

Article

Canopy Hotspot Effects Improve Root-Zone Soil Moisture Content Estimation in Winter Wheat Based on LESS Simulations and UAV Multi-Angular Observations

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Abstract

Soil moisture content (SMC) is critical for crop growth and precision irrigation. Multi-angular remote sensing can capture directional reflectance variations that may provide additional information related to crop water status. However, the potential of hotspot-sensitive multi-angular observations for root-zone SMC estimation remains insufficiently explored, particularly in winter wheat. This study evaluated the potential of hotspot-sensitive multi-angular observations for root-zone SMC estimation using UAV observations and the LESS (Large-Scale remote sensing data and image Simulation framework) radiative transfer model. Multispectral imagery of winter wheat was acquired under four irrigation treatments (T1–T4). The LESS model was parameterized using field-measured canopy characteristics to simulate bidirectional reflectance factors (BRFs) across the observation hemisphere. The simulated and observed datasets were used to analyze hotspot dynamics and evaluate the contribution of hotspot-sensitive observations to SMC estimation. Among the investigated bands, hotspot characteristics at 560 nm exhibited the strongest response to water stress. LESS-simulated BRFs showed greater angular variability ($CV \approx 0.30$) than UAV-observed BRFs ($CV \approx 0.18$). The highest SMC estimation performance was obtained in hotspot-sensitive backscattering directions, with an $R^2 \approx 0.60$ and an $RMSE \approx 0.022 \text{ m}^3 \text{ m}^{-3}$. These findings indicate that hotspot-sensitive multi-angular observations provide useful complementary information for SMC estimation.

Keywords: soil moisture content; UAV; LESS; multi-angle; hotspot effect



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1. Introduction

Soil moisture content (SMC) is a critical factor regulating crop growth, yield formation, and physiological processes [1–3]. Accurate information on root-zone SMC is essential for irrigation scheduling, drought monitoring, and precision agricultural management [4,5]. Traditional methods for measuring SMC, including gravimetric sampling and in situ

sensor observations, generally provide reliable measurements but are labor-intensive, time-consuming, and difficult to implement over large agricultural areas [6]. Consequently, remote sensing techniques have become increasingly important for estimating SMC and monitoring crop water conditions at field and regional scales.

In recent years, unmanned aerial vehicle (UAV)-based remote sensing has emerged as an effective platform for agricultural water assessment because of its high spatial resolution, operational flexibility, and rapid data acquisition capability [7]. Numerous studies have demonstrated the potential of UAV multispectral imagery for estimating SMC through spectral indices, machine learning algorithms, and physically based approaches. For example, Zhang et al. (2021) demonstrated the potential of vegetation-index-based approaches for SMC estimation, whereas Zhang et al. (2023) further explored the use of spectral feature combinations to improve retrieval performance [8,9]. However, most of these approaches rely primarily on nadir-view observations and focus mainly on spectral information, while canopy directional reflectance characteristics are often overlooked.

Vegetation canopies exhibit pronounced anisotropic reflectance due to the complex interactions among leaves, stems, shadows, and background soil. Multi-angular remote sensing provides observations from different viewing geometries and can capture additional structural information that is unavailable in conventional nadir observations [10–12]. Previous studies have demonstrated the advantages of multi-angular observations for retrieving various vegetation biophysical parameters. For instance, He et al. (2022) collected hyperspectral data at 13 viewing zenith angles and evaluated leaf nitrogen concentration estimation performance across different observation geometries [13]; Lu et al. (2019) proposed a multi-angle observation approach to enhance the estimation of nitrogen nutrient indicators using multispectral imagery acquired by UAVs [14]. These studies indicate that multi-angular observations can provide complementary information on canopy architecture, shadow distribution, vegetation anisotropy, and physiological responses that cannot be fully characterized by single-angle observations [15]. More recently, Zhang et al. (2024) demonstrated the feasibility of estimating root-zone SMC using UAV-based multi-angle multispectral imagery in winter wheat [16]. Although these studies confirm the potential value of multi-angular observations for SMC estimation, the physical mechanisms through which directional reflectance contributes to water-related parameter retrieval remain insufficiently understood.

One of the most distinctive manifestations of canopy reflectance anisotropy is the hotspot effect. The hotspot phenomenon occurs when the sensor viewing direction approaches the solar illumination direction, causing shadows cast by canopy elements to be largely hidden from the sensor and resulting in a localized increase in reflectance [17]. Hotspot regions contain abundant information related to canopy structure and crop growth status, thereby enhancing the sensitivity of directional reflectance to vegetation characteristics [18]. Water stress can alter leaf turgor, leaf orientation, canopy closure, and overall canopy architecture, thereby modifying shadow distributions and hotspot characteristics within the canopy. Consequently, observations acquired at hotspot viewing angles may enhance the sensitivity of remote sensing measurements to canopy structural responses induced by soil moisture variations, thereby providing complementary information for root-zone SMC estimation [17].

Although UAV-based multi-angular observations provide directional reflectance information, practical data acquisition is constrained by flight safety, battery endurance, weather conditions, and observation geometry. As a result, UAV measurements are typically limited to a finite number of viewing angles and cannot continuously characterize canopy reflectance across the entire observation hemisphere. This limitation makes it difficult to comprehensively investigate hotspot dynamics and anisotropic reflectance responses under

varying soil moisture conditions. Therefore, physically interpretable approaches are needed to complement field observations and explore directional reflectance behavior over a wider range of viewing geometries [19]. Three-dimensional radiative transfer models provide an effective framework for analyzing canopy anisotropy and the physical mechanisms underlying directional reflectance. Among them, the LESS (Large-Scale remote sensing data and image Simulation framework) model has demonstrated strong capabilities in reproducing realistic three-dimensional canopy structures and directional reflectance distributions. By integrating realistic canopy representations with radiative transfer simulations, LESS can generate continuous directional reflectance information across the observation hemisphere, thereby enabling a more comprehensive investigation of hotspot characteristics and their responses to different water conditions [20].

Therefore, the objectives of this study were to (1) evaluate the capability of the LESS model to reproduce multi-angular reflectance characteristics of winter wheat under different irrigation treatments, (2) investigate the temporal and spatial variations in canopy hotspot characteristics throughout the growing season, and (3) explore the potential of hotspot-sensitive multi-angular observations for root-zone SMC estimation. The findings are expected to advance the understanding of canopy directional reflectance mechanisms and provide new insights into the application of multi-angular remote sensing for agricultural water management.

2. Materials and Methods

2.1. Experimental Site and Design

The experimental site was located at the Institute of Water-Saving Agriculture in Arid Areas, Northwest A&F University, Yangling, Shaanxi Province, China (34°17'42" N, 108°4'2" E), with an altitude of 525 m. The study area is a typical dryland agricultural region in Northwest China, characterized by a semi-humid to arid climate. The long-term average annual rainfall is 640 mm, mainly concentrated in July–September. The soil texture of the experimental area is medium loam, with a wilting coefficient of 8.6% and a soil organic matter content of 14.48 g·kg⁻¹. Groundwater is deeply buried, and its upward recharge is negligible. The soil dry bulk density is 1.44 g·cm⁻³, and the average soil field capacity is 22% (volumetric water content).

The experiment included four moisture treatments corresponding to irrigation gradients: fully irrigated (T1), mild water stress (T2), moderate water stress (T3), and severe water stress (T4). Specifically, T1 to T4 corresponded to 80–95%, 65–80%, 50–65%, and 40–50% of the soil field capacity, respectively. Each treatment was replicated three times, with replicates randomly arranged, resulting in a total of 12 experimental plots. Each plot measured 4 m × 4 m with a row spacing of 0.25 m; 30 g of wheat seeds were sown per row, corresponding to a planting density of 1.0 × 10⁶ plants·ha⁻¹ (as shown in Figure 1). The winter wheat cultivar used was Denghai 111, a locally promoted variety in central Shaanxi Province. Growth phases of winter wheat were recorded throughout the growing season and classified according to the Zadoks scale. The six major phases observed in this study were regreening (Zadoks 25–29), standing (Zadoks 30–31), jointing (Zadoks 32–39), tasseling (Zadoks 50–59), grouting (Zadoks 70–79), and maturity (Zadoks 90–92). The experimental area was equipped with a drip irrigation system and rain shelters to eliminate interference from precipitation. Winter wheat was sown on 19 October 2022, and harvested on 1 June 2023.

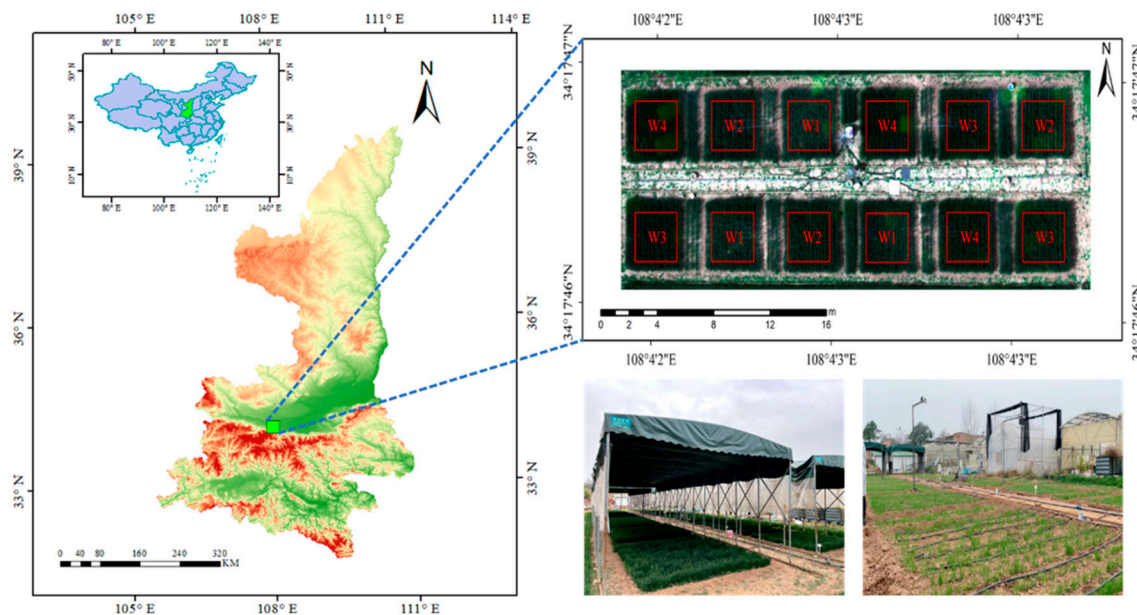


Figure 1. Layout of the test site and experimental plots.

