Analysis of Spectral Reflectance Derived from UAV-Embedded Multispectral and Thermal Sensors as a Function of Soil Moisture Gradient

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Abstract

Soil moisture is a key variable for agriculture and environmental management, yet its field measurement remains time-consuming and spatially limited..This study investigated the relationship between gravimetric soil moisture (Ug%) and spectral responses, derived from Unmanned Aerial Vehicle (UAV) mounted multispectral and thermal sensors. The methodology involved acquiring thermal and multispectral imagery over an experimental area with laboratory-identified moisture gradients. An analysis of the importance of moisture predictive variables was performed using machine learning techniques, such as the Random Forest algorithm The Random Forest model achieved R = 0.70 and RMSE = 1.7%, with the thermal band explaining over 50% of the variance, confirming its strong relationship with soil moisture and the ability to distinguish different soil water conditions. The investigation highlighted the importance of precise sensor calibration to ensure the consistency and comparability of data acquired at different times or environmental conditions, a critical factor for analyzing temporal changes and evaluating the effectiveness of management practices

1. Introduction

Spectral reflectance is sensitive to variations in soil moisture, as water significantly impacts absorption and reflection across different wavelengths. The use of remote sensing with Unmanned Aerial Vehicles (UAVs) enables precise and efficient monitoring of soil moisture across extensive areas. This technology provides data with high temporal, spatial, and spectral resolution, allowing frequent monitoring of soil conditions. The study of spectral responses is particularly relevant in Soil Science, as the content of water, organic matter, and soil mineralogy exhibit distinct and quantifiable spectral behaviors at different wavelengths of the electromagnetic spectrum.

The integration of spectral data with machine learning models for soil moisture prediction is crucial for precision agriculture and has direct implications for agricultural productivity, as it supports the identification of areas requiring irrigation or management adjustments (Ferreira Neto et al., 2024). Wet soils generally exhibit reduced reflectance across the visible, near-infrared, and shortwave infrared regions, particularly around wavelengths strongly absorbed by water (1400, 1900, and 2200 nm). This highlights the importance of calibrating models for specific soil moisture conditions, as soil moisture can indicate scenarios that may either favor or limit agricultural productivity. In UAV-based monitoring systems, the application of sensors that integrate multiple spectral bands to obtain moisture data is crucial for accurate interpretation of spectral responses (Freitas et al., 2022).

By capturing these changes, the combined analysis of multispectral reflectance and thermal data provides valuable inputs for soil conservation and ecosystem recovery strategies, underscoring the role of remote sensing technologies in advancing sustainability. This study investigated the relationship between gravimetric soil moisture (Ug%) and spectral responses obtained from UAV-mounted multispectral and thermal sensors, aiming to evaluate their potential for soil moisture prediction field conditions.

2. Materials and Methods

2.1 Study Area

The study was conducted at the Urussanga Experimental Station of the Agricultural Research and Rural Extension Company of Santa Catarina - Epagri (Figure 1), located in the state of Santa Catarina, Brazil. The experimental site is an agricultural area with exposed soil that was harrowed one day prior to data collection. Field work took place between August 2024 and April 2025, covering different seasons to capture temporal variations in the study area over time. Six sampling campaigns were carried out, resulting in 90 samples. The selection of sampling points was guided by pedological criteria observed in situ, with particular attention to soil texture, distinguishing between medium- and sandy-texture classes.

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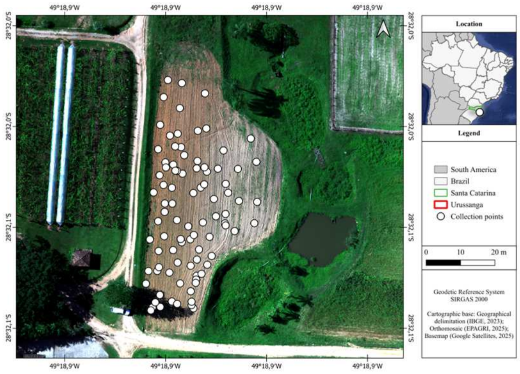

Figure 1. Experimental area at the Urussanga Experimental Station (EPAGRI) with the distribution of soil sampling points.

