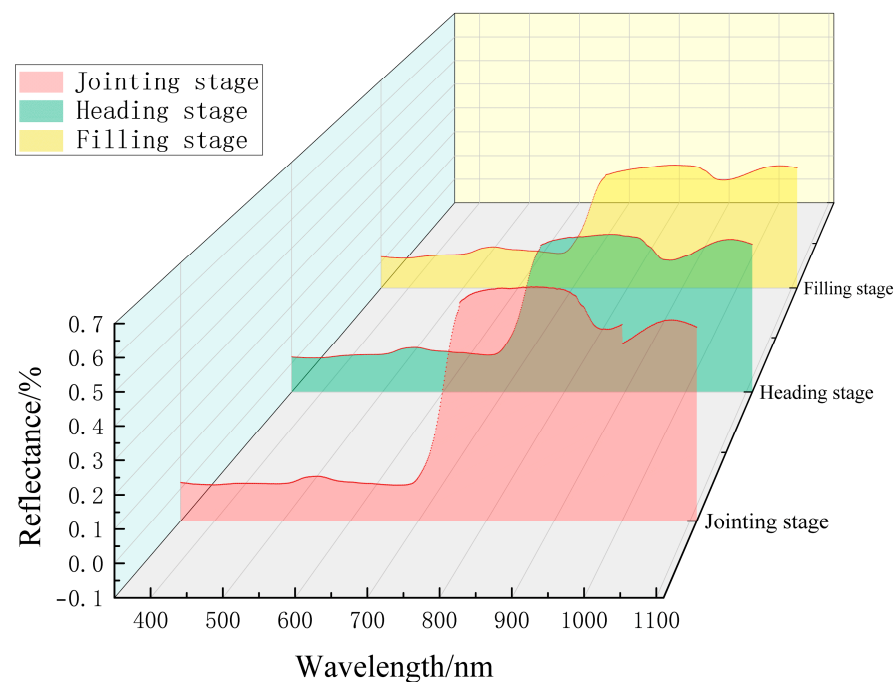


Figure 5. The changes in winter wheat canopy reflectance at different reproductive stages under the treatment of the irrigation scheme.

At the jointing, heading, and filling stages, five hyperspectral indices, ground temperature, canopy temperature, canopy temperature difference, and soil moisture content were selected, all of which are sensitive to plant moisture content. The hyperspectral indices and environmental factors selected at the three growth stages were different, but most of these hyperspectral indices were closely related to the green and red bands of the spectrum. Simultaneously, environmental factors also showed a high correlation with the water content of winter wheat plants. The correlation coefficient between soil temperature and plant water content at the jointing stage was -0.70 , the correlation coefficient between canopy temperature and plant water content at the heading stage was -0.91 , and the correlation coefficient between soil water content and plant water content at 40 cm at the filling stage was 0.81 (Figure 6).

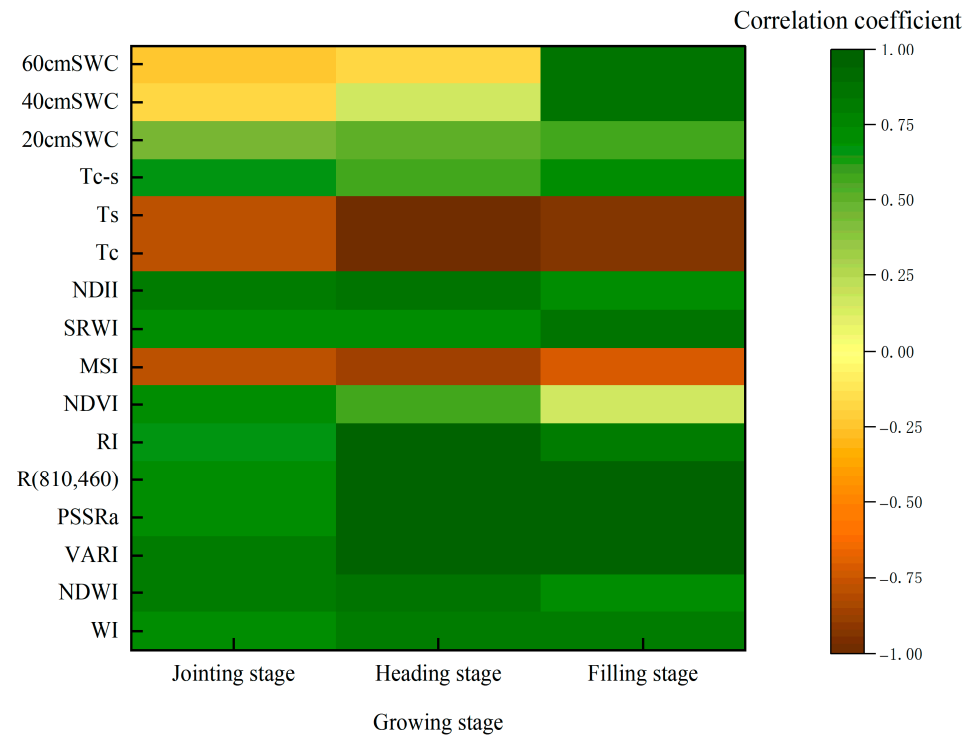


Figure 6. Analysis of the correlation between hyperspectral indices, environmental factors, and plant water content at different reproductive periods.

3.4. Estimating Winter Wheat Plant Water Content Across Growth Stages Using Canopy Hyperspectral Indices

This study utilizes 2023–2024 data to develop a model and 2018–2019 data to validate the model's accuracy. In 2023–2024, 30 samples were taken at the jointing, heading, and filling stages to establish the model. In 2018–2019, 18 samples were taken at the jointing, heading, and filling stages to verify the model. Near-end hyperspectral remote sensing data were used as input variables to estimate the water content of winter wheat plants. The R^2 , RMSE, and R values of each model were significantly different (Table 3). In the jointing stage, the RF model modeling set ($R^2 = 0.81$, RMSE = 2.08%, RE = 2.66%) and the validation set ($R^2 = 0.74$, RMSE = 2.61%, RE = 3.33%) exhibited higher accuracy and generalization ability. In the heading stage modeling set, the SVM model validation set had a higher fitting effect ($R^2 = 0.92$, RMSE = 2.08%, RE = 3.14%), and the validation set model also had a better fitting effect ($R^2 = 0.59$, RMSE = 4.17%, RE = 6.24%). During the grain filling stage, the Random Forest (RF) model demonstrated superior fitting performance in the training set ($R^2 = 0.93$, RMSE = 2.02%, RE = 3.83%), while the Support Vector Machine (SVM) model showed better results in the validation set ($R^2 = 0.70$, RMSE = 4.86%, RE = 9.52%).

