

Article

Comparative Evaluation of UAV Multispectral Sensors for Precision Agriculture: Spectral and Structural Consistency in Maize Canopies

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Highlights

What are the main findings?

- The Sentera Double 4K sensor systematically produced 36% higher mean NDVI values than the DJI Phantom 4 Multispectral (P4M) with no linear correlation ($r = 0.07$), whereas their NDRE outputs demonstrated a statistically significant, moderately strong correlation ($r = 0.66$) and a much narrower limit of agreement.
- Photogrammetric structural reconstruction severely underestimated the true maize canopy height, performing markedly worse on the P4M platform due to its lower 2.08 MP resolution and multi-lens parallax, while the 12.3 MP Sentera platform better captured spatial variations despite an “inflated” terrain model caused by dense canopy closure.

What are the implications of the main findings?

- The Red Edge band-based NDRE index is highly recommended over NDVI for multi-sensor data fusion in precision agriculture, as it delivers superior cross-platform interchangeability and resists physical sensor architecture and bandwidth discrepancies.
- Rigorous Ground Control Point (GCP) calibration is a critical requirement to successfully merge structural elevation models (DSM/DTM) derived from distinct UAV platforms. UAV photogrammetry often suffers from high structural compression under very dense crop canopies; specifically, multi-lens configurations with lower resolutions (like the P4M) are poorly suited for absolute canopy height tracking, requiring high-resolution sensors to properly capture standing crop volume variations.



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Abstract

Precision agriculture increasingly relies on UAV-based multispectral sensors, but cross-platform data fusion remains limited by differences in spectral response, image geometry, and structural reconstruction accuracy. This challenge is particularly important in dense crop canopies, where vegetation indices and canopy height estimates may vary substantially between sensor platforms. This study compared the multi-lens DJI Phantom 4 Multispectral (P4M) and the dual-lens Sentera Double 4K in a maize hybrid trial (DKC 4596) in Debrecen, Hungary, using aerial surveys conducted at 35.5 m to assess DSM, DTM, NDVI, and NDRE outputs across 15 synchronized sampling plots processed in WebODM and RStudio. Agreement between platforms was evaluated using Bland–Altman

analysis and Pearson correlation. The results showed a substantial systematic bias for NDVI, with Sentera producing 36% higher mean values than P4M and showing almost no linear association between platforms ($r = 0.07$). In contrast, NDRE demonstrated stronger and more manageable cross-platform agreement, with a significant positive correlation ($r = 0.66$, $p = 0.007$). Dense canopy closure reduced the reliability of absolute canopy height estimation for both platforms, but the P4M performed particularly poorly because of lens parallax and lower effective pixel density, while the higher-resolution Sentera imagery provided a more representative structural trend. Overall, NDRE is more suitable than NDVI for cross-platform vegetation index fusion between P4M and Sentera, while reliable structural assessment in tall, dense maize requires higher-resolution imagery, rigorous ground control, or complementary technologies such as LiDAR.

Keywords: UAV platform; Phantom 4; Sentera; multispectral; vegetation indices; surface models; NDRE; NDVI

1. Introduction

In recent years, the rapid advancement of digital technologies has transformed modern agriculture into a data-driven industry, often referred to as Agriculture 4.0 [1]. Precision agriculture (PA) aims to optimize crop yields and minimize environmental impact by managing spatial and temporal variability within fields [2]. Remote sensing (RS) stands as a cornerstone of this paradigm, providing non-destructive, high-resolution insights into crop health status and soil conditions [3]. Vegetation index (VI) maps have emerged as essential tools for planning and optimizing agricultural workflows, enabling producers and decision-makers to access vast amounts of information regarding nitrogen supply, water status, and biomass production [4–7]. The deployment of Unmanned Aerial Vehicles (UAVs) has bridged the gap between satellite imagery, which often suffers from low resolution and cloud interference, and ground-based measurements, which are labor-intensive [8,9]. While UAVs bridge the gap between satellites and ground measurements, their multispectral sensors, critical for vegetation indices, often lack interchangeability, hindering large-scale precision agriculture.