2.2 Flight Planning and Image Processing

For data acquisition, a DJI Matrice 300 RTK drone equipped with a MicaSense Altum camera and a Downwelling Light Sensor (DSL) was used. The MicaSense Altum integrates five multispectral bands with an additional thermal band, enabling simultaneous acquisition of optical and thermal imagery. Radiometric accuracy was ensured using the MicaSense Reflectance Calibration Panel (CRP) together with DSL data allowing consistent calibration and comparability across different flights.

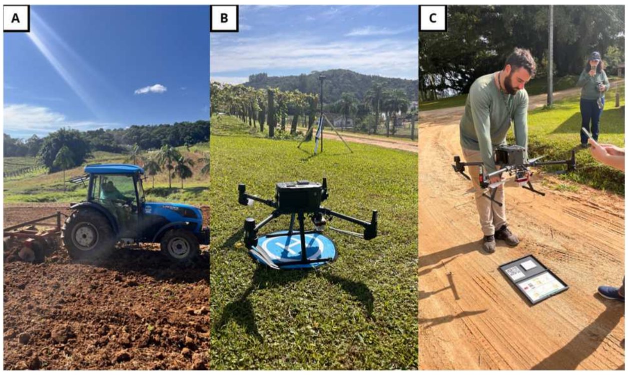

Figure 2: Field activities: (A) soil tillage prior to UAV flights; (B) UAV setup with DSL attached for multispectral acquisition; and (C) radiometric calibration of multispectral sensors using a reflectance calibration panel (CRP).

Flight planning was conducted using DJI Pilot 2 software, which defined optimized routes and parameters to ensure adequate image overlap and complete coverage of the study area.. Two flight missions were carried out at different altitudes: the first, at 60 m, aimed at acquiring accurate coordinates of soil sampling points using ground targets; the second, at 40 m, was performed without targets to capture the multispectral and thermal images for preprocessing. All flights were conducted between 11:00 a.m. and 1:00 p.m., when the sun was near its zenith, in order to minimize illumination effects throughout the year. The MicaSense Altum camera captured data across a total of six spectral bands, including a thermal band. The five multispectral bands are centered at 475 nm (Blue), 560 nm (Green), 668 nm (Red), 717 nm (Red Edge), and 842 nm (Near-IR). In addition to these, the camera also acquired data in a thermal band centered at 11 µm with a bandwidth of 6 µm. CRP images were collected before and after each flight to ensure radiometric consistency. Multispectral and thermal data processing was carried out using Agisoft Metashape software, which enabled the generation of Digital Surface Models (DSMs) and orthomosaics. Radiometric calibration of the images was performed using images from CRP and DLS data, ensuring the accuracy of reflectance values. Subsequent analyses, including spatial statistical and vegetation indices calculations, were performed in Python to extract temporal information on exposed soil reflectance.

2.3 Soil Collection and Analysis

The soil samples were collected at random points within the 0.3 hectare area, at a depth of 0-5 cm, stored in labeled plastic bags, and kept protected from direct sunlight to preserve their physical integrity and original moisture content. The study area was harrowed in the week prior to each flight.

In the laboratory, each sample was transferred to pre-tared, labeled weighing capsules. Drying was conducted in an oven at a constant temperature of 105 ± 2º C for a period of 48 hours, ensuring complete elimination of free water. After the drying period, the samples were removed from the oven, cooled in a desiccator to prevent moisture reabsorption, and subsequently weighed on an analytical balance with a precision of 0.01 g.