2.2. Data Acquisition and Processing

2.2.1. Ground Data Acquisition and Processing

In this study, winter wheat soil moisture content (SMC) data, canopy chlorophyll content (LCC) data, leaf area data, and aboveground biomass (AGB) data were collected on 5, 12, 21, and 30 March; 9, 18, and 29 April; and 24 May 2023, resulting in a total of 96 samples.

Acquisition of SMC

Considering that the majority of fine roots of winter wheat are distributed within the upper soil layer during early and middle growth stages, the 0–20 cm soil layer was selected as an indicator of root-zone soil moisture. Soil samples at this depth were collected using the five-point sampling method for soil moisture determination. Fresh soil samples were weighed, oven-dried at 105 °C to constant weight, and reweighed. Equation (1) was used to calculate the gravimetric water content (θ_m , g g⁻¹) as the ratio of water loss to dry soil mass. The volumetric water content (VWC, m³ m⁻³) was then obtained by multiplying the gravimetric water content by the soil bulk density. The final VWC for each plot was the average of the five sampling points [21].

$$\theta_m = \frac{W1 - W2}{W2 - W3} \times 100\% \quad (1)$$

where W1 is the mass of the wet soil sample plus aluminum box (g), W2 is the mass of the oven-dried soil sample plus aluminum box (g), and W3 is the mass of the empty aluminum box (g).

Acquisition of Canopy Chlorophyll Data

Leaf chlorophyll content (LCC) was determined using the standard ethanol extraction method [22]. Fresh leaves (0.2 g) from the middle and upper canopy were collected from three plants per plot. Chlorophyll was extracted with 95% ethanol, and the absorbance of the extract was measured at 665 nm and 649 nm using a spectrophotometer, with 95% ethanol as the blank. LCC(mg g⁻¹) was then calculated using Equations (2)–(4).

$$C_a \text{ (mg} \cdot \text{g}^{-1}) = [(13.95 \times A_{665} - 6.88 \times A_{649}) \times V_T \text{ (mL)}] / [M \text{ (g)} \times 1000] \quad (2)$$

$$C_b \text{ (mg} \cdot \text{g}^{-1}) = [(24.96 \times A_{649} - 7.32 \times A_{665}) \times V_T \text{ (mL)}] / [M \text{ (g)} \times 1000] \quad (3)$$

$$C_{ab} \text{ (mg} \cdot \text{g}^{-1}) = C_a \text{ (mg/g)} + C_b \text{ (mg/g)} \quad (4)$$

where C_a , C_b and C_{ab} are chlorophyll a content, chlorophyll b content and total chlorophyll content, respectively, with all units in $\text{mg} \cdot \text{g}^{-1}$; A_{665} and A_{649} are absorbance of the extract at 665 nm and 649 nm, respectively; V_T is the volume of the extract in ml; and M is the weight of fresh leaves in g.

Acquisition of Crop Leaf Area Data

Leaf area was measured from three destructively sampled winter wheat plants per plot using a digital imaging method. The leaves were photographed, and leaf area was extracted with an image processing script [23].

Extraction of Crop Biomass

Biomass collection was synchronized with leaf area measurement. Fresh weights of the leaves were measured using an analytical balance, followed by spreading the leaves evenly in an oven for a killing treatment at 110 °C for 50 min. Subsequently, the leaves were transferred to a desiccator and dried at 85 °C for 24 h, after which their dry weights were determined [24].

2.2.2. Calculation of Leaf Area Mass and Equivalent Water Thickness

Leaf area mass (LMA, g cm^{-2}) is defined as the ratio of leaf dry mass to leaf area [25], and the formula is shown in Equation (5).

$$\text{LMA} = \frac{\text{DW}}{A} \text{ (g} \cdot \text{cm}^{-2}) \quad (5)$$

Equivalent water thickness (EWT, g cm^{-2}) is defined as the ratio of leaf water to leaf area [25], and the formula is shown in Equation (6).

$$\text{EWT} = \frac{\text{FW} - \text{DW}}{A} \text{ (g} \cdot \text{cm}^{-2}) \quad (6)$$

where DW is the leaf dry mass (g), FW is the leaf fresh mass (g), and A is the leaf area (cm^2).

2.3. Acquisition and Processing of UAV Images

Remote sensing data were collected on clear, windless, and well-illuminated days. A Phantom 4 multispectral UAV manufactured by DJI Innovations (Shenzhen, China) was utilized, equipped with an FC6360 lens and six 1/2.9-inch CMOS sensors—including one color sensor for visible light imaging and five monochrome sensors for multispectral imaging, covering wavelengths of 450 nm, 560 nm, 650 nm, 730 nm, and 840 nm. The UAV's technical parameters were as follows: field of view (FOV) of 62.7°, focal length of 5.74 mm, and resolution of 1600×1300 pixels. Flight routes over the experimental area were planned using DJI Go Pro software, with 85% heading overlap, 70% side overlap, a flight speed of 1 m/s, and a flight altitude of 25 m. The UAV's azimuth was adjusted by modifying the main route angle, while the observation zenith angle was controlled by adjusting the gimbal pitch angle.

The time when the solar zenith angle (SZA) reached 45° and the corresponding solar azimuth were pre-calculated prior to the experiment to determine the UAV's flight time and flight azimuth, as presented in Table 1. UAV flights were conducted at the time and azimuth corresponding to a 45° SZA. Subsequently, data collection was performed sequentially across two observation planes (solar principal plane and plane perpendicular to the solar

principal plane) and one vertical plane (main course angle of 90° , gimbal pitch angle of 0°). At each observation plane, two observation azimuths (forward and backward scattering directions) were set, and three observation zenith angles (30° , 45° , 60°) were configured for each observation azimuth. The total flight duration was 15 min, and the impact of solar zenith angle variations on albedo during the flight was negligible [26].

Table 1. Time of the test and azimuthal angle of the sun.

Trial Date	5 March	12 March	21 March	30 March	9 April	18 April	29 April	24 May
The time when the sun's zenith angle is 45°	13:20	13:44	14:05	14:20	9:25	14:48	15:00	15:15
The azimuth of the sun	60°	51°	42°	35°	153°	21°	15°	4°

The processing workflow for UAV multispectral images has become relatively mature, encompassing noise removal, halo correction, lens aberration correction, band alignment, band synthesis, and radiometric correction [14]. In this study, images of the five bands were first aligned using ENVI 5.3 (L3Harris Geospatial, Boulder, CO, USA). Subsequently, custom code was executed in Matlab R2020b (MathWorks, Natick, MA, USA) to perform radiometric calibration and geometric correction. Radiometric calibration of the UAV multispectral imagery followed the DN-based reference panel method. The DN values of a standard reflectance gray cloth were placed at the center of the experimental plots, yielding calibrated images. DN values corresponding to different observation angles were then extracted for each plot using ENVI 5.3. The bidirectional reflectance factor (BRF) value for each pixel was calculated using Equation (7) [17].

$$\text{BRF} = \frac{\text{DN}(\Omega, \lambda) / t(\Omega, \lambda)}{\text{DN}_{\text{ref}}(\Omega_o, \lambda) / t_{\text{ref}}(\Omega_o, \lambda)} \text{BRF}_{\text{ref}}(\Omega_o, \lambda) \quad (7)$$

where λ denotes the spectral band; $\Omega = [\theta_v, \varphi_v, \theta_s, \varphi_s]$, in which θ_v and φ_v are the viewing zenith and azimuth angles, and θ_s and φ_s are the solar zenith and azimuth angles, respectively; and t is the acquisition time.

2.4. Modeling Based on the LESS Three-Dimensional Radiative Transfer Model

The LargeE-Scale remote sensing data and image Simulation framework (LESS) is a ray-tracing-based 3D radiative transfer model that incorporates realistic scene structures, and its underlying physical process can be described by the rendering equation (Equation (8)). This model simulates the transmission processes of incident light within the scene, thereby generating and outputting the corresponding simulated datasets. BRFs at different observation angles are derived by defining sensor types, constructing the 3D structure of the winter wheat scene, configuring optical properties, and setting lighting parameters. All LESS simulations were performed using LESS version 1.8.1.

$$L_o(q, w_o) = L_e(q, w_o) + \int_{4\pi} f(q, w_i, w_o) L_i(q, w_i) |\cos \theta_i| dw_i \quad (8)$$

Formula $L_o(q, w_o)$ —Irradiance outgoing in the w_o direction from point q ;

$L_e(q, w_o)$ —Irradiance emitted in the w_o direction from point q ;

$f(q, w_i, w_o)$ —Bidirectional scattering distribution function in the neighborhood of q ;

$L_i(q, w_i)$ —Incident irradiation along the w_o direction near the q point;

θ_i —Angle between incident light and local surface normal vector.

To reduce spectral noise and enhance the stability of simulated BRF curves, Savitzky–Golay (SG) smoothing was employed to improve the smoothness of LESS-simulated spectral curves, thereby facilitating the selection of a representative subset of bands. The

smoothing operation in this study was performed using The Unscrambler X 10.4 software (CAMO Software, Oslo, Norway). Corresponding results are presented in Section 3.1.

2.4.1. Defining Sensors

In this study, since image generation was not required, the sensor type was set to PhotoTracing. However, the incident photon density needed to be configured: lower values result in higher precision, and a value of 0.05 was selected for this parameter. Additionally, the number of small surface elements (stereangular divisions) for spatial subdivision of the upper hemisphere required definition; each element generates a corresponding reflectance value, and this number was set to 150 in this study. Furthermore, the number of small surface element divisions for the upper hemispherical space (cubic corner divisions) also needed to be specified, with each division generating a corresponding reflectance value, which was similarly set to 150.

2.4.2. Defining the 3D Scene

The LESS is a remote sensing observation signal simulation tool based on a virtual 3D scene. First, individual scene element maps corresponding to different winter wheat growth stages were imported, with the file extension *.obj (as shown in Figure 2b–g). The *.obj models were constructed per growth stage using the averaged structural parameters across all treatments at each stage. The structural model was not adjusted per irrigation treatment (T1–T4), because the primary treatment-induced variations were expected to manifest through changes in leaf biochemical and optical properties (via PROSPECT inputs) rather than through large-scale structural changes. The simulated plane was set to 4 m × 4 m, consistent with the size of the experimental plots. The layout of scene elements followed a UNIFORM pattern: individual wheat elements were arranged with a spacing of 0.05 m between plants and 0.25 m between rows, thus replicating the planting density of the experimental site. Additionally, the orientation of each individual wheat element was randomized (as shown in Figure 2a).