Table 3. Different modeling methods for different reproductive periods are based on hyperspectral index model analysis ($p < 0.05$).

Growth Stage	Algorithm	Hyperspectral Index	Model Training			Model Testing		
			R^2	RMSE/%	RE/%	R^2	RMSE/%	RE/%
Jointing stage ($n = 48$)	RF	NDWI, NDVI, MSI,	0.805	2.080	2.658	0.742	2.612	3.334
	SVM	SRWI, NDII	0.572	3.888	3.482	0.332	2.265	2.878
	SR	SRWI	0.564	3.922	4.866	0.498	1.963	2.494

Table 3. Cont.

Growth Stage	Algorithm	Hyperspectral Index	Model Training			Model Testing		
			R ²	RMSE/%	RE/%	R ²	RMSE/%	RE/%
Heading stage (n = 48)	RF	VARI, PSSRa, R(810,460),	0.893	2.178	3.284	0.315	5.394	8.074
	SVM	RI, MSI	0.923	2.082	3.143	0.590	4.169	6.241
	SR	VARI	0.747	3.346	5.047	0.549	4.374	6.547
filling stage (n = 48)	RF	VARI, PSSRa, R(810,460),	0.928	2.019	3.829	0.541	6.042	11.823
	SVM	SRWI, WI	0.902	1.933	3.601	0.702	4.864	9.518
	SR	VARI	0.724	4.081	7.743	0.675	5.078	9.938

In the model analysis based on the hyperspectral index at different growth stages, the RF fitting effect was the best at the jointing stage, the SVM model fitting effect was better at the heading stage, and the SVM model fitting effect was even better at the filling stage (Figure 7).

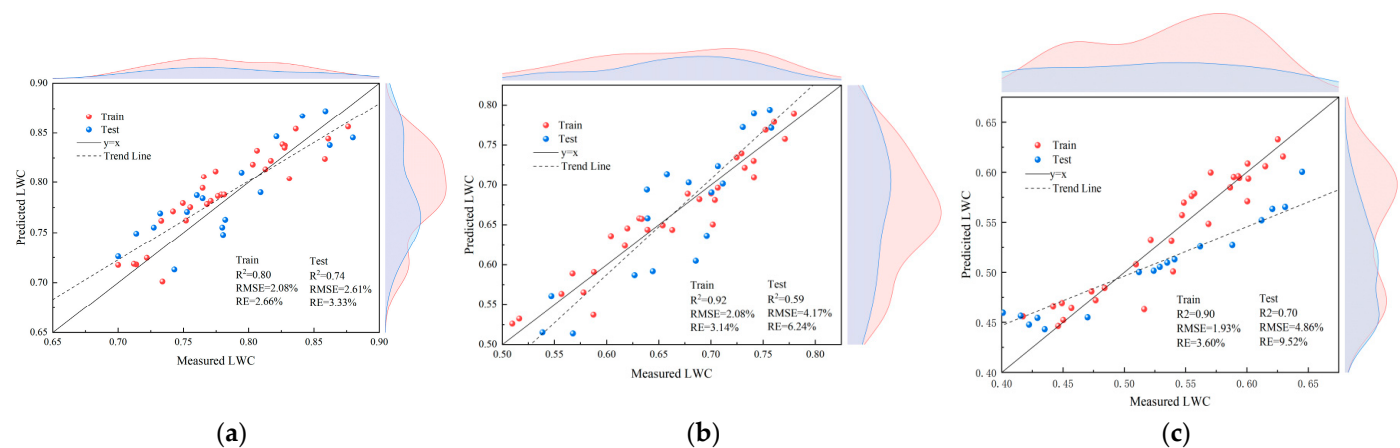


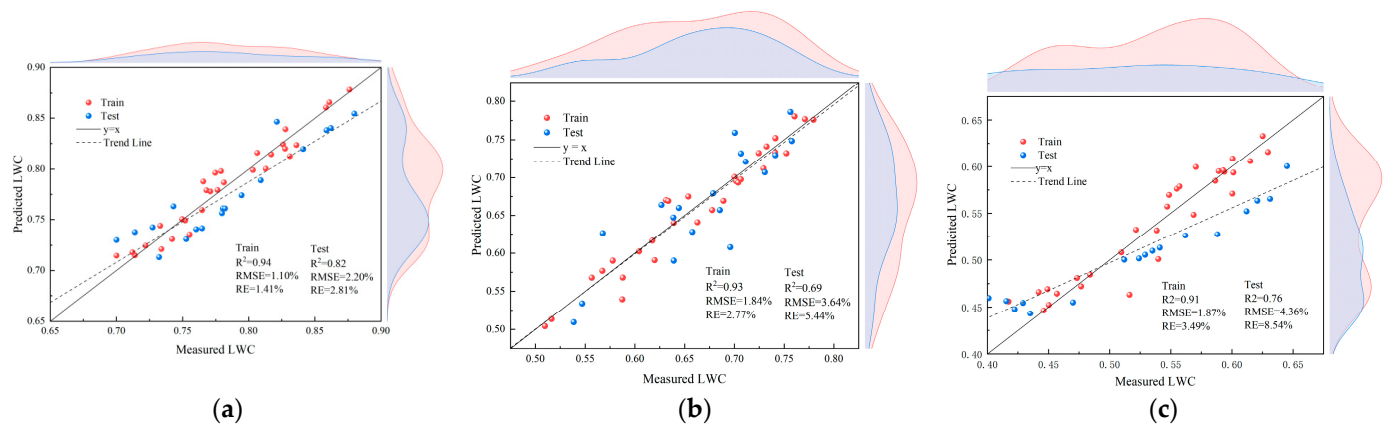
Figure 7. Fitting effect diagrams of modeling sets and validation sets at different growth stages: (a) random forest model for the jointing period; (b) simple regression model for the heading period; (c) support vector machine model for the filling period.