The gravimetric soil moisture content (Ug%) was determined using the following equation:

$$Ug = \frac{P_{wet} - P_{dry}}{P_{dry}} x\ 100, \tag{1}$$

where P_{wet} corresponded to the mass of the sample before drying and $P_{Dry}$to the remaining mass after oven drying. The calculated value expresses the percentage ratio between the mass of water and the mass of dry soil, serving as a parameter to characterize soil moisture at the time collection.

2.4 Statistical analyses

The methodology was based on the integration of statistical and geostatistical techniques to characterize and model gravimetric soil moisture. Descriptive statistics and normality tests (Shapiro-Wilk and Anderson-Darling) were applied, followed by Spearman's correlation coefficient to assess monotonic relationships. Principal Component Analysis (PCA) was applied to identify multivariate patterns, and predictive modeling employed Linear Regression and Random Forest, with 70% of the data for training and 30% reserved for testing, validated through k-fold cross-validation (R^2, RMSE, and MAE as metrics). For geostatistical analysis, empirical variograms were fitted to the spherical model to evaluate spatial dependence, considering parameters of range, sill, and nugget, and anisotropy was assessed through directional analysis. Ordinary Kriging was then used for spatial interpolation. employed for spatial interpolation.

3. Results

Gravimetric soil moisture (Ug, %) had a mean value of 11.57% (SD = 3.79%), with a coefficient of variation of 32.8%, indicating moderate variability. The mean and median values (11.57% and 11.82%, respectively) were very close, suggesting a relatively symmetric distribution of soil moisture (Table 1). The reflectance of spectral bands 1 to 5 ranged from 0.064 to 0.214, with coefficients of variation between 31% and 35%, evidencing high variability across the area. In contrast, the thermal band presented a mean of 46.55 and a median of 46.26, with a lower coefficient of variation (19.1%), indicating more homogeneous data, although some asymmetry was observed.

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Parameter	Mean	Min	Max	Standard Deviation	Coefficient of Variation (%)
Ug (%)	11.57	5.59	19.63	3.79	32.80
Band 1	0.064	0.008	0.114	0.022	34.55
Band 2	0.113	0.010	0.189	0.039	34.61
Band 3	0.165	0.007	0.266	0.052	31.61
Band 4	0.193	0.016	0.299	0.061	31.41
Band 5	0.214	0.020	0.341	0.070	32.78
Thermal	46.55	28.70	61.11	8.90	19.12

Table 1: Descriptive statistics of reference gravimetric soil moisture (Ug%) and corresponding multispectral reflectance and thermal radiance values from 90 sampling points.

The Spearman correlation analysis (Table 2) showed that only the thermal band presented a statistically significant association with gravimetric soil moisture (Ug%), with $\rho = 0.23$ ($p < 0.05$). Despite its significance, this correlation was weak, indicating that soil temperature captured by the thermal sensor is moderately sensitive to moisture gradients, whereas optical reflectance alone was not. Bands 1 to 5 exhibited non-significant and near-zero coefficients, suggesting limited monotonic relationships under the study conditions.

Variable	Correlation	P-value
Band 1	-0.07	0.465
Band 2	0.012	0.903
Band 3	0.000	0.993
Band 4	0.043	0.683
Band 5	0.068	0.520
Thermal	0.225	0.032

Table 2: Spearman's rank correlation coefficients between multispectral/thermal bands and reference gravimetric soil moisture (Ug %).

Principal Component Analysis (PCA) of the dataset showed that the PC1 and PC2 together explained 93.06% of the total data variance, with PC1 (77.71%) dominated by spectral bands (1 to 5) and PC2 (15.35%) strongly associated with soil moisture content (Ug%). The thermal band contributes to both components, reinforcing its hybrid behavior and closer alignment with Ug% compared to optical bands. The biplot revealed clear sample groupings: higher Ug% clustered in the upper central region, while intermediate values aligned with PC1 (better explained by optical bands) and the extreme values (very dry or wet) were separated along PC2. This pattern indicates that optical reflectance had low direct correlation with soil moisture, while thermal data captured the variability more effectively, consistent with correlation analysis and with previous studies reporting the stronger sensibility of thermal imagery to soil water content (Bertalan et al., 2022; Ge et al., 2021).