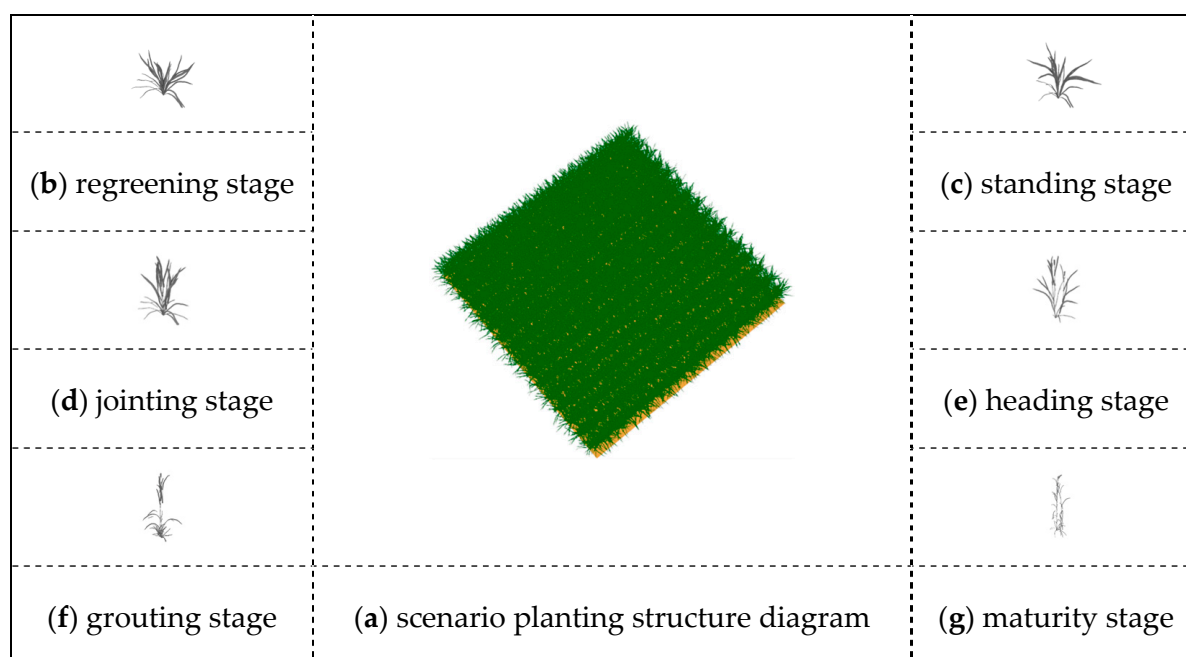


Figure 2. Defining three-dimensional scenarios for different growth stages of winter wheat.

2.4.3. Setting Optical Properties

After completing the basic parameterization of the scene, wheat leaves and stems were assigned identical optical properties to reduce the number of free parameters and focus on the analysis of angular hotspot characteristics; thus, only the leaf spectral properties required configuration. In LESS, the leaf spectrum includes frontal reflectance, reverse reflectance, and transmittance, which can be simulated by the LESS-embedded PROSPECT model. Leaf spectral attributes were configured by inputting key parameters: leaf structural parameter ($N = 1.5$), leaf dry matter mass (C_m , $\text{g}\cdot\text{cm}^{-2}$, 0–0.05), brown pigments (0), carotenoids (Car , $\mu\text{g}\cdot\text{cm}^{-2}$, 8), anthocyanins (Anth , $\mu\text{g}\cdot\text{cm}^{-2}$, 0), chlorophyll content (Cab , $\mu\text{g}\cdot\text{cm}^{-2}$, 0–100), and equivalent water thickness (C_w , $\text{g}\cdot\text{cm}^{-2}$, 0–0.05), among others. The value ranges of the simulation parameters were determined based on field experimental data and relevant literature to ensure the dataset was representative of canopy spectral responses under different water stress conditions across various growth stages. The optical properties of the soil were adopted from the default parameters provided by LESS.

2.4.4. Setting the Light Parameters

In LESS simulations, illumination parameters were configured according to UAV acquisition conditions. The solar zenith angle was fixed at 45° , while the solar azimuth angle was adjusted according to each acquisition date. Sensor viewing geometries were consistent with UAV observations to ensure comparability between simulated and measured BRF datasets.

For the angular sampling, the LESS model was configured to generate BRF values at a finer angular resolution than the UAV observations, enabling comprehensive characterization of hotspot dynamics across the observation hemisphere. Specifically, BRF values were simulated at 5° intervals along the zenith direction (from -60° to $+60^\circ$) and 10° intervals along the azimuth direction (from 0° to 360°), resulting in a total of 600 simulated viewing geometries per band, treatment, and growth stage.

2.5. Experimental and Analytical Framework

In this study, a model was constructed based on SMC data of winter wheat across multiple growth stages and spectral data simulated by LESS. The 96 collected SMC samples were averaged across the three replicates of each treatment and then matched with the LESS-simulated spectral data under different water stress conditions, resulting in a total of 32 final SMC samples, all of which were utilized for the development of linear regression models. This sample size is appropriate for the exploratory comparative analyses conducted in this study.

Multiple linear regression (MLR) was employed to establish the linear relationship between spectral data and SMC, and its fitting performance was comprehensively assessed using the coefficient of determination (R^2) and root mean square error (RMSE). The closer R^2 is to 1, the stronger the model stability; the smaller the RMSE, the higher the model accuracy and the superior the modeling performance [27].

The primary objective of the SMC regression models in this study is to quantify the relative information content of different viewing geometries for SMC estimation, and to compare the angular patterns between simulated and observed datasets. The LESS-simulated dataset enables us to examine angular effects under controlled conditions, free from confounding factors such as atmospheric variations, illumination fluctuations, and image registration errors that are inherent in UAV measurements. The UAV-derived dataset, though limited in angular sampling, serves as a reference to assess whether the simulation-based angular patterns are consistent with real observations.

2.6. Modeling and Validation

The overall workflow of this study is illustrated in Figure 3.

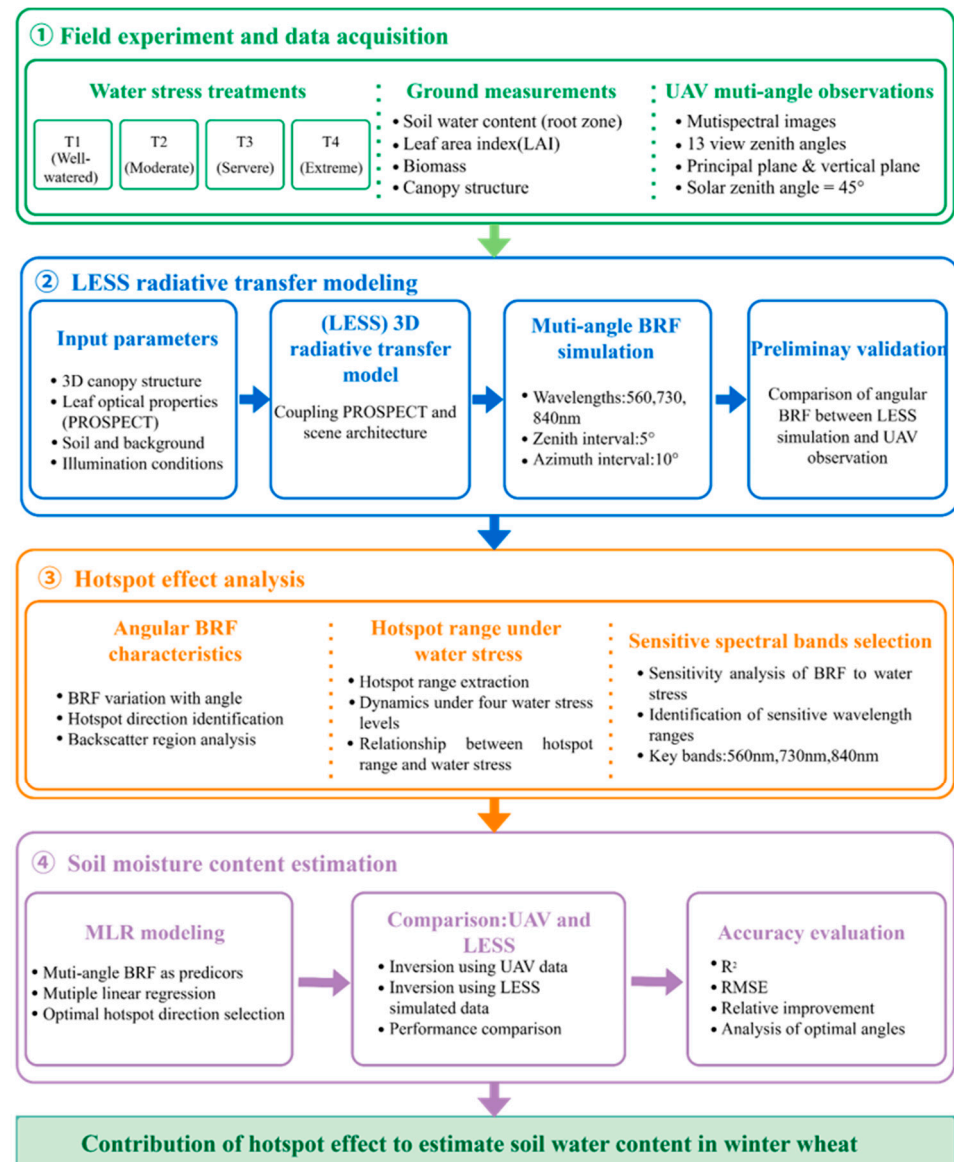


Figure 3. Flowchart of experimental research.

3. Results

3.1. Selecting a Representative Collection of Bands

Remote sensing data and LESS-simulated data corresponding to relevant observation angles under different water stress treatments were collected during the winter wheat tasseling stage (18 April).

As presented in Figure 4, the canopy bidirectional reflectance factor (BRF) varied with observation angles and water stress levels. Across the simulation experiments involving three observation zenith angles, the spectral variation patterns exhibited consistent trends. Overall, reflectance in the hotspot direction was higher than that in the vertical observation and specular reflection directions. With 730 nm as the boundary, in the 450~730 nm range, reflectance in the vertical observation direction was higher than that in the specular reflection direction; in the 730~950 nm range, reflectance in the specular reflection direction exceeded that in the vertical observation direction. This phenomenon is likely attributed to

the higher energy of light in the 730~950 nm range, which is more easily reflected by crop canopy surfaces. At the same observation angle, the sensitivity of canopy reflectance to different water stress treatments varied across spectral bands, with enhanced sensitivity primarily observed in the 530~680 nm and 770~850 nm ranges. Notably, water stress sensitivity was most pronounced in the hotspot direction, peaking at 560 nm. Accordingly, three bands were selected as a representative subset: water stress-sensitive bands (560 nm and 840 nm) and an angle-discriminating band (730 nm).