3.5. Estimating Winter Wheat Water Content Across Growth Stages by Integrating Canopy Hyperspectral Indices and Environmental Variables

By combining environmental information with near-end hyperspectral data, RF, SVM, and SR algorithms were systematically employed to develop stage-specific predictive models for assessing crop water status. As shown in Table 4, the SVM model ($R^2 = 0.96$, $RMSE = 1.15\%$, $RE = 1.43\%$) in the jointing stage was better than the other models, and the RF model ($R^2 = 0.82$, $RMSE = 2.20\%$, $RE = 2.81\%$) in the validation set was better than the other models. The RF model ($R^2 = 0.95$, $RMSE = 1.43\%$, $RE = 2.16\%$) performed better in the heading stage modeling, while the simple linear regression (SR) model ($R^2 = 0.69$, $RMSE = 3.64\%$, $RE = 5.44\%$) performed better in the verification. The results showed that the canopy temperature used in the linear regression model to predict plant water content at the heading stage was superior to that of the other algorithms in terms of fitting effect, prediction accuracy, and stability. During the filling stage, the RF model ($R^2 = 0.95$, $RMSE = 1.66\%$, $RE = 3.15\%$) was superior to the other two algorithm models in the modeling set, and the SVM model ($R^2 = 0.76$, $RMSE = 4.36\%$, $RE = 8.53\%$) in the validation set was better than the other two algorithms. The comprehensive analysis reveals that the fitting effect, accuracy, and stability of the model improved after incorporating environmental factors, demonstrating a more pronounced improvement than those of the model based solely on the hyperspectral index (Figure 8).

Table 4. Model analysis of different growth stages based on different modeling methods of hyperspectral index and environmental factors ($p < 0.05$).

Growth Stage	Algorithm	Hyperspectral Index	Model Training			Model Testing		
			R ²	RMSE/%	RE/%	R ²	RMSE/%	RE/%
Jointing stage ($n = 48$)	RF	NDWI, NDVI, MSI,	0.941	1.101	1.407	0.817	2.203	2.811
	SVM	SRWI, NDII	0.962	1.153	1.429	0.455	2.049	2.604
	SR	SRWI	0.564	3.922	4.866	0.498	1.963	2.494
Heading stage ($n = 48$)	RF	VARI, PSSRa, R(810,460),	0.953	1.434	2.162	0.460	4.657	6.971
	SVM	RI, MSI	0.938	1.650	2.489	0.481	4.564	6.832
	SR	VARI	0.932	1.836	2.771	0.688	3.636	5.444
filling stage ($n = 48$)	RF	VARI, PSSRa, R(810,460),	0.950	1.660	3.150	0.617	5.516	10.749
	SVM	SRWI, WI	0.911	1.871	3.485	0.761	4.362	8.535
	SR	VARI	0.724	4.082	7.743	0.675	5.078	9.938

**Figure 8.** Integrating Canopy Hyperspectral Indices and Environmental Variables, fitting effect diagrams of modeling sets and validation sets at different growth stages: (a) Random forest model for the jointing period; (b) Simple regression model for the heading period; (c) Support vector machine model for the filling period.

3.6. Hyperspectral-Environmental Fusion Approach for Winter Wheat Water Content Monitoring Across Growth Stages

After incorporating environmental factors into different growth stages, the model's fitting effect, accuracy, and stability were improved. In this study, hyperspectral indices and ecological factors were also integrated when constructing the water content model of winter wheat plants throughout their entire growth period. In this study, we selected 90 samples from 2024 as the modeling set and chose 54 samples from 2019 as the validation set when constructing the model to predict the water content of winter wheat plants throughout their entire growth period. After Pearson correlation analysis, this study used Origin 2024 b software to draw a radar map (Figure 9), and compared the effects of multiple variables on the water content of winter wheat plants to show the relative relationship between each variable. The hyperspectral index, canopy temperature, ground temperature, and soil moisture content at a depth of 40 cm were used as influencing factors in the modeling set to establish the model. Then, RF, SVM, and SR were used to predict the whole growth period (Table 5). From the performance of the modeling set, the RF algorithm performed best, with an R^2 as high as 0.97, RMSE and RE of 3.79% and 6.57%, respectively, indicating extremely high fitting accuracy. The SVM algorithm was closely followed, yielding an R^2 of 0.95, along with RMSE and RE of 2.95% and 4.60%, respectively. Although it is slightly inferior to RF, it still exhibits a strong modeling ability. In contrast, the performance of the SR algorithm was poor, with R^2 , RMSE, and RE values of only 0.53, 15.63%, and 27.07%, respectively, which

has certain limitations in complex models. In the validation set, the SVM algorithm was the best, with an R^2 of 0.85 and RMSE and RE of 5.11% and 7.79%, respectively, showing good generalization ability. The verification results of the RF algorithm decreased, with R^2 decreasing to 0.80, and RMSE and RE increasing to 8.22% and 13.10%, respectively, indicating poor stability. The validation results of the SR algorithm were also not ideal, with R^2 , RMSE, and RE values of 0.41, 12.13%, and 15.34%, respectively. In a comprehensive analysis, the SVM algorithm performed best in modeling and verifying the entire growth period (Figure 10), which is suitable for predicting plant water content throughout the winter wheat growth period. To prevent the SVM algorithm from overfitting, this study conducted a cross-validation verification of the SVM model. The average R^2 of the SVM algorithm under 10-fold spatial CV was 0.81, RMSE = 7.49%, RE = 9.07, ($p < 0.05$). The results show that although there is a slight deviation in the model verification effect, there is no serious overfitting phenomenon.

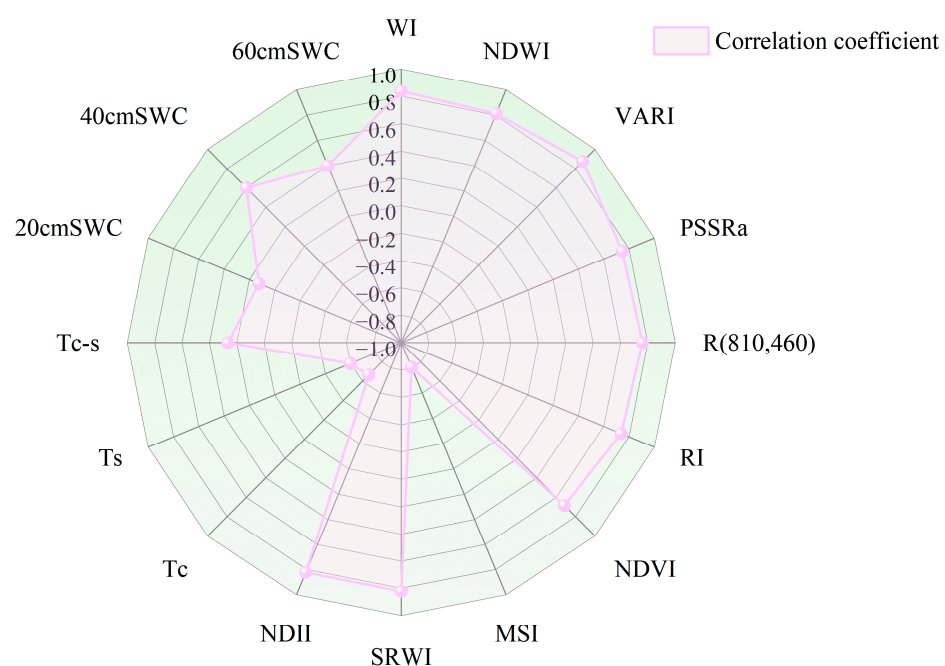


Figure 9. Analysis of the correlation between the complete life cycle hyperspectral index and environmental factors and plant water content.