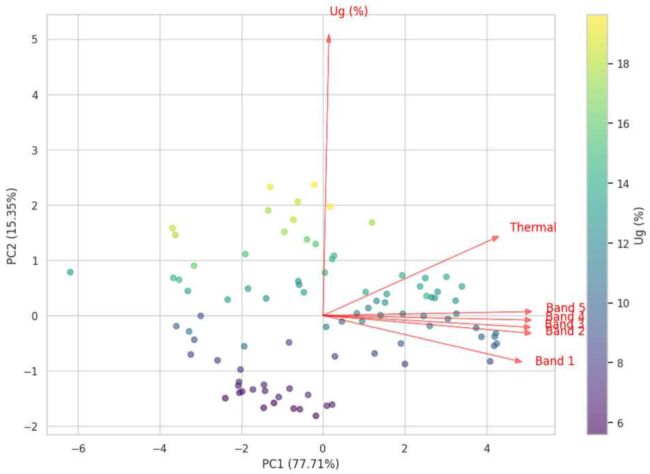

Figure 3: Principal Component Analysis (PCA) biplot showing the relationship between gravimetric soil moisture (Ug%) and multispectral/thermal spectral attributes. PC1 (77.71%) is mainly explained by spectral bands, while PC2 (15.35%) is associated with soil moisture variability.

Additionally, a Random Forest model was implemented to capture nonlinear interactions and complex interactions between gravimetric soil moisture (Ug%) and the spectral variables. The model achieved a prediction correlation (R) of 0.69, with RMSE of 1.70%, demonstrating robust performance in estimating soil moisture. Variable importance analysis revealed the predominance of the thermal band (>0.5), more than double the contribution of the next most relevant variable, while Bands 1 and 2 contributed less than 0.10, indicating their low explanatory power within the multivariate context (Figure 4).

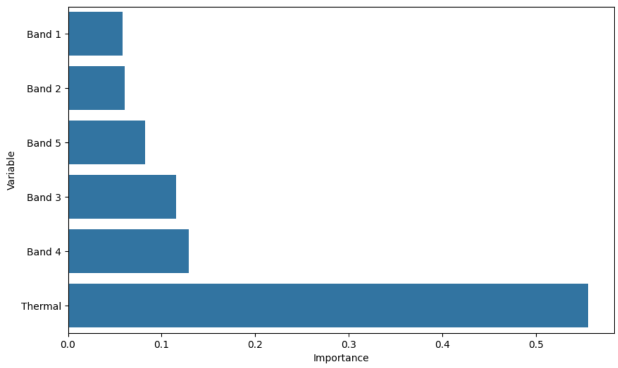

Figure 4: Variable importance from the Random Forest model for gravimetric soil moisture prediction. The thermal band was the most influential predictor (>0.5), followed by Band 4, Band 3, and Band 5 (0.10–0.15). Bands 1 and 2 showed the lowest contributions (<0.10).

The gravimetric soil moisture (Ug %) values were spatialized using ordinary kriging which generated a distribution map across the study area. The directional variogram revealed clear spatial anisotropy (Figure 5): while the spherical model indicated spatial continuity of ~20 m in the 0°, 45°, and 135° directions, the range dropped sharply to only 4.3 m at 90°. This pronounced directional difference suggests that soil moisture variability was influenced by structural controls such as microtopography and textural transitions between medium- and sandy-textured soils. The sill stabilized at ~14, and the nugget effect (~2.5) represented only a small fraction of the total variance, indicating limited micro-scale variability relative to the structured component. Cross-validation of the kriging interpolation confirmed high accuracy (MAE = 1.2%, RMSE = 1.5%). These findings are consistent with classical geostatistical theory on anisotropy (Vieira, 2000; Goovaerts, 1997) and reinforce the importance of considering directionality in soil moisture modeling for precision agriculture.