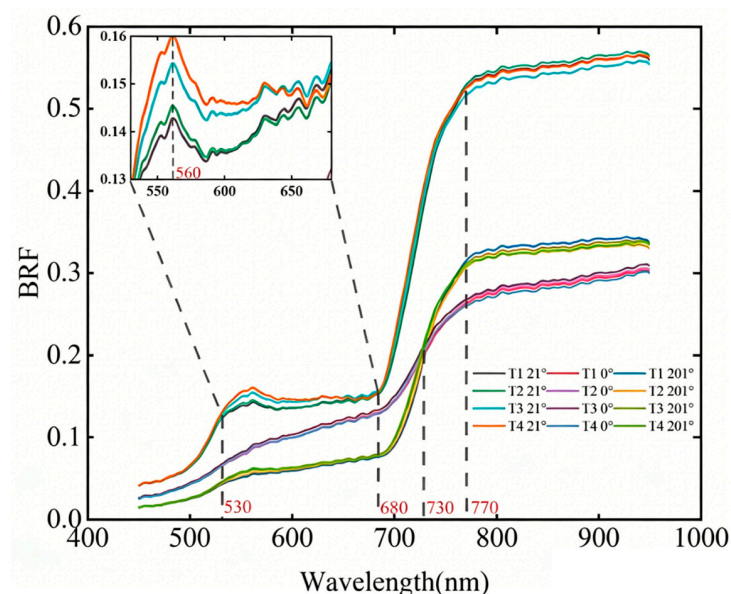


Figure 4. BRFs of winter wheat canopy at 560 nm, 730 nm, and 840 nm under four water stress treatments (T1–T4), comparing hotspot, specular, and nadir viewing directions, as simulated by LESS.

For each viewing angle and spectral band, the four samples from left to right correspond to irrigation treatments T1–T4, respectively.

The accuracy of LESS simulations at each angle was verified by fitting to UAV-acquired spectral data. Figure 5a shows that LESS-simulated reflectance at the hotspot angle exhibited smaller errors relative to other angles, with errors increasing as wavelength increases. Figure 5b indicates that the R^2 between LESS-simulated and UAV-acquired spectral data was 0.82, with an RMSE of 0.07. Overall, the accuracy between LESS-simulated and UAV-measured reflectance was relatively high, thus confirming that the LESS model is appropriate for modeling the multi-angular spectral responses of winter wheat canopies.

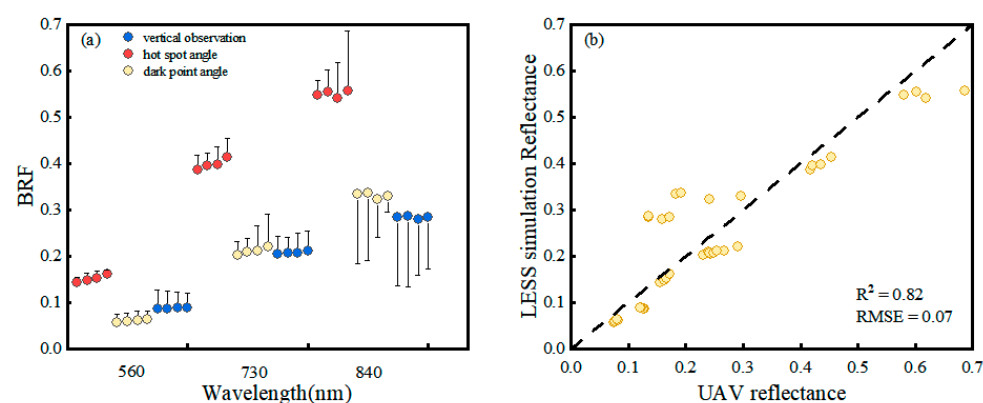


Figure 5. Comparison of bidirectional reflectance factors (BRFs) derived from LESS simulations and UAV observations under different viewing geometries (a) BRF comparison across different bands and viewing geometries; (b) Correlation between LESS-simulated and UAV-observed BRFs.

3.2. Analysis of BRF Non-Lambertianity in Wheat Canopy Under Different Water Stresses

The CV of the winter wheat canopy BRF under each water stress treatment was calculated, and this parameter was used to quantitatively characterize the non-Lambertian characteristics of the winter wheat canopy BRF across different growth stages.

As presented in Figure 6, LESS-simulated and UAV-observed BRFs exhibited consistent variability patterns within the same spectral bands, but the magnitudes of their CV differed substantially. For the 560 nm band, CV values varied significantly across winter wheat growth stages, peaking at the grouting stage with approximate values of 0.2 (UAV) and 0.4 (LESS). For the 730 nm band, CV variability across growth stages was less pronounced, with CV values of around 0.18 (UAV) and 0.3 (LESS). For the 840 nm band, the magnitude of CV variability fell between that of the 560 nm and 730 nm bands, with CV values of approximately 0.15 (UAV) and 0.25 (LESS).

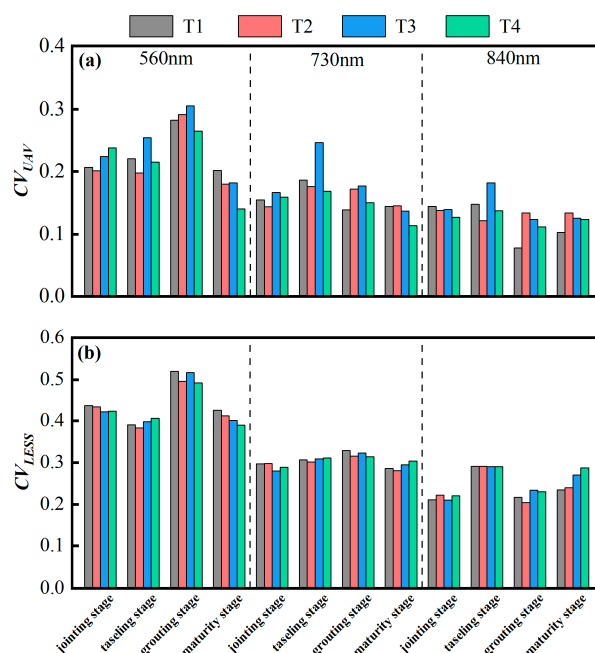


Figure 6. Comparison of the CV of canopy BRF between LESS-simulated and UAV-observed datasets at 560 nm, 730 nm, and 840 nm across different growth stages. (a) CV of UAV-observed BRFs across different growth stages and spectral bands; (b) CV of LESS-simulated BRFs across different growth stages and spectral bands.

A comparative analysis of winter wheat canopy BRFs across different growth stages revealed that the 560 nm band exhibits strong non-Lambertian characteristics and a significant correlation with growth stages, leading to substantial differences in BRFs across different observation angles and growth stages. The spectral non-Lambertian characteristics of the 730 nm and 840 nm bands were less pronounced than those of the 560 nm band, and their CV was largely independent of growth stages.

The CV of LESS-simulated BRFs was larger than that of UAV-observed counterparts across all observation angles and within the same growth stage. This indicates that the LESS model provides enhanced angular sensitivity for investigating the influence of observation angles on winter wheat canopy BRFs. By reducing the measurement uncertainties inherent in UAV observations—such as illumination fluctuations, image registration errors, and sensor noise—the LESS simulations allow angular reflectance variations to be resolved more clearly, thereby providing a physically consistent framework for analyzing directional effects.

3.3. Effects of Water Stress on Hotspot Range

The BRF values at different observation angles were generated by the LESS model at 5° intervals along the zenith direction and 10° intervals along the azimuth direction. These BRF values were linearly interpolated to generate polar plots.

In this study, the hotspot range was extracted from the BRF polar plots using the following procedure:

- (1) BRF values were generated by the LESS model at 5° intervals along the zenith direction and 10° intervals along the azimuth direction. The simulated BRF values were arranged into angular grids for each spectral band, growth stage, and water treatment.

- (2) The angular BRF grids were interpolated to generate continuous polar BRF distribution maps for visualization of directional reflectance characteristics. The interpolation was only used to represent the angular distribution and did not alter the original simulated BRF samples.

- (3) The hotspot center was identified as the observation direction corresponding to the maximum BRF value within the solar principal plane.

- (4) The hotspot range was defined as the continuous angular extent of the enhanced-reflectance region surrounding the hotspot center. The boundary was determined based on the transition from the hotspot-enhanced region to the surrounding background reflectance region. The same criterion was consistently applied to all spectral bands, growth stages, and water treatments to ensure comparable analysis of hotspot variation.

3.3.1. Main Direction Characteristics

As presented in Figures 7–9, across different growth stages and water stress levels, the three selected spectral bands exhibited symmetry on both sides of the solar principal plane (the plane containing the solar direction). Hotspot effects varied among the three bands; different growth stages alter the spectral peak distribution of winter wheat canopy BRFs, thereby influencing the occurrence of shadowed hotspot effects and specular reflections. Water stress affects the extent of both hotspot effects and specular reflections. At 560 nm, the hotspot range gradually expanded with increasing water stress intensity. With the progression of the growing season, the hotspot range exhibited a trend of first decreasing and then increasing. At 730 nm, the hotspot range showed no significant variation with increasing water stress intensity; similarly, with the progression of the growing season, the hotspot range at this band first increased and then decreased. At 840 nm, the hotspot range was virtually identical to that at 730 nm, but the hotspot effect was more pronounced during the grouting stage compared to the other two bands. Notably, at the jointing stage, all three bands exhibited specular reflection phenomena in the forward scattering direction. This observation is presumably attributed to the relatively uniform arrangement of winter wheat leaves with respect to leaf inclination at this growth stage: leaf angles were relatively consistent, resulting in a dense leaf arrangement structure around the stems.

From the comparative analysis of winter wheat canopy BRFs across the three selected bands under different water stress conditions and growth stages, the following conclusions can be drawn: the hotspot range at 560 nm and 730 nm exhibited significant variability; with the intensification of water stress, the hotspot range increased, and the magnitude of increase at 560 nm was greater than that at 730 nm. However, it is noteworthy that the hotspot range at 840 nm reached stabilization except during the maturity stage.

It should be noted that the hotspot range delineation described above is qualitative and lacks a fixed numerical threshold. All analyses and conclusions focus on relative differences among irrigation treatments and growth stages, using the same delineation criterion throughout.