Table 5. Evaluation of different modeling approaches for hyperspectral-environmental data fusion in the whole growth cycle of winter wheat ($p < 0.05$).

Growth Stage	Algorithm	Hyperspectral Index	Model Training			Model Testing		
			R^2	RMSE/%	RE/%	R^2	RMSE/%	RE/%
maturation stage ($n = 144$)	RF	WI, VARI, MSI, SRWI, NDII,	0.973	3.789	6.565	0.789	8.216	13.103
	SVM	Tc, Ts, 40 cmSWC	0.951	2.953	4.598	0.845	5.105	7.792
	SR	NDWI	0.533	15.625	27.070	0.409	12.129	15.335

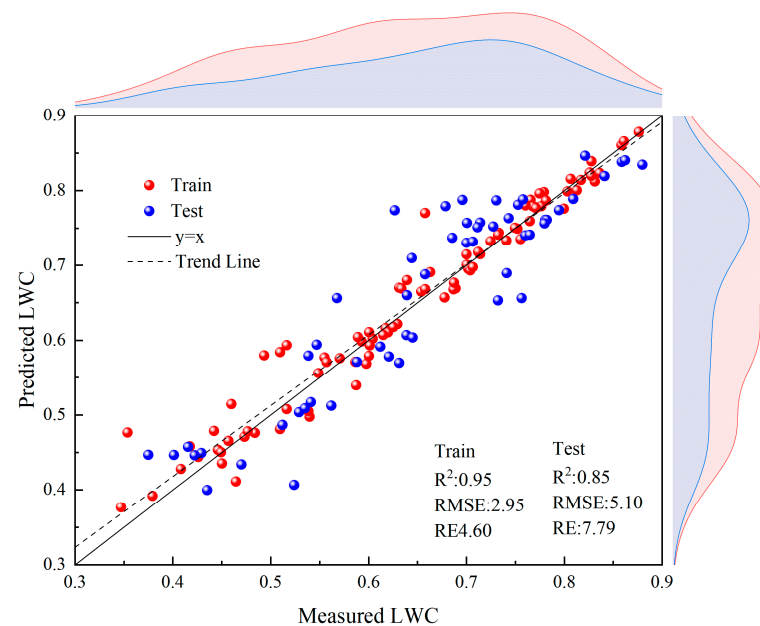


Figure 10. The SVM model for predicting plant water content based on hyperspectral indices and environmental factors throughout the entire growth period.

4. Discussion

4.1. Spectral Reflectance and Water Content Relationship in Winter Wheat Plants

Hyperspectral reflectance (especially near-infrared moisture-sensitive bands) significantly correlates with plant water content. The canopy water status of winter wheat is a critical physiological parameter for monitoring crop growth. Researchers can retrieve leaf water content by analyzing the spectral reflectance characteristics in water-sensitive bands (e.g., 1450 nm and 1940 nm). Hyperspectral imaging captures detailed spectral signatures across the visible (400–700 nm) and shortwave infrared (1400–2500 nm) ranges, demonstrating remarkable sensitivity to subtle variations in vegetation biophysical and biochemical properties [42,43]. Additionally, vegetation spectral signatures in the near-infrared (NIR, 700–1300 nm) and shortwave infrared (SWIR, 1300–2500 nm) regions exhibit strong sensitivity to leaf internal cellular structures and hydration levels. Therefore, this study can indirectly monitor wheat moisture by examining the relationship between plant parameters related to plant water status [44]. In this study, the wheat canopy's spectral response exhibited a unimodal trend during crop development. At the jointing, heading, and filling stages, the post-irrigation canopy reflectance of winter wheat increased linearly with the volume of water applied. When irrigation is sufficient, the canopy spectral reflectance of winter wheat is high, and the canopy spectral reflectance of winter wheat is low when irrigation is insufficient. These findings likely stem from the enhanced wheat biomass and leaf area during the jointing stage. Timely irrigation at critical growth phases improves plant water uptake capacity, elevating tissue water content, which subsequently accelerates wheat growth and ultimately enhances canopy reflectance. However, progressive leaf senescence reduced leaf area index and cellular water content during late grain filling, consequently diminishing canopy spectral reflectance characteristics, which is consistent with previous findings [45,46].

4.2. Environmental Factors and Water Content in Winter Wheat Plants

Environmental factors (temperature and soil moisture content) have a significant influence on the water content of winter wheat plants. With the development of high-resolution, non-contact, and high-throughput thermal infrared imaging technology, sig-

nificant progress has been made in water stress monitoring technology based on canopy temperature [47,48]. Crop surface temperatures obtained using thermal imaging technology can accurately diagnose water stress status and provide a reliable basis for assessing crop water demand [49,50]. In addition, changes in temperature and soil moisture content can affect soil microbial activity, soil organic matter mineralization, plant root development, and water absorption and transport, thereby affecting the overall moisture content of the crops [51–54]. This study found a high correlation between environmental factors and plant water content through correlation analysis. The correlation coefficient between ground temperature and plant water content at the jointing stage was -0.70 , the correlation coefficient between canopy temperature and plant water content at the heading stage was -0.91 , and the correlation coefficient between soil water content and plant water content at 40 cm at the filling stage was 0.81 . Therefore, it is feasible to diagnose the water status of winter wheat on a field scale by combining hyperspectral remote sensing data with temperature and soil water content.

4.3. Improving Winter Wheat Water Content Prediction During Critical Growth Stages by Integrating Proximal Hyperspectral Indices and Environmental Factors

After introducing a coupled hyperspectral index and environmental factor model for the collaborative inversion of winter wheat water content, the estimation accuracy improved significantly across all growth stages. In this study, various hyperspectral indices were utilized as input variables to predict water content, and different algorithms were employed to develop models for estimating the water content of winter wheat plants. However, the model's accuracy still needs improvement. Although machine learning algorithms can process diverse data formats in large, complex datasets and effectively prevent overfitting caused by excessive indices, they often overlook sensitive spectral information in hyperspectral data [55,56]. Additionally, spectral data produce varying results due to differences in experimental conditions and environmental factors [57,58]. To improve the prediction accuracy of winter wheat water content, this study coupled hyperspectral indices with environmental factors using both traditional simple regression (SR) models and machine learning algorithms (RF and SVM) to predict water content at individual growth stages. It was found that the prediction accuracy of winter wheat plant water content was significantly improved in the prediction model of coupling spectral data and environmental factors at the jointing stage, heading stage, and filling stage. Our results indicate a 0.07 – 0.14 improvement in the coefficient of determination (R^2) for plant water content (PWC) prediction models. Demonstrating that optimizing multisource data integration with machine learning algorithms significantly enhances model performance.