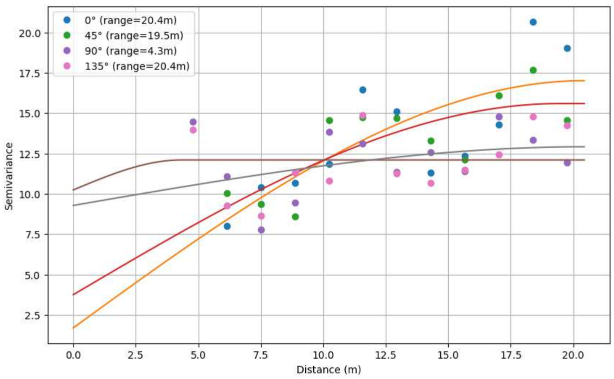

Figure 5: Directional variogram of gravimetric soil moisture (Ug%) at the Urussanga Experimental Station (EPAGRI), showing strong anisotropy and differences in range, sill and nugget across azimuths.

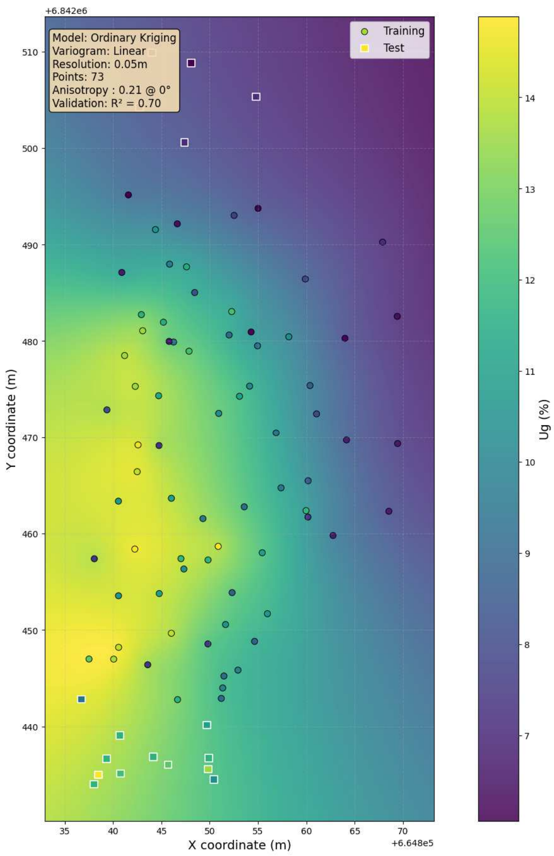

Figure 6: Ordinary kriging map of gravimetric soil moisture (Ug %) at the Urussanga Experimental Station (EPAGRI), showing an east–west gradient consistent with the anisotropy identified in the directional variograms..

Based on the descriptive statistics for the Temperature-Vegetation Dryness Index (TVDI), Table 2, the values ranged from a minimum of 0.174713 to a maximum of 1.0, with a mean value of 0.882522. The relatively high mean and median (as implied by the mean's proximity to the maximum) suggest that, on average, the soil was quite dry. The standard deviation (Std) of 0.180884 indicates a moderate spread in the TVDI values across the 90 sampling points. The coefficient of variation (CV) of 20.496256% confirms this moderate variability. While there was some variation in soil moisture conditions, the data set as a whole points towards a predominance of dry conditions.

Parameter	Mean	Max	Min	Std	CV (%)
TVDI	0.882522	1.0	0.174713	0.180884	20.496256

Table 2: Descriptive statistics of reference gravimetric soil moisture (Ug%) and corresponding TVDI values from 90 sampling points.