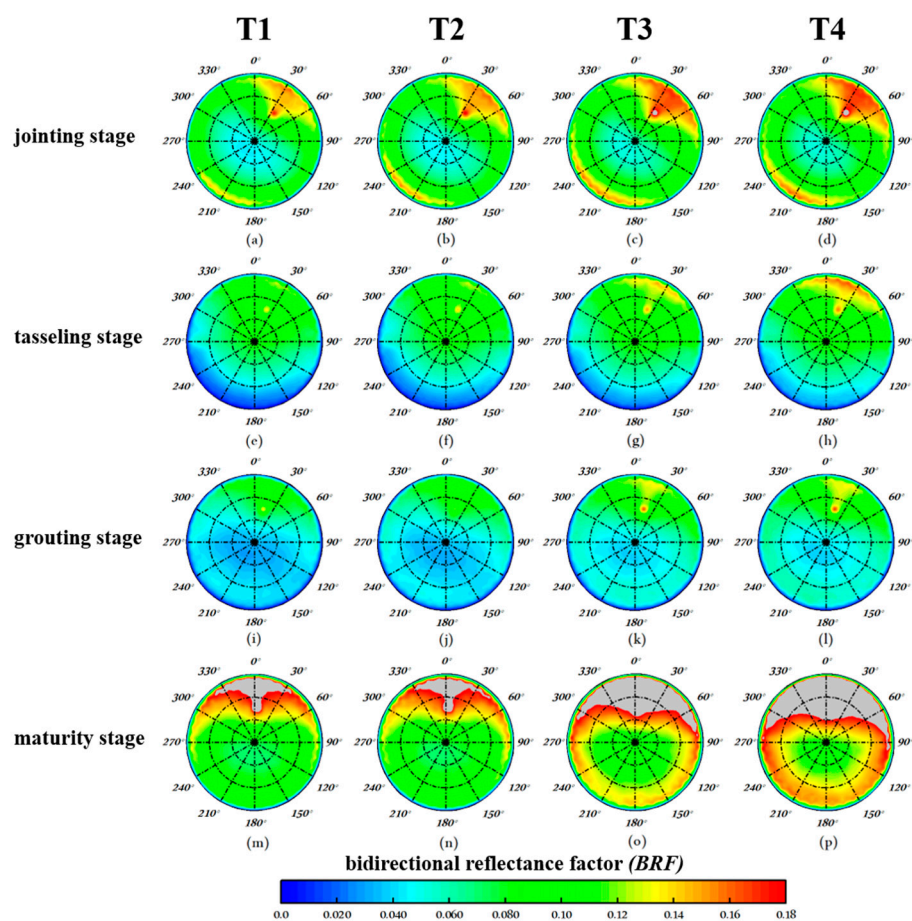


Figure 7. Polarized representation of the BRF distribution in the 560 nm band.

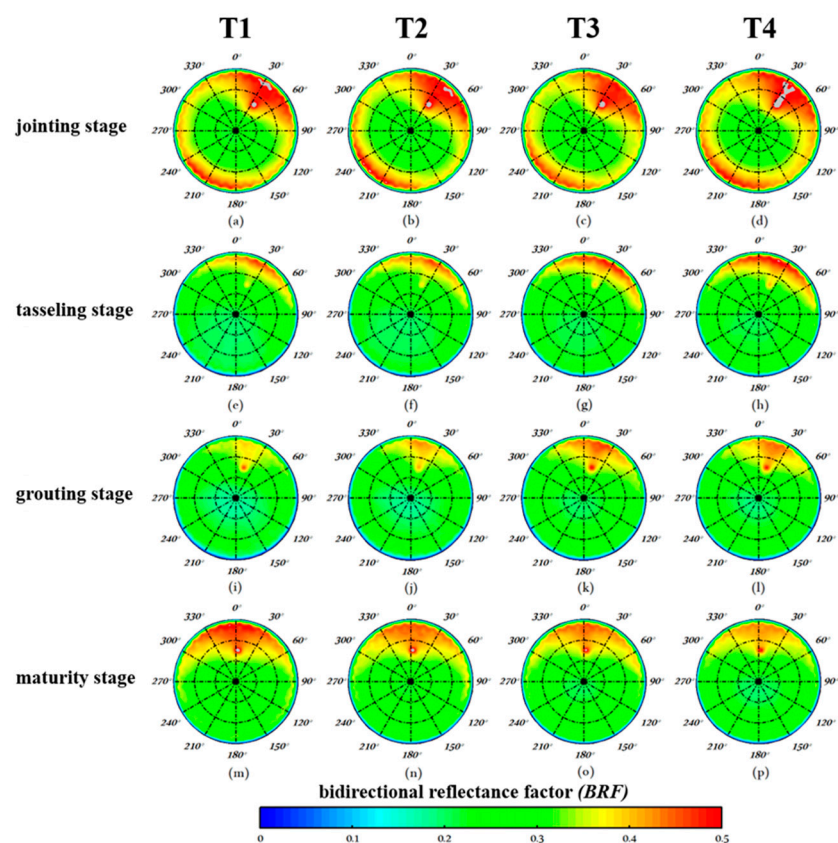


Figure 8. Polarized representation of the BRF distribution in the 730 nm band.

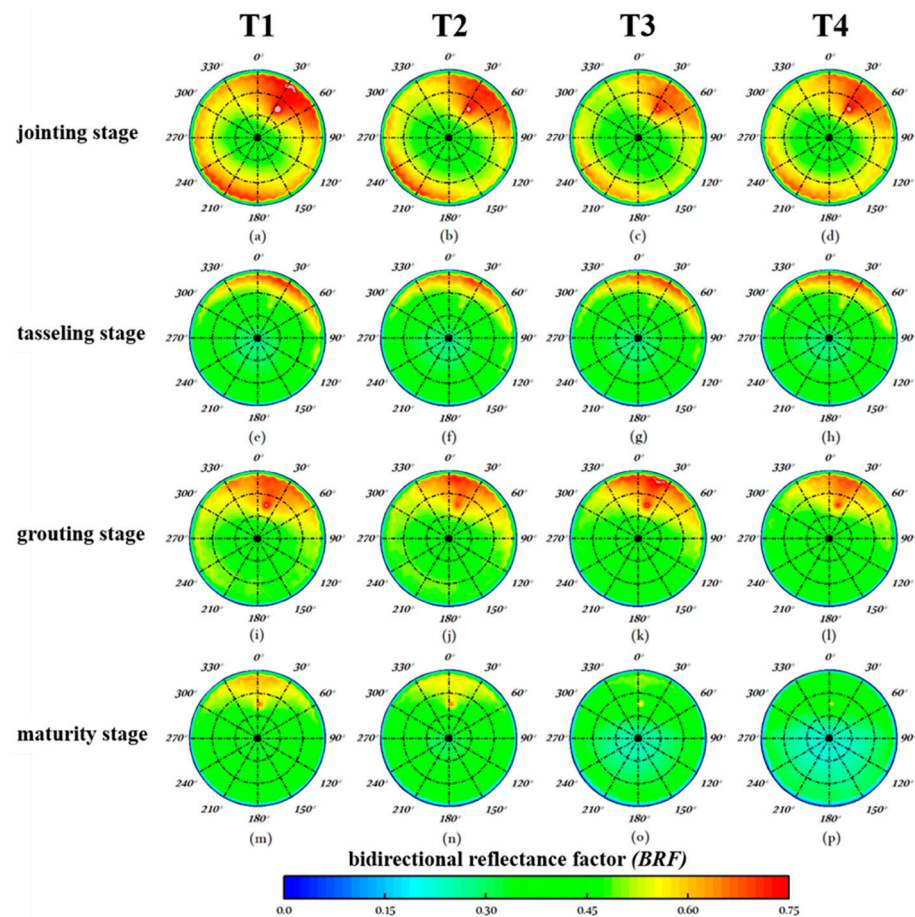


Figure 9. Polarized representation of the BRF distribution in the 840 nm band.

3.3.2. Orientation Features on Special Planes

As presented in Figure 10, winter wheat exhibited consistent trends in BRF across the three selected bands during the same growing season, although the magnitude of BRF variability differed substantially. The observed maximum BRF consistently aligned with the predicted hotspot direction, while the minimum BRF generally occurred around the 10° zenith angle. During the jointing stage, all three bands displayed pronounced bilateral symmetry. Across the solar principal plane, the maturity stage was more sensitive to water stress compared to the other three studied growth stages. Additionally, high zenith angles in the backscattering direction (-90° to -45°) exhibited higher sensitivity to water stress. Shorter wavelengths exhibited greater sensitivity to the T4 treatment, but this sensitivity gradually diminished with increasing wavelength—at 840 nm, sensitivity shifted to even greater responsiveness to the T1 treatment, with the lowest sensitivity to the T4 treatment observed at this wavelength. In the hotspot direction, BRF differences among different water stress treatments were minimal during the jointing, tasseling, and grouting stages, but these differences were slightly larger at the maturity stage.

Negative viewing angles represent backscattering directions, whereas positive viewing angles represent forward-scattering directions.

3.4. Quantifying the Effect of Wheat Canopy Spectral Directionality on Estimating SMC

3.4.1. Relationship Between Reflectance and Soil Moisture Content at Different Observation Planes

Reflectance values at 560 nm, 730 nm, and 840 nm were selected for establishing correlations with soil moisture content (SMC). The variation pattern of these correlations is presented in Figure 11.