4.4. Improving Winter Wheat Water Content Prediction Across Growth Stages by Integrating Hyperspectral Indices and Environmental Factors

Based on the above findings, we have developed a winter-wheat water-content prediction model that is applicable throughout the entire growing season. Among the various algorithms tested in the whole growth period model, the support vector machine (SVM) showed the best performance in the model training and verification stages. The support vector machine model demonstrated excellent fitting accuracy in the training dataset, with an R^2 of 0.95 , RMSE of 2.95% , and RE of 4.60% . In the validation dataset, the R^2 of 0.85 , along with RMSE and RE values of 5.10% and 7.79% respectively, demonstrates that the model maintains strong generalization capability. The comprehensive evaluation results show that the SVM algorithm is superior to the other methods in the process of model calibration and verification (Figure 10). Compared with the validation set R^2 of the plant water content model based on hyperspectral indices and environmental factors at different growth stages, it was increased by 3.53% , 23.19% , and 11.84% , respectively. Compared

with previous similar studies, the SVM water prediction model of winter wheat during the whole growth period based on hyperspectral index and environmental factors proposed in this study showed obvious advantages regarding accuracy, stability, and cross-stage generalization ability. The results of this study are close to the accuracy of the winter wheat water model ($R^2 = 0.86$) obtained by Shi et al. [59] using multi-source data combined with machine learning. Compared with Yang et al.'s [60] hyperspectral combined with thermal infrared based on continuous wavelet transform, the accuracy of the winter wheat leaf water content estimation model ($R^2 > 0.75$) was improved by 12.7%, which fully proves that it has significant application value in the accurate prediction of plant water content during the entire growth period of winter wheat and provides a theoretical basis for efficient agricultural irrigation regulation.

4.5. Practical Significance, Limitations, and Future Research Directions

The research results demonstrate that combining proximal hyperspectral reflectance with environmental factors using machine learning can effectively minimize the limitations of single spectral indices for predicting plant water content, enabling nondestructive, real-time, and accurate estimation of wheat water status. The model-predicted plant water content information can help smallholder farmers make field-specific irrigation management decisions during the growing season. We recommend that smallholders use portable near-infrared spectrometers (such as NeoSpectra MEMS spectrometers, which cost approximately USD 500–2000) combined with a smartphone APP to achieve data collection and analysis. However, the point-by-point sampling method of the proximal sensor leads to insufficient spatial coverage, which makes it difficult to use directly in 100-hectare farmland, and the field operation efficiency is low. The large amount of data and high demand for real-time transmission and processing hardware pose challenges to farmers' technical threshold and cost. Subsequent studies can use satellite remote sensing or UAV–ground collaborative sampling architecture combined with environmental factors to construct a winter wheat plant water content prediction model to improve the monitoring efficiency of extensive farmlands or village cross-farmland. To achieve more effective monitoring of the large-area crop water content status [61]. For example, Wang et al. [62] integrated ground-air-satellite multi-scale data through hyperspectral imaging and deep learning techniques, effectively addressing the accuracy loss in multi-scale monitoring of agricultural residue cover. This approach achieved high-precision ($R^2 = 0.82$) and cost-effective quantification of crop residues from field to regional scales, providing a reliable technical solution for conservation tillage assessment.; Jin et al. [63] used canopy and satellite sensor spectra to screen band combinations and spectral indices sensitive to crop water status and estimated leaf water content. Therefore, using machine learning models to develop multi-source data fusion strategies based on UAV or satellite remote sensing data is feasible.

On the other hand, this study employed only simple temperature variables and soil moisture content in the model. Future research should explore the integration of more diverse and accessible data sources into plant water content prediction models, including the average daily sunshine hours, soil texture, leaf area index, crop health status (disease index, pest index, SPAD value), seeding rate, crop variety information, pre-seeding nitrogen application rate, irrigation amount, etc., into the multi-source data framework to improve the robustness and universality of the model in adversity or pest stress scenarios to enhance the effectiveness and applicability of monitoring plant water content.

5. Conclusions

This study innovatively combined near-edge hyperspectral data with environmental factors and constructed a high-precision prediction model of winter wheat plant water

content based on machine learning language. The results showed that the water content of winter wheat plants in the key growth period (jointing, heading, and filling periods) highly correlated with environmental factors, and the correlation coefficient could reach -0.91 . After the introduction of highly correlated environmental factors, the modeling set achieved significant improvements in prediction accuracy. The model performance (R^2) increased from 0.74, 0.59, and 0.70 to 0.82, 0.69, and 0.76, respectively. Based on these findings, we further developed a full-growth-cycle prediction model for the water content of winter wheat. The final SVM model demonstrated excellent predictive ability: The validation set R^2 value was 0.85, and the RMSE and RE were 5.11% and 7.79%, respectively. The prediction model of winter wheat PWC for the entire growth period was 3.53%, 23.19%, and 11.84% higher than the verification set R^2 of the prediction model of plant water content based on hyperspectral indices and environmental factors for the single growth period. These results not only verify the high-precision characteristics of the model but also demonstrate its good generalization performance, providing a fast and non-destructive prediction tool for precision irrigation management of farmland. However, in the future, it is necessary to explore further the monitoring efficiency of extensive farmlands or village cross-farmlands. Additionally, it is necessary to verify the applicability of the new model on a regional scale through multipoint experiments.

Author Contributions: Conceptualization, N.H., M.W. and Q.Z.; data curation, N.H., M.W., Z.P. and X.L.; methodology, N.H., Q.Z. and X.H.; funding acquisition, N.H.; software, M.W.; validation, N.H. and Q.Z.; writing—original draft, N.H., M.W., Q.Z., X.H. and S.L.; writing—review and editing, N.H. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by Tianjin Wanbanghui Ecological Technology Co., Ltd. under Project “Research on Crop Water and Nutrient Status Diagnostic Techniques Based on Hyperspectral Remote Sensing” (No. TNH XKJ2024030); Open Research Fund of State Key Laboratory of Efficient Utilization of Agricultural Water Resources (Grant No. SKLAWR-2025-06); National Key R&D Program of China (2022YFD1900504); College Students’ Innovation And Entrepreneurship Training Program (202410061112).

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy restrictions.

Acknowledgments: All individuals included in this section have consented to the acknowledgement.