The comparison with the Temperature Vegetation Dryness Index (TVDI), a classical method traditionally applied with satellite data but here derived from UAV multispectral and thermal bands, revealed important differences in performance. Despite the high spatial resolution of UAV imagery, the correlation matrix (Figure 7) showed that TVDI maintained moderate and inconsistent associations with gravimetric soil moisture (Ug%), ranging from r = 0.66 to negative values in April 2025.

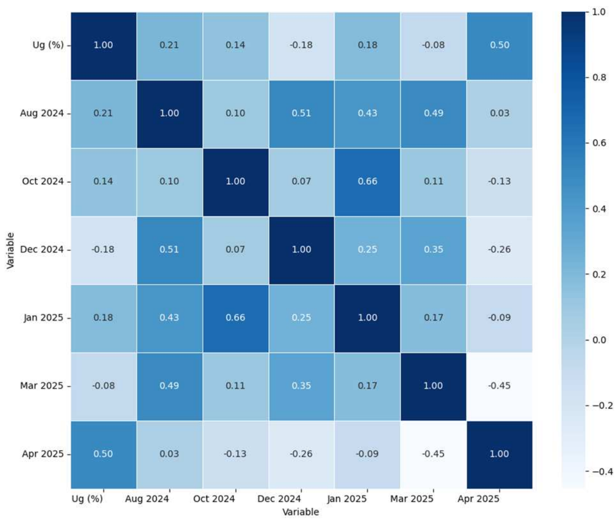

Figure 7: Correlation matrix showing the relationships between UAV-derived TVDI values (at different dates), gravimetric soil moisture (Ug %), and kriging-interpolated values. The results highlight temporal variability, with correlations ranging from moderate positive to negative, reflecting seasonal and management-related influences on soil moisture estimation.

4. Discussion

Coefficients of variation above 30% for both gravimetric soil moisture (Ug%) and spectral bands (1–5) indicate marked heterogeneity in the dataset. This variability can be explained by seasonal environmental fluctuations during the sampling period (August 2024 to April 2025), since soil moisture dynamics are strongly affected by precipitation, temperature, and evapotranspiration patterns. Differences in soil texture also contributed: sandy soils, with lower water retention, responded faster to moisture deficits, while medium-textured soils retained water for longer, producing distinct moisture gradients that influenced spectral responses. Similar findings were reported in UAV-based studies, where spectral variability and soil heterogeneity limited prediction accuracy, reinforcing the need for multi-date surveys to capture a wider range of moisture conditions (Bertalan et al., 2022; Ge et al., 2021).

Building on this variability analysis, it is also important to consider the role of management practices. Sampling was conducted over six different dates, and the study area was harrowed in the week prior to each flight. This management practice likely altered soil surface roughness and exposure, increasing variability in spectral responses across dates and reducing the accuracy of multispectral imagery. Similar findings were reported by Bertalan et al. (2022), who showed that thermal imagery tends to capture more stable relationships with soil water content, while multispectral reflectance is more affected by surface conditions and temporal variability. In addition, precise calibration is essential to ensure data consistency and comparability, allowing for more robust and reliable analysis of the relationships between spectral variables and soil moisture (Sousa et al., 2025).

In line with these effects, the PCA results further illustrate the influence of management. The coloration of the sample points in the PCA biplot (Figure 3) shows a visible separation into three groups of Ug%, reflecting temporal variability likely influenced by management practices, such as soil harrowing prior to each flight. This additional source of heterogeneity can reduce the predictive power of multispectral data. Future modeling should incorporate more soil samples and consider stratification by moisture classes, combined with multi-date datasets and robust machine learning approaches, to minimize management-related effects and improve the stability of predictions.

Complementing the PCA analysis, the Random Forest model provided further evidence. The descending order of variable importance was: Thermal, Band 4, Band 3, Band 5, Band 1, Band 2. This hierarchy corroborates trends reported in previous UAV-based studies, where thermal data provided stronger sensitivity to soil moisture variability than optical reflectances, due to its closer relationship with surface energy balance and water content (Bertalan et al., 2022).