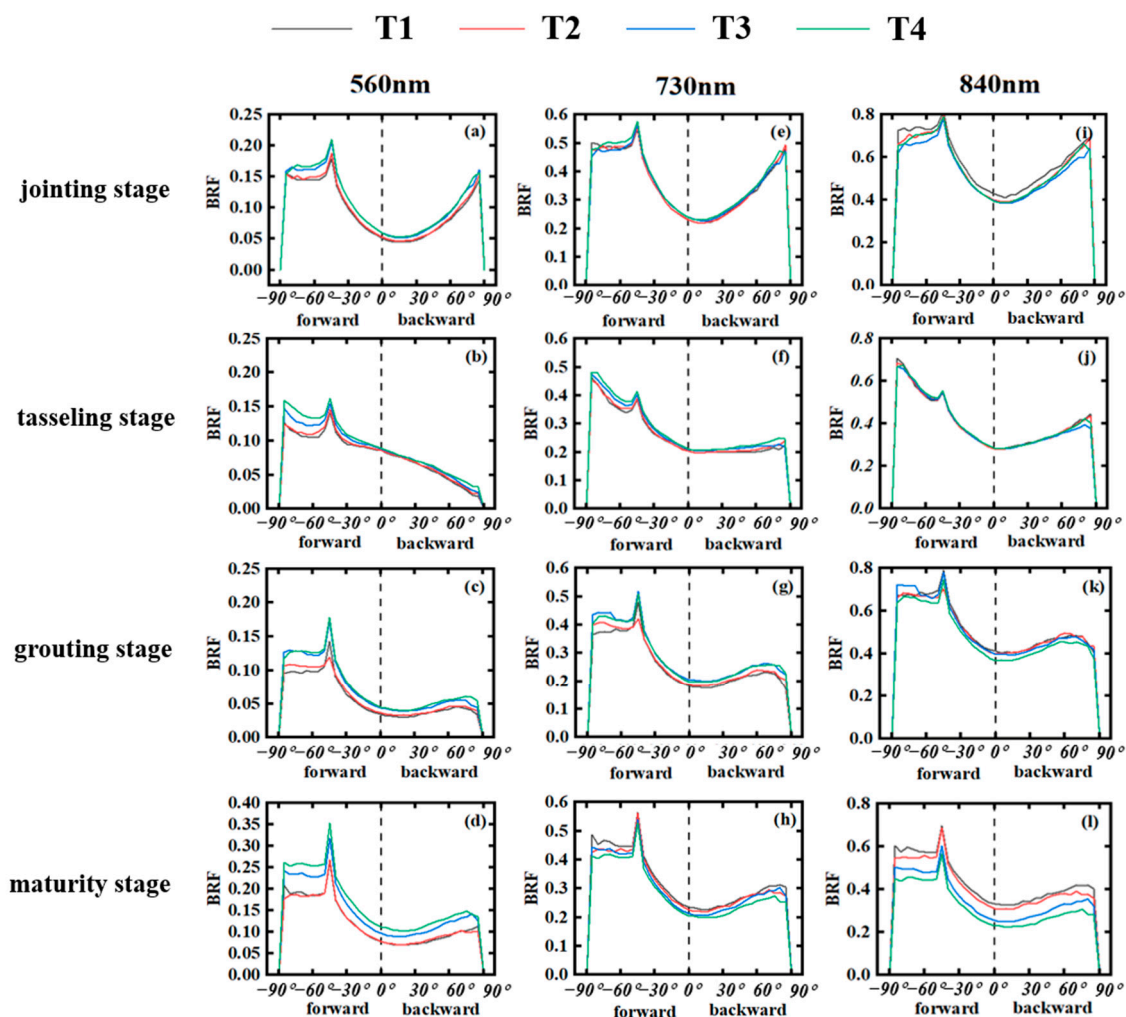


Figure 10. Bidirectional reflectance factors (BRFs) of the winter wheat canopy at 560, 730, and 840 nm along the solar principal plane.

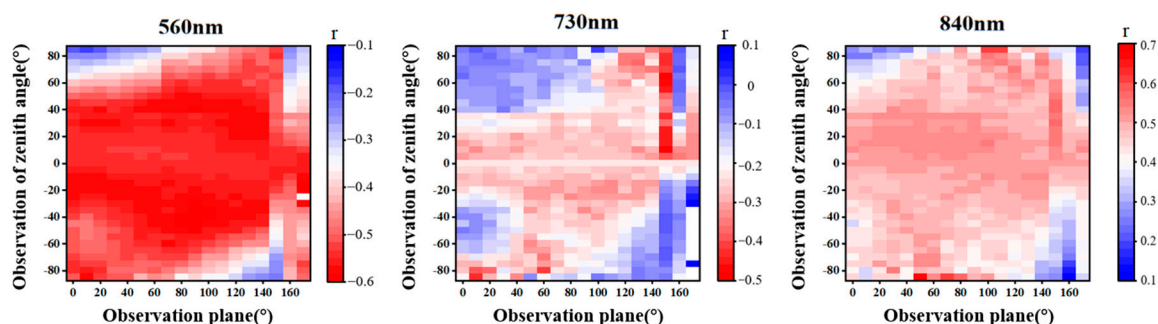


Figure 11. Correlations between canopy bidirectional reflectance factors (BRFs) and root-zone soil moisture content (SMC) at different spectral bands and observation planes.

The 0° plane represents the solar principal plane, and the remaining observation planes were arranged at 10° azimuth intervals.

From the comparative analysis of the correlations between the three selected bands, the following patterns were observed: the 560 nm band exhibited a negative correlation with SMC and the strongest correlation among the three. This band showed no strong dependency on the observation plane; as long as the zenith angle ranged from -60° to 60° , it maintained a strong correlation with SMC and was insensitive to background effects. The 730 nm band was characterized by abrupt reflectance variations, primarily attributed to the

combined effects of spectral absorption in the red wavelength range and scattering in the near-infrared range. It was mostly negatively correlated with SMC, though the correlation strength was weaker than that at 560 nm. However, this band was highly sensitive to zenith angle: at high zenith angles, it showed a weak correlation with SMC; at zenith angles between -20° and 20° , it was largely independent of the observation plane and insensitive to background effects. The correlation characteristics of the 840 nm band were similar to those of the 560 nm band, with the key distinction that the 840 nm band exhibited a positive correlation with SMC.

3.4.2. Estimation of Soil Moisture Content Based on Multiple Linear Regression

To investigate the effect of observation zenith angle on SMC estimation, correlations were established between SMC and selected bands (450 nm, 560 nm, 650 nm, 730 nm, and 840 nm) using both UAV-extracted and LESS-simulated datasets, with the bands serving as the independent variables.

From the angle-wise performance distribution shown in Figure 12, the nadir-view SMC estimation yielded an R^2 of approximately 0.45 and an RMSE of approximately 0.026. In comparison, the optimal backscattering directions near the solar principal plane achieved an R^2 of approximately 0.60 and an RMSE of approximately 0.022, representing a relative improvement of approximately 33% in R^2 and 15% in RMSE over the nadir baseline. This comparison suggests that hotspot-sensitive observations provide additional information that is not fully captured by conventional nadir measurements.

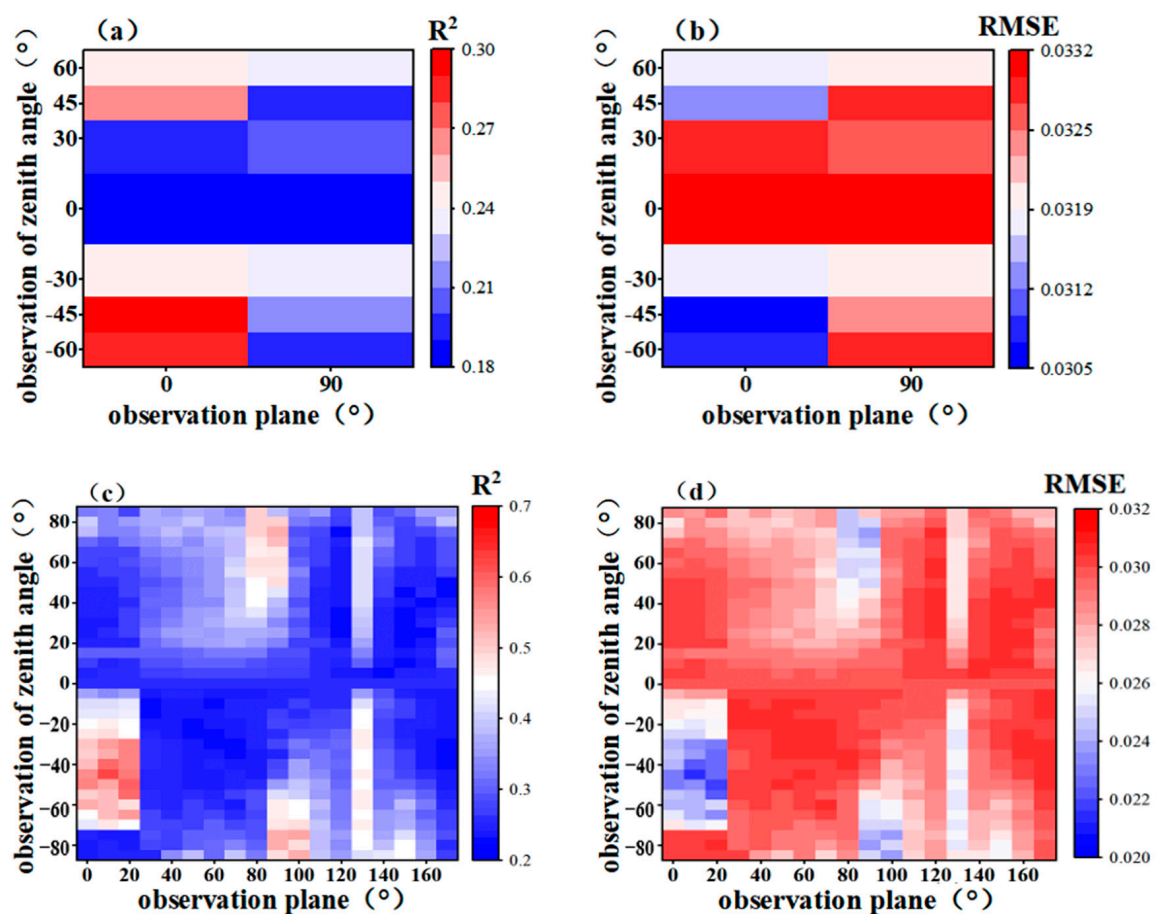


Figure 12. Performance of root-zone soil moisture content (SMC) estimation based on multiple linear regression using UAV-derived and LESS-simulated datasets. Panels (a,b) show the R^2 and RMSE obtained from the UAV-derived dataset, respectively, whereas panels (c,d) show the corresponding R^2 and RMSE obtained from the LESS-simulated dataset.

The SMC estimation accuracy achieved using LESS-simulated data at each observation angle was higher than that achieved using UAV-extracted data at the corresponding angles.

4. Discussion

Soil moisture content (SMC), as a critical parameter regulating crop growth and development, plays a crucial role in enhancing agricultural productivity and safeguarding food security [28,29]. Given the sensitivity of observation angles to monitoring accuracy [30,31], this study utilized UAV and the LESS model to acquire multi-angular spectral data for estimating winter wheat soil moisture content across different observation angles.

4.1. Sensitivity Analysis of LESS Model-Simulated Multi-Angle BRF by UAV

The multi-angular acquisition strategy adopted in this study was designed to characterize directional reflectance variations associated with both canopy anisotropy and hotspot effects. Compared with conventional nadir observations, multi-angular measurements provide additional information on canopy structure, shadow distribution, and directional scattering behavior, which are closely related to crop growth conditions and water status [32]. However, practical UAV observations are constrained by flight duration, weather conditions, and the limited number of achievable viewing geometries, making it difficult to continuously characterize canopy reflectance across the entire observation hemisphere.

Compared with traditional one-dimensional radiative transfer models such as SAIL, the LESS framework explicitly represents the three-dimensional canopy architecture and therefore provides a more realistic description of directional reflectance behavior. By incorporating actual canopy structures from different winter wheat growth stages, LESS can simulate the spatial distribution of illumination, shadowing, and multiple scattering processes within the canopy [33]. These characteristics are particularly important for hotspot analysis because hotspot formation is fundamentally controlled by shadow hiding and canopy structural configuration. Additionally, the embedded PROSPECT sub-model is capable of simulating the frontal and reverse reflectance as well as leaf transmittance, enabling more accurate simulation of vegetation canopy reflectance across different observation angles compared to UAV-based measurements.