Conflicts of Interest: The authors declare that this study received funding from Tianjin Wanbanghui Ecological Technology Co., Ltd. The funder was not involved in the study design, collection, analysis, interpretation of data, the writing of this article or the decision to submit it for publication.

References

1. Ahmed, U.; Jamal, A.; Iqbal, W.; Durrishahwar; Qayyum, U.; Saeed, M.F.; Ali, A.; Ronga, D.; Dewir, Y.H.; Černý, J. Integrated management of nitrogen and spent mushroom compost for improved wheat yield and soil fertility. *J. Soil Sci. Plant Nut.* **2025**, *25*, 3354–3371. [CrossRef]
2. Jamal, A.; Saeed, M.F.; Mihoub, A.; Hopkins, B.G.; Ahmad, I.; Naeem, A. Integrated use of phosphorus fertilizer and farmyard manure improves wheat productivity by improving soil quality and P availability in calcareous soil under subhumid conditions. *Front. Plant Sci.* **2023**, *14*, 1034421. Available online: <https://pubmed.ncbi.nlm.nih.gov/36755699/> (accessed on 13 July 2025). [CrossRef]
3. Wang, Y.; Peng, Y.; Lin, J.; Wang, L.; Jia, Z.; Zhang, R. Optimal nitrogen management to achieve high wheat grain yield, grain protein content, and water productivity: A meta-analysis. *Agric. Water Manag.* **2023**, *290*, 108587. [CrossRef]
4. Triana-Martinez, J.C.; Álvarez-Meza, A.M.; Gil-González, J.; De Swaef, T.; Fernandez-Gallego, J.A. Crop water status analysis from complex agricultural data using UMAP-based local biplot. *Remote Sens.* **2024**, *16*, 2854. [CrossRef]
5. Gong, X.; Zhang, H.; Ren, C.; Sun, D.; Yang, J. Optimization allocation of irrigation water resources based on crop water requirement under considering effective precipitation and uncertainty. *Agric. Water Manag.* **2020**, *239*, 106264. Available online: <https://www.sciencedirect.com/science/article/abs/pii/S0378377419323716> (accessed on 13 July 2025). [CrossRef]

6. Zhao, W.; Liu, L.; Shen, Q.; Yang, J.; Han, X.; Tian, F.; Wu, J. Effects of water stress on photosynthesis, yield, and water use efficiency in winter wheat. *Water* **2020**, *12*, 2127. [CrossRef]
7. Jihua, W.; Chunjiang, Z.; Wenjiang, H.; Xiaowei, G.; Hongxiang, L. Effect of soil water content on the wheat leaf water content and the physiological function. *J. Triticeae Crops* **2001**, *21*, 42–47.
8. Zhang, C.W.; Qi, Y.Q.; Dai, M.H.; Zhang, Y.C.; Shen, Y.J. Effects of multi-factor on water use efficiency as identified by the SEM method in irrigated wheat farmlands in the North China Plain. *Chin. J. Eco Agric.* **2020**, *28*, 876–886. Available online: <https://ecoagri.ac.cn/en/article/doi/10.13930/j.cnki.cjea.190924?viewType=HTML> (accessed on 13 July 2025).
9. Scholander, P.F.; Bradstreet, E.D.; Hemmingsen, E.A.; Hammel, H.T. Sap Pressure in Vascular Plants: Negative hydrostatic pressure can be measured in plants. *Science* **1965**, *148*, 339–346. Available online: <https://pubmed.ncbi.nlm.nih.gov/17832103/> (accessed on 13 July 2025). [CrossRef] [PubMed]
10. Jones, H.G. Monitoring plant and soil water status: Established and novel methods revisited and their relevance to studies of drought tolerance. *J. Exp. Bot.* **2007**, *58*, 119–130. [CrossRef] [PubMed]
11. Gu, Z.; Qi, Z.; Burghate, R.; Yuan, S.; Jiao, X.; Xu, J. Irrigation scheduling approaches and applications: A review. *J. Irrig. Drain. Eng.* **2020**, *146*, 4020007. [CrossRef]
12. Li, Z.; Leng, P.; Zhou, C.; Chen, K.; Zhou, F.; Shang, G. Soil moisture retrieval from remote sensing measurements: Current knowledge and directions for the future. *Earth Sci. Rev.* **2021**, *218*, 103673. [CrossRef]
13. Qu, T.; Li, Y.; Zhao, Q.; Yin, Y.; Wang, Y.; Li, F.; Zhang, W. Drone-based multispectral remote sensing inversion for typical crop soil moisture under dry farming conditions. *Agriculture* **2024**, *14*, 484. [CrossRef]
14. Li, K.; Chang, Q.R.; Chen, Q.; Chen, X.K.; Mo, H.Y.; Zhang, Y.D.; Zhang, Z.K. Estimation of water content in canopy leaf of winter wheat based on continuous wavelet transform coupled cars algorithm. *J. Triticeae Crops* **2023**, *43*, 251–258. Available online: https://jglobal.jst.go.jp/en/detail?JGLOBAL_ID=202302218960762545 (accessed on 13 July 2025).
15. Zhou, J.; Zhang, Y.; Han, Z.; Liu, X.; Jian, Y.; Hu, C.; Dian, Y. Evaluating the performance of hyperspectral leaf reflectance to detect water stress and estimation of photosynthetic capacities. *Remote Sens.* **2021**, *13*, 2160. [CrossRef]
16. Zhao, S.; Wang, Q.; Yao, Y.; Du, S.; Zhang, C.; Li, J.; Zhao, J. Estimating and validating wheat leaf water content with three modis spectral indexes: A case study in Ningxia Plain, China. *J. Agric. Sci. Technol.* **2016**, *18*, 387–398.
17. Mali, S.S.; Scobie, M.; Baillie, J.; Plant, C.; Shammi, S.; Das, A. Integrating UAV-based multispectral and thermal infrared imagery with machine learning for predicting water stress in winter wheat. *Precis. Agric.* **2025**, *26*, 44. [CrossRef]
18. Zhang, J.; Zhang, W.; Xiong, S.; Song, Z.; Tian, W.; Shi, L.; Ma, X. Comparison of New Hyperspectral Index and Machine Learning Models for Prediction of Winter Wheat Leaf Water Content. *Plant Methods* **2021**, *17*, 34. [CrossRef]
19. Das, B.; Sahoo, R.N.; Pargal, S.; Krishna, G.; Verma, R.; Chinnusamy, V.; Sehgal, V.K.; Gupta, V.K. Comparison of different uni-and multi-variate techniques for monitoring leaf water status as an indicator of water-deficit stress in wheat through spectroscopy. *Biosyst. Eng.* **2017**, *160*, 69–83. [CrossRef]
20. Jones, H.G. Use of infrared thermometry for estimation of stomatal conductance as a possible aid to irrigation scheduling. *Agric. For. Meteorol.* **1999**, *95*, 139–149. [CrossRef]
21. Wang, G.Y.; Song, S.Y.; Fan, T.L.; Li, S.Z.; Zhao, G. Relationship of canopy temperature with grain yield and water use efficiency in various genotypes of maize. *J. Maize Sci.* **2019**, *17*, 92–95. Available online: <https://www.dissertationtopic.net/doc/497528> (accessed on 13 July 2025).
22. Gontia, N.K.; Tiwari, K.N. Development of crop water stress index of wheat crop for scheduling irrigation using infrared thermometry. *Agric. Water Manag.* **2008**, *95*, 1144–1152. [CrossRef]
23. Mangus, D.L.; Sharda, A.; Zhang, N. Development and evaluation of thermal infrared imaging system for high spatial and temporal resolution crop water stress monitoring of corn within a greenhouse. *Comput. Electron. Agric.* **2016**, *121*, 149–159. [CrossRef]
24. Bo, L.; Guan, H.; Mao, X. Diagnosing crop water status based on canopy temperature as a function of film mulching and deficit irrigation. *Field Crops Res.* **2023**, *304*, 109154. [CrossRef]
25. Zhang, X.; Zhang, X.; Liu, X.; Shao, L.; Sun, H.; Chen, S. Incorporating root distribution factor to evaluate soil water status for winter wheat. *Agric. Water Manag.* **2015**, *153*, 32–41. [CrossRef]
26. Peng, Z.; Lin, S.; Zhang, B.; Wei, Z.; Liu, L.; Han, N.; Cai, J.; Chen, H. Winter Wheat Canopy Water Content Monitoring Based on Spectral Transforms and “Three-edge” Parameters. *Agric. Water Manag.* **2020**, *240*, 106306. [CrossRef]
27. Cai, J.; Wang, Y.; Liu, Y. Feature Parameters of Evapotranspiration Estimation Model for Winter Wheat and Summer Maize Based on Lysimeter Monitoring System. *Trans. Chin. Soc. Agric. Mach.* **2021**, *52*, 285–295. Available online: http://www.j-csam.org/jcsam/article/abstract/20210332?st=article_issue (accessed on 13 July 2025).
28. Peñuelas, J.; Pinol, J.; Ogaya, R.; Filella, I. Estimation of plant water concentration by the reflectance water index WI (R900/R970). *Int. J. Remote Sens.* **1997**, *18*, 2869–2875. [CrossRef]
29. Eitel, J.U.; Gessler, P.E.; Smith, A.M.; Robberecht, R. Suitability of existing and novel spectral indices to remotely detect water stress in *Populus* spp. *For. Ecol. Manag.* **2006**, *229*, 170–182. [CrossRef]