The spatial analysis also confirmed the influence of heterogeneity. As shown in Figure 1, the experimental area exhibits visible contrasts in surface soil conditions, with lighter zones of exposed soil in the eastern sector and darker areas towards the west. This spatial heterogeneity is consistent with textural transitions between medium- and sandy-textured soils. Such differences explain the directional anisotropy observed in the variograms (Figure 5), where the east–west orientation (90°) showed the shortest range (~4.3 m), indicating abrupt changes in soil moisture over short distances. These same patterns are visible in the kriging map (Figure 6), which highlights a marked east–west gradient, with higher Ug values (12–14%) in the western portion and lower values (7–9%) in the east. Together, these results demonstrate that the spatial variability of soil moisture is strongly influenced by inherent soil heterogeneity, reinforcing the importance of integrating field observations with geostatistical modeling.

When comparing our approach with classical indices, additional limitations were evident. The Temperature Vegetation Dryness Index (TVDI), here derived from the same multispectral and thermal UAV bands rather than from satellite imagery, still exhibited the constraints commonly reported in the literature, being highly sensitive to seasonal dynamics, vegetation cover, and microclimatic variations. Although the UAV-based TVDI achieved moderate correlations with Ug% (up to $r = 0.66$, and negative in April), its performance remained inconsistent across dates. In contrast, the combination of thermal data and Random Forest modeling provided higher predictive accuracy, while geostatistical analysis (kriging and variograms) revealed spatial anisotropy and local gradients. Taken together, these findings reinforce that thermal data are more sensitive to soil moisture than optical reflectance (Bertalan et al., 2022), and highlight the need for hybrid approaches that integrate UAV data with geostatistics and machine learning to overcome the limitations of classical vegetation–temperature indices.

Furthermore, the anisotropy observed in variograms (range reduced to 4.3 m at 90°) illustrates how soil heterogeneity affects moisture patterns, emphasizing the importance of spatially explicit modeling. It is also worth noting that soil tillage prior to the UAV surveys may have contributed to the observed micro-scale variability; however, this effect was not directly assessed in the present study.

Finally, in a broader perspective, the relevance of these tools extends beyond methodological aspects. The use of remote sensing tools in agricultural production has gained relevance in the context of environmental sustainability and food security. Advances in technologies, sensors and data analysis methods are improving soil moisture monitoring, with UAVs offering new opportunities for high-resolution field-scale applications. These tools should be seen not only as technological complements but also as valuable resources to support strategic decisions, contributing to more efficient water use and the adoption of sustainable agricultural practices in a context of growing food demand.

5. Conclusions

The results demonstrated that thermal information is more effective than optical reflectance for soil moisture prediction, as confirmed by both correlation analysis and the Random Forest model, where the thermal band accounted for more than half of the explained variability. In contrast, multispectral bands showed limited sensitivity under the studied conditions. Geostatistical modeling revealed spatial anisotropy, with shorter ranges in the east–west direction, consistent with textural transitions observed in the field and reinforcing the importance of spatially explicit approaches.

The comparison with TVDI indicated that, even when derived from UAV imagery, this classical index retained known limitations, with variable correlations and inconsistent responses across dates. In contrast, the use of thermal data combined with machine learning (Random Forest) provided the best predictive accuracy, while geostatistical analysis was fundamental to reveal the spatial anisotropy of soil moisture. These findings highlight the value of integrating UAV data with both machine learning and geostatistical approaches to improve reliability and spatial understanding.

Finally, the use of a radiometric calibration panel (CRP) together with the Downwelling Light Sensor (DLS), as well as the consideration of management practices such as soil tillage prior to flights, are essential to reduce variability not related to soil properties and to ensure consistency across acquisitions, particularly in view of seasonal variations in illumination throughout the year. Although promising, these results represent an initial step, and further studies are needed to evaluate the approach across different soil types, climatic conditions, and monitoring scales.

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