The larger CV values observed in the LESS-simulated BRF indicate that the model preserved stronger directional reflectance variability than the UAV observations. This phenomenon may be attributed to two factors. First, the radiative transfer simulation eliminates part of the measurement uncertainty associated with illumination fluctuations, image registration errors, atmospheric effects, and sensor noise. Second, the model provides a physically consistent representation of canopy structure and radiative transfer processes, allowing angular reflectance differences to be expressed more clearly. Therefore, the stronger angular sensitivity observed in the LESS dataset should be interpreted as an enhanced ability to characterize directional reflectance patterns.

4.2. Effects of Changing Dynamics of Water Stress on the Extent of Hotspots Generated by Multi-Angle Observations

The hotspot effect is primarily controlled by the shadow-hiding mechanism within vegetation canopies. When the viewing direction approaches the solar illumination direction, shadows cast by leaves and stems become increasingly obscured from the sensor, resulting in a localized increase in reflectance. Consequently, hotspot characteristics are strongly influenced by canopy architecture, leaf angle distribution, vegetation density, and shadow configuration.

Winter wheat crops are subjected to varying degrees of water stress during their growth period, which inevitably induces changes in leaf morphology and canopy structure [34]. Water stress not only affects leaf biochemical properties but also induces structural

changes within the canopy. Reduced leaf turgor may alter leaf inclination angles, decrease canopy closure, and modify the spatial distribution of sunlit and shaded components. Because hotspot formation is fundamentally associated with shadow hiding, these structural changes can directly influence hotspot extent and intensity. Therefore, the observed hotspot dynamics under different irrigation treatments may reflect both physiological and structural responses of winter wheat to soil moisture variations.

In this study, variations in winter wheat canopy hotspot ranges under different water stress levels and across different growth stages were explored by selecting two previously identified moisture-sensitive bands (560 nm and 840 nm) and one angle-sensitive band (730 nm). All three bands exhibited perfect bilateral symmetry with the solar principal plane as the axis, which demonstrates that solar radiation is the source of canopy BRFs. At 560 nm, the winter wheat canopy hotspot range increased with increasing water stress intensity across all four growth stages, and this increasing trend was pronounced. This phenomenon is closely associated with the moisture sensitivity of the 560 nm band: water stress generally leads to a reduction in leaf water content and an increase in reflectance within the vegetation's visible spectral range [35]. At 730 nm and 840 nm, stable hotspot ranges were observed across most growth stages, with the effect of water stress on hotspot ranges weakened only during individual stages. Pronounced variations in hotspot ranges were observed across different growth stages, primarily attributed to substantial changes in leaf chlorophyll content as the growing season progressed—these changes affected leaf greenness and spectral characteristics, even leading to leaf yellowing and chlorosis in the late stages. Additionally, changes in LAI constituted another key factor influencing hotspot range variations: during the late growth stages, wheat leaves turned yellow, resulting in reduced leaf area due to shrinkage. Moreover, the presence of winter wheat spikelets exhibited substantial temporal variations, thereby influencing the direction and characteristics of the canopy spectral signature [36]. During the jointing stage, the hotspot range reached its maximum, and specular reflection was observed in the forward-scattering region. This phenomenon is closely associated with the growth status and leaf orientation of winter wheat during the jointing stage. Across the solar principal plane, shorter wavelength bands exhibited sensitivity to the T4 treatment; with increasing wavelength, this sensitivity gradually diminished, shifting to sensitivity to the T1 treatment at longer wavelengths. This change was minimally influenced by growth stages, presumably due to water stress-induced changes in winter wheat leaf water content, which modified the leaf spectral properties.

4.3. Contribution of Hotspot-Sensitive Multi-Angular Observations to SMC Estimation

Estimating SMC using UAV remote sensing remains challenging because soil moisture does not directly influence canopy reflectance. Instead, soil moisture variations affect vegetation physiological status and canopy structural characteristics, which subsequently alter spectral and directional reflectance responses. Consequently, the relationship between remotely sensed signals and soil moisture is often indirect and may vary across growth stages and environmental conditions. Most previous studies have relied primarily on nadir-view observations, which capture spectral information but provide limited insight into canopy anisotropy and directional scattering behavior. In contrast, multi-angular observations provide additional information related to canopy architecture, shadow distribution, and bidirectional reflectance characteristics, thereby offering greater potential for SMC estimation [11].

The results of this study demonstrated that observation directions located within or near hotspot-sensitive regions generally achieved higher SMC estimation performance than other viewing geometries, with the R^2 reaching approximately 0.6. This finding suggests

that hotspot-related directional signatures may contain complementary information relevant to SMC estimation. When the viewing direction approaches the solar illumination direction, canopy shadows become increasingly obscured due to the hotspot effect, causing reflectance signals to be more strongly influenced by canopy structural characteristics and vegetation physiological responses. Because soil moisture stress can modify leaf turgor, leaf inclination, canopy closure, and shadow distribution, hotspot-sensitive observations may enhance the sensitivity of directional reflectance to water-related changes within the canopy. The superiority of backscattering directions observed in this study is consistent with previous findings reported by Lu et al. [14], who found that backscattering observations improved the estimation accuracy of wheat nitrogen status. Therefore, the improved performance observed in backscattering directions reflects the enhanced ability of hotspot-sensitive observations to capture structural and anisotropic canopy information that cannot be fully characterized using conventional nadir observations alone.

4.4. Implications and Limitations

Although the results demonstrate the potential of hotspot-sensitive multi-angular observations for improving root-zone SMC estimation, several limitations should be acknowledged. First, the proposed approach does not directly measure SMC but estimates it indirectly through canopy physiological and structural responses to water stress. Therefore, the observed relationships may also be influenced by crop phenology, canopy architecture, and biomass accumulation. It should be noted that the 0–20 cm soil moisture was used as an indicator of root-zone water status; deeper soil layers may contribute differently during later growth stages. Therefore, our SMC measurements have limited representativeness for the entire root zone across the full growing season. Second, the LESS simulations were parameterized using measured canopy characteristics, including LCC, EWT, and LMA, which are themselves related to plant water status. Consequently, part of the predictive capability of the simulated dataset may originate from embedded water-related information within the model parameterization. Therefore, we interpret the simulation-based SMC estimation results as a proof-of-concept demonstration that hotspot-sensitive directions contain useful angular information related to soil moisture conditions. Third, the hotspot range delineation employed in this study is qualitative and lacks a fixed numerical threshold. Future studies should explore quantitative hotspot characterization methods to enable more objective and reproducible hotspot quantification. Finally, the dataset used in this study was relatively limited, and independent validation datasets were not available. Future studies should incorporate larger datasets, independent validation schemes, and denser multi-angular observations to further evaluate the robustness and operational applicability of hotspot-sensitive SMC estimation approaches.

5. Conclusions

To explore the potential of hotspot-sensitive multi-angular observations for root-zone SMC estimation in winter wheat, this study first identified water stress-responsive bands (560 nm and 840 nm) and an angle-sensitive band (730 nm). Subsequently, it compared the effects of water stress on canopy hotspot ranges across different growth stages using UAV experimental data and LESS-simulated multi-angle spectral data, and finally developed a multi-angle SMC estimation model utilizing multiple linear regression. The conclusions drawn from this study are as follows: the LESS model successfully reproduced the directional reflectance characteristics of winter wheat canopies and exhibited stronger angular variability than UAV-derived observations ($CV_{UAV} \approx 0.18$, $CV_{LESS} \approx 0.30$), indicating its capability to characterize canopy anisotropy and hotspot-related reflectance patterns. Water stress substantially influenced canopy hotspot characteristics through its effects on canopy

structure and leaf optical properties. The hotspot extent generally increased with increasing water stress intensity, particularly in the moisture-sensitive bands (560 and 840 nm), indicating that hotspot dynamics may provide useful information on canopy responses to soil moisture variation. Using multiple linear regression, the highest estimation performance was achieved in backscattering directions dominated by the hotspot effect across the solar principal plane ($R^2 \approx 0.6$, $RMSE \approx 0.022 \text{ m}^3 \text{ m}^{-3}$), where significant angular effects were observed. Notably, the LESS-derived dataset achieved substantially higher estimation performance than the UAV-derived dataset in hotspot-sensitive directions. These findings improve the understanding of the physical relationship between the canopy hotspot effect and soil moisture conditions, and highlight the potential value of hotspot-sensitive multi-angular observations for root-zone SMC estimation in winter wheat.

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Abbreviations

The following abbreviations are used in this manuscript:

SMC	Soil moisture content
LESS	Large-Scale remote sensing data and image Simulation framework
BRF	Bidirectional reflectance factor
LCC	Canopy chlorophyll content
AGB	Aboveground biomass
VWC	Volumetric water content
LMA	Leaf area mass
EWT	Equivalent water thickness
FOV	Field of view
SZA	Solar zenith angle

References

1. Li, Y.; Yan, S.; Gong, J. Quantifying uncertainty in soil moisture retrieval using a Bayesian neural network framework. *Comput. Electron. Agric.* **2023**, *215*, 108414. [\[CrossRef\]](#)
2. Liu, H.; Chen, J.; Xiang, Y.; Geng, H.; Yang, X.; Yang, N.; Du, R.; Wang, Y.; Zhang, Z.; Shi, L.; et al. Improving UAV hyperspectral monitoring accuracy of summer maize soil moisture content with an ensemble learning model fusing crop physiological spectral responses. *Eur. J. Agron.* **2024**, *160*, 127299. [\[CrossRef\]](#)
3. Xie, P.; Zhang, Y.; Yang, X.; Ba, Y.; Zhang, Z.; Yang, N.; Huang, J.; Cheng, Z.; Chen, J. Complement time-series UAV spectral data based on Ambrals kernel-driven model to monitor soil moisture content. *Int. J. Remote Sens.* **2024**, *45*, 4236–4254. [\[CrossRef\]](#)
4. Gerhards, M.; Schlerf, M.; Rascher, U.; Udelhoven, T.; Juszczak, R.; Alberti, G.; Miglietta, F.; Inoue, Y. Analysis of Airborne Optical and Thermal Imagery for Detection of Water Stress Symptoms. *Remote Sens.* **2018**, *10*, 1139. [\[CrossRef\]](#)
5. Hu, Q.; Zhao, Y.; Hu, X.; Qi, J.; Suo, L.; Pan, Y.; Song, B.; Chen, X. Effect of saline land reclamation by constructing the “Raised Field -Shallow Trench” pattern on agroecosystems in Yellow River Delta. *Agric. Water Manag.* **2022**, *261*, 107345. [\[CrossRef\]](#)