30. Elvidge, C.D.; Lyon, R.J. Estimation of the vegetation contribution to the 1.65/2.22 μm ratio in airborne thematic-mapper imagery of the Virginia Range, Nevada. *Int. J. Remote Sens.* **1985**, *6*, 75–88. [CrossRef]
31. Hunt, E.R., Jr.; Rock, B.N. Detection of changes in leaf water content using near-and middle-infrared reflectances. *Remote Sens. Environ.* **1989**, *30*, 43–54. [CrossRef]
32. Hardisky, M.A.; Klemas, V.; Smart, R. The influence of soil salinity, growth form, and leaf moisture on-the spectral radiance of. *Photogramm. Eng. Remote Sens.* **1983**, *49*, 77–83.
33. Zarco-Tejada, P.J.; Ustin, S.L. Modeling Canopy Water Content for Carbon Estimates from MODIS Data at Land EOS Validation Sites. In Proceedings of the IEEE 2001 International Geoscience and Remote Sensing Symposium, Sydney, NSW, Australia, 9–13 July 2001. [CrossRef]
34. Bai, Q.M.; Han, Y.G.; Peng, Z.G.; Liu, L.; Lin, S.J. Optimization of the hyperspectral water prediction model of winter wheat with the leaf area index. *Chin. J. Appl. Environ. Biol.* **2020**, *26*, 943–950. [CrossRef]
35. Gao, B.C. NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sens. Environ.* **1996**, *58*, 257–266. [CrossRef]
36. Cassanelli, D.; Lenzini, N.; Ferrari, L.; Rovati, L. Partial least squares estimation of crop moisture and density by near-infrared spectroscopy. *IEEE Trans. Instrum. Meas.* **2021**, *70*, 1004510. [CrossRef]
37. Li, C.; Wang, Y.C.; Li, X.Q.; Yang, X.F.; Gu, X.P. Quantitative inversion of water content of plant components in winter wheat based on wavelet technology. *Trans. Chin. Soc. Agric. Mach.* **2021**, *52*, 193. [CrossRef]
38. Cheng, M.; Jiao, X.; Liu, Y.; Shao, M.; Yu, X.; Bai, Y.; Wang, Z.; Wang, S.; Tuohuti, N.; Liu, S. Estimation of soil moisture content under high maize canopy coverage from UAV multimodal data and machine learning. *Agric. Water Manag.* **2022**, *264*, 107530. [CrossRef]
39. Wan, L.; Zhou, W.; He, Y.; Wanger, T.C.; Cen, H. Combining transfer learning and hyperspectral reflectance analysis to assess leaf nitrogen concentration across different plant species datasets. *Remote Sens. Environ.* **2022**, *269*, 112826. [CrossRef]
40. Wang, L.G.; Zheng, G.Q.; Guo, Y.; He, J.; Cheng, Y.Z. Prediction of Winter Wheat Yield Based on Fusing Multi-source Spatio-temporal Data. *Trans. Chin. Soc. Agric. Mach.* **2022**, *53*, 198–204. [CrossRef]
41. Xue, X.; Cai, J.B.; Yu, Y.D.; Han, Y.A. Quantifying Groundwater Contributions and Threshold in the Growth Stages for Winter Wheat. *Trans. Chin. Soc. Agric. Eng.* **2024**, *40*, 101–111. [CrossRef]
42. El-Hendawy, S.E.; Al-Suhaibani, N.A.; Elsayed, S.; Hassan, W.M. Potential of the existing and novel spectral reflectance Potential of the existing and novel spectral reflectance indices for estimating the leaf water status and grain yield of spring wheat exposed to different irrigation rates. *Agric. Water Manag.* **2019**, *217*, 356–373. [CrossRef]
43. Vescovo, L.; Wohlfahrt, G.; Balzarolo, M.; Pilloni, S.; Sottocornola, M.; Rodeghiero, M.; Gianelle, D. New spectral vegetation indices based on the near-infrared shoulder wavelengths for remote detection of grassland phytomass. *Int. J. Remote Sens.* **2012**, *33*, 2178–2195. [CrossRef] [PubMed]
44. Wang, X.; Zhao, C.; Guo, N.; Li, Y.; Kai, Y. Determining the canopy water stress for spring wheat using canopy hyperspectral reflectance data in Loess Plateau semiarid regions. *Spectrosc. Lett.* **2015**, *48*, 492–498. [CrossRef]
45. Yang, C.; Feng, M.; Sun, H.; Wang, C.; Yang, W.; Xie, Y.; Jing, B. Hyperspectral monitoring of aboveground dry biomass of winter wheat under different irrigation treatments. *Chin. J. Ecol.* **2019**, *38*, 1767. Available online: <http://www.cje.net.cn/CN/Y2019/V38/I6/1767> (accessed on 13 July 2025).
46. Guo, R.; Zhou, J.; Yang, F.; Li, F.; Xia, X.; Liu, Q. Growth metabolism of wheat under drought stress at the jointing-booting stage. *Chin. J. Plant Ecol.* **2016**, *40*, 1319–1327. [CrossRef]
47. Zhao, C.; Han, N.N.; Zhou, Q.Y.; Li, S.M. Estimation of winter wheat plant water content based on canopy hyperspectral. *J. Triticeae Crops* **2024**, *43*, 2569. Available online: https://lib.cqvip.com/Qikan/Article/Detail?id=7112492996&from=Qikan_Search_Index (accessed on 13 July 2025).
48. Santesteban, L.G.; Di Gennaro, S.F.; Herrero-Langreo, A.; Miranda, C.; Royo, J.B.; Matese, A. High-resolution UAV-based thermal imaging to estimate the instantaneous and seasonal variability of plant water status within a vineyard. *Agric. Water Manag.* **2017**, *183*, 49–59. [CrossRef]
49. Pappalardo, S.; Consoli, S.; Longo-Minnolo, G.; Vanella, D.; Longo, D.; Guarrera, S.; D’Emilio, A.; Ramírez-Cuesta, J.M. Performance evaluation of a low-cost thermal camera for citrus water status estimation. *Agric. Water Manag.* **2023**, *288*, 108489. [CrossRef]
50. Morales, I.; Alvaro, J.E.; Urrestarazu, M. Contribution of thermal imaging to fertigation in soilless culture. *J. Therm. Anal. Calorim.* **2014**, *116*, 1033–1039. [CrossRef]
51. Jiang, J.; Atkinson, P.M.; Zhang, J.; Lu, R.; Zhou, Y.; Cao, Q.; Tian, Y.; Zhu, Y.; Cao, W.; Liu, X. Combining fixed-wing UAV multispectral imagery and machine learning to diagnose winter wheat nitrogen status at the farm scale. *Eur. J. Agron.* **2022**, *138*, 126537. [CrossRef]
52. Kirschbaum, M.U. The temperature dependence of soil organic matter decomposition, and the effect of global warming on soil organic C storage. *Soil Biol. Biochem.* **1995**, *27*, 753–760. [CrossRef]