6. Helman, D.; Lensky, I.M.; Bonfil, D.J. Early prediction of wheat grain yield production from root-zone soil water content at heading using Crop RS-Met. *Field Crops Res.* **2019**, *232*, 11–23. [[CrossRef](#)]
7. Shi, H.; Liu, Z.; Li, S.; Jin, M.; Tang, Z.; Sun, T.; Liu, X.; Li, Z.; Zhang, F.; Xiang, Y. Monitoring Soybean Soil Moisture Content Based on UAV Multispectral and Thermal-Infrared Remote-Sensing Information Fusion. *Plants* **2024**, *13*, 2417. [[CrossRef](#)] [[PubMed](#)]
8. Zhang, Z.; Zhou, Y.; Yang, S.; Tan, C.; Lao, C.; Xu, C. Inversion Method for Soil Water Content in Winter Wheat Root Zone with Eliminating Effect of Soil Background. *Trans. Chin. Soc. Agric. Mach.* **2021**, *52*, 197–207.
9. Zhang, Y.; Han, W.; Zhang, H.; Niu, X.; Shao, G. Evaluating soil moisture content under maize coverage using UAV multimodal data by machine learning algorithms. *J. Hydrol.* **2023**, *617*, 129086. [[CrossRef](#)]
10. Galvão, L.S.; Breunig, F.M.; Santos, J.R.d.; Moura, Y.M.d. View-illumination effects on hyperspectral vegetation indices in the Amazonian tropical forest. *Int. J. Appl. Earth Obs. Geoinf.* **2013**, *21*, 291–300. [[CrossRef](#)]
11. Zhang, H.-Y.; Liu, M.-R.; Feng, Z.-H.; Song, L.; Li, X.; Liu, W.-D.; Wang, C.-Y.; Feng, W. Estimations of Water Use Efficiency in Winter Wheat Based on Multi-Angle Remote Sensing. *Front. Plant Sci.* **2021**, *12*, 614417. [[CrossRef](#)] [[PubMed](#)]
12. Song, X.; Feng, W.; He, L.; Xu, D.; Zhang, H.-Y.; Li, X.; Wang, Z.-J.; Coburn, C.A.; Wang, C.-Y.; Guo, T.-C. Examining view angle effects on leaf N estimation in wheat using field reflectance spectroscopy. *ISPRS J. Photogramm. Remote Sens.* **2016**, *122*, 57–67. [[CrossRef](#)]
13. He, L.; Liu, M.-R.; Guo, Y.-L.; Wei, Y.-K.; Zhang, H.-Y.; Song, X.; Feng, W.; Guo, T.-C. Angular effect of algorithms for monitoring leaf nitrogen concentration of wheat using multi-angle remote sensing data. *Comput. Electron. Agric.* **2022**, *195*, 106815. [[CrossRef](#)]
14. Lu, N.; Wang, W.; Zhang, Q.; Li, D.; Yao, X.; Tian, Y.; Zhu, Y.; Cao, W.; Baret, F.; Liu, S.; et al. Estimation of Nitrogen Nutrition Status in Winter Wheat From Unmanned Aerial Vehicle Based Multi-Angular Multispectral Imagery. *Front. Plant Sci.* **2019**, *10*, 1601. [[CrossRef](#)] [[PubMed](#)]
15. He, L.; Zhang, H.-Y.; Zhang, Y.-S.; Song, X.; Feng, W.; Kang, G.-Z.; Wang, C.-Y.; Guo, T.-C. Estimating canopy leaf nitrogen concentration in winter wheat based on multi-angular hyperspectral remote sensing. *Eur. J. Agron.* **2016**, *73*, 170–185. [[CrossRef](#)]
16. Zhang, B.; Chen, Y.; Liu, H.; Wu, Y.; Ye, S.; Yang, N.; Bai, X.; Huang, J.; Xie, P.; Zhang, Z.; et al. Monitoring soil moisture content in the root zone of winter wheat with multi-angle multispectral imagery. *Int. J. Remote Sens.* **2024**, *45*, 4692–4709. [[CrossRef](#)]
17. Li, W.; Jiang, J.; Weiss, M.; Madec, S.; Tison, F.; Philippe, B.; Comar, A.; Baret, F. Impact of the reproductive organs on crop BRDF as observed from a UAV. *Remote Sens. Environ.* **2021**, *259*, 112433. [[CrossRef](#)]
18. Li, W.; Yan, G.; Mu, X.; Tong, Y.; Zhou, K.; Xie, D. Modeling the hotspot effect for vegetation canopies based on path length distribution. *Remote Sens. Environ.* **2024**, *303*, 113985. [[CrossRef](#)]
19. Du, R.; Chen, J.; Xiang, Y.; Zhang, Z.; Yang, N.; Yang, X.; Tang, Z.; Wang, H.; Wang, X.; Shi, H.; et al. Incremental learning for crop growth parameters estimation and nitrogen diagnosis from hyperspectral data. *Comput. Electron. Agric.* **2023**, *215*, 108356. [[CrossRef](#)]
20. Cheng, J.; Yang, H.; Qi, J.; Sun, Z.; Han, S.; Feng, H.; Jiang, J.; Xu, W.; Li, Z.; Yang, G.; et al. Estimating canopy-scale chlorophyll content in apple orchards using a 3D radiative transfer model and UAV multispectral imagery. *Comput. Electron. Agric.* **2022**, *202*, 107401. [[CrossRef](#)]
21. Du, R.; Xiang, Y.; Zhang, F.; Chen, J.; Shi, H.; Liu, H.; Yang, X.; Yang, N.; Yang, X.; Wang, T.; et al. Combining transfer learning with the OPTical TRapezoid Model (OPTRAM) to diagnosis small-scale field soil moisture from hyperspectral data. *Agric. Water Manag.* **2024**, *298*, 108856. [[CrossRef](#)]
22. Zhao, X.; Zhang, Z.; Shi, C.; Zhao, F.; Gao, Y.; He, W.; Wang, X. Estimation of chlorophyll content in cotton canopy leaves based on drone multispectral sensors: Multiple spectral information fusion. *Ind. Crops Prod.* **2025**, *235*, 121710. [[CrossRef](#)]
23. Liu, S.; Jin, X.; Bai, Y.; Wu, W.; Cui, N.; Cheng, M.; Liu, Y.; Meng, L.; Jia, X.; Nie, C.; et al. UAV multispectral images for accurate estimation of the maize LAI considering the effect of soil background. *Int. J. Appl. Earth Obs. Geoinf.* **2023**, *121*, 103383. [[CrossRef](#)]
24. Liu, Y.; Feng, H.; Yue, J.; Jin, X.; Fan, Y.; Chen, R.; Bian, M.; Ma, Y.; Song, X.; Yang, G. Improved potato AGB estimates based on UAV RGB and hyperspectral images. *Comput. Electron. Agric.* **2023**, *214*, 108260. [[CrossRef](#)]
25. Féret, J.B.; le Maire, G.; Jay, S.; Berveiller, D.; Bendoula, R.; Hmimina, G.; Cheraiet, A.; Oliveira, J.C.; Ponzoni, F.J.; Solanki, T.; et al. Estimating leaf mass per area and equivalent water thickness based on leaf optical properties: Potential and limitations of physical modeling and machine learning. *Remote Sens. Environ.* **2019**, *231*, 110959. [[CrossRef](#)]
26. Shibayama, M.; Wiegand, C.L. View azimuth and zenith, and solar angle effects on wheat canopy reflectance. *Remote Sens. Environ.* **1985**, *18*, 91–103. [[CrossRef](#)]
27. Chen, H.; Chen, H.; Zhang, S.; Chen, S.; Cen, F.; Zhao, Q.; Huang, X.; He, T.; Gao, Z. Comparison of CWSI and Ts-Ta-VIs in moisture monitoring of dryland crops (sorghum and maize) based on UAV remote sensing. *J. Integr. Agric.* **2024**, *23*, 2458–2475. [[CrossRef](#)]
28. Sreeram, R.; Adithya Krishna, S.; Kumar, A.S.; Remya, S.; Cho, Y.Y. Soil moisture monitoring technologies in smart agriculture: A comprehensive review. *Farming Syst.* **2026**, *4*, 100189. [[CrossRef](#)]
29. Luo, L.; Li, Y.; Guo, F.; Huang, Z.; Wang, S.; Zhang, Q.; Zhang, Z.; Yao, Y. Research on robust inversion model of soil moisture content based on GF-1 satellite remote sensing. *Comput. Electron. Agric.* **2023**, *213*, 108272. [[CrossRef](#)]

30. Hasegawa, K.; Matsuyama, H.; Tsuzuki, H.; Sweda, T. Improving the estimation of leaf area index by using remotely sensed NDVI with BRDF signatures. *Remote Sens. Environ.* **2010**, *114*, 514–519. [[CrossRef](#)]
31. Stagakis, S.; Markos, N.; Sykioti, O.; Kyparissis, A. Monitoring canopy biophysical and biochemical parameters in ecosystem scale using satellite hyperspectral imagery: An application on a *Phlomis fruticosa* Mediterranean ecosystem using multiangular CHRIS/PROBA observations. *Remote Sens. Environ.* **2010**, *114*, 977–994. [[CrossRef](#)]
32. Dong, Y.; Jiao, Z.; Cui, L.; Zhang, H.; Zhang, X.; Yin, S.; Ding, A.; Chang, Y.; Xie, R.; Guo, J. Assessment of the Hotspot Effect for the PROSAIL Model with POLDER Hotspot Observations Based on the Hotspot-Enhanced Kernel-Driven BRDF Model. *IEEE Trans. Geosci. Remote Sens.* **2019**, *57*, 8048–8064. [[CrossRef](#)]
33. Zhang, X.; Jiao, Z.; Dong, Y.; Zhang, H.; Li, Y.; He, D.; Ding, A.; Yin, S.; Cui, L.; Chang, Y. Potential Investigation of Linking PROSAIL with the Ross-Li BRDF Model for Vegetation Characterization. *Remote Sens.* **2018**, *10*, 437. [[CrossRef](#)]
34. Hovi, A.; Schraik, D.; Kuusinen, N.; Fabiánek, T.; Hanuš, J.; Homolová, L.; Juola, J.; Lukeš, P.; Rautiainen, M. Synergistic use of multi- and hyperspectral remote sensing data and airborne LiDAR to retrieve forest floor reflectance. *Remote Sens. Environ.* **2023**, *293*, 113610. [[CrossRef](#)]
35. Elsayed, S.; El-Hendawy, S.; Dewir, Y.H.; Schmidhalter, U.; Ibrahim, H.H.; Ibrahim, M.M.; Elsherbiny, O.; Farouk, M. Estimating the Leaf Water Status and Grain Yield of Wheat under Different Irrigation Regimes Using Optimized Two- and Three-Band Hyperspectral Indices and Multivariate Regression Models. *Water* **2021**, *13*, 2666. [[CrossRef](#)]
36. Li, H.; Zhao, C.; Yang, G.; Feng, H. Variations in crop variables within wheat canopies and responses of canopy spectral characteristics and derived vegetation indices to different vertical leaf layers and spikes. *Remote Sens. Environ.* **2015**, *169*, 358–374. [[CrossRef](#)]

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