53. Leirós, M.C.; Trasar-Cepeda, C.; Seoane, S.; Gil-Sotres, F. Dependence of mineralization of soil organic matter on temperature and moisture. *Soil Biol. Biochem.* **1999**, *31*, 327–335. [[CrossRef](#)]
54. Naylor, D.; Sadler, N.; Bhattacharjee, A.; Graham, E.B.; Anderton, C.R.; McClure, R.; Lipton, M.; Hofmockel, K.S.; Jansson, J.K. Soil microbiomes under climate change and implications for carbon cycling. *Annu. Rev. Environ. Resour.* **2020**, *45*, 29–59. [[CrossRef](#)]
55. He, T.; Xie, C.; Liu, Q.; Guan, S.; Liu, G. Evaluation and comparison of random forest and A-LSTM networks for large-scale winter wheat identification. *Remote Sens.* **2019**, *11*, 1665. [[CrossRef](#)]
56. Torres-Tello, J.W.; Ko, S. A novel approach to identify the spectral bands that predict moisture content in canola and wheat. *Biosyst. Eng.* **2021**, *210*, 91–103. [[CrossRef](#)]
57. Ray, S.S.; Das, G.; Singh, J.P.; Panigrahy, S. Evaluation of hyperspectral indices for LAI estimation and discrimination of potato crop under different irrigation treatments. *Int. J. Remote Sens.* **2006**, *27*, 5373–5387. [[CrossRef](#)]
58. Zhao, T.; Nakano, A.; Iwaski, Y.; Umeda, H. Application of hyperspectral imaging for assessment of tomato leaf water status in plant factories. *Appl. Sci.* **2020**, *10*, 4665. [[CrossRef](#)]
59. Shi, B.; Yuan, Y.; Zhuang, T.; Xu, X.; Schmidhalter, U.; Ata-UI-Karim, S.T.; Zhao, B.; Liu, X.; Tian, Y.; Zhu, Y.; et al. Improving water status prediction of winter wheat using multi-source data with machine learning. *Eur. J. Agron.* **2022**, *139*, 126548. [[CrossRef](#)]
60. Yang, N.; Zhang, Z.; Zhang, J.; Yang, X.; Liu, H.; Chen, J.; Ning, J.; Sun, S.; Shi, L. Accurate estimation of winter-wheat leaf water content using continuous wavelet transform-based hyperspectral combined with thermal infrared on a UAV platform. *Eur. J. Agron.* **2025**, *168*, 127624. [[CrossRef](#)]
61. Zhang, Z.; Zhu, L. A review on unmanned aerial vehicle remote sensing: Platforms, sensors, data processing methods, and applications. *Drones* **2023**, *7*, 398. [[CrossRef](#)]
62. Wang, S.; Guan, K.; Zhang, C.; Zhou, Q.; Wang, S.; Wu, X.; Jiang, C.; Peng, B.; Mei, W.; Li, K.; et al. Cross-Scale Sensing of Field-Level Crop Residue Cover: Integrating Field Photos, Airborne Hyperspectral Imaging, and Satellite Data. *Remote Sens. Environ.* **2023**, *285*, 113366. [[CrossRef](#)]
63. Jin, N.; Zhang, D.; Li, Z.; He, L. Evaluation of Water Status of Winter Wheat Based on Simulated Reflectance of Multispectral Satellites. *Trans. Chin. Soc. Agric. Mach.* **2020**, *51*, 243–252. Available online: <http://www.j-csam.org/jcsam/article/abstract/20201127> (accessed on 13 July 2025).

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