As remote sensing technology and manufacturing processes have evolved, multispectral and hyperspectral sensors have become increasingly prevalent in the market [10]. Currently, these types of camera systems are widely used in agriculture for vegetation studies and crop health assessments. Spectral resolution is a critical factor; as the number of spectral channels increases, the width of the wavelength range (bandwidth) narrows, allowing for more precise spectral information capture [11]. While standard multispectral sensors typically perceive the blue channel at 450 nm, hyperspectral sensors can detect the spectrum in hundreds of narrow bands, providing unparalleled detail for disease detection and physiological monitoring [12,13]. Multispectral systems generally capture data across five specific channels—Red [R], Green [G], Blue [B], Red Edge [RE], and Near-Infrared [NIR], plus an RGB composite [14]. These systems are ideal for monitoring biotic and abiotic stress events in the field [15]. In the VIS-NIR spectral range, physiological changes induced by pests or diseases, such as pigment degradation, chlorophyll reduction, necrosis, and cell damage can occur. Specific alterations in spectral reflectance can be detected long before they become visible to the human eye [16,17].

Vegetation indices are numerical values used to quantify plant health by exploiting the differences between the high reflectance of healthy leaves in the near-infrared (NIR) and the high absorption in the Visible (VIS) spectrum (400–700 nm) [18]. The Normalized Difference Vegetation Index (NDVI) remains the most widely used VI [19]. However, in

dense canopies such as maize at peak growth, NDVI often reaches a “saturation point”, where its sensitivity to further increases in biomass decreases [20]. To overcome this, the Normalized Difference Red Edge (NDRE) index is employed [21]. NDRE utilizes the Red Edge band, which can penetrate deeper into the canopy, providing a more accurate assessment of chlorophyll and nitrogen contents in mature or dense stands [22].

Beyond spectral data, UAV-based photogrammetry allows for the generation of high-resolution 3D models [23]. The Digital Surface Model (DSM) captures the top layer of all objects, including crop canopy, while the Digital Terrain Model (DTM) represents the bare earth surface [24]. The difference between DSM and DTM, often referred to as the Canopy Height Model (CHM), is used to estimate crop height and volume [25]. However, for the purposes of this study and the database categorization, these relative height values were denoted as ‘ALT’ (referring to altitude, or relative height based on our values). Despite its potential, estimating terrain under dense canopies remains a significant challenge for Structure from Motion (SfM) algorithms, often leading to a phenomenon known as “canopy closure” where the ground is obscured, resulting in underestimated height values. While many sensors exist on the market, their radiometric and geometric outputs are not always interchangeable. Differences in sensor architecture, such as the multi-lens array of the DJI Phantom 4 M3C compared to the high-resolution single lens system of the Sentra Double 4K, can lead to significant discrepancies in data, alongside systematic offsets that further complicate data fusion. While newer platforms (e.g., DJI Mavic 3 Multispectral, Sentra 6X) have since entered the market, the DJI Phantom 4 Multispectral (P4M) and Sentra Double 4K remain widely deployed in precision agriculture, particularly in regions with limited access to cutting-edge technology. Furthermore, the methodological findings—such as the superior cross-platform agreement of NDRE over NDVI and the challenges of photogrammetric canopy-height estimation under dense canopies—are independent of sensor generation and provide actionable insights for both legacy and modern systems. Prior sensor-comparison studies have typically evaluated either spectral or structural consistency in isolation, and rarely under dense-canopy field conditions where both types of error are likely to interact. This study aims to evaluate the consistency of these two widely used multispectral platforms in maize hybrids (DKC 4596) in a trial located in Debrecen, Hungary, by jointly assessing spectral (NDVI/NDRE) and structural (DSM/DTM/canopy height) agreement, a combination not addressed together in the existing literature. By employing Pearson correlation matrices and Bland–Altman plots, we investigate the reliability of DTM/DSM generation and the compatibility of NDVI/NDRE measurements under field conditions.

2. Materials and Methods

2.1. Study Area

The study was conducted in the eastern region of Debrecen (Figure 1), Hungary, at the coordinates 47.5547° N, 21.6930° E. According to the soil classification of the area, the experiment was situated on humic sandy soil. The subject of the investigation was the DKC 4596 forage maize hybrid. All agrotechnical operations were carried out uniformly across the experimental site; weed control was managed using post-emergence herbicide treatment of Laudis 2.4 L/ha. The UAV measurements were focused on a 0.4-hectare representative subplot within the larger 3.1-hectare field. In the study, we used two different UAV platforms equipped with different camera systems (Figure 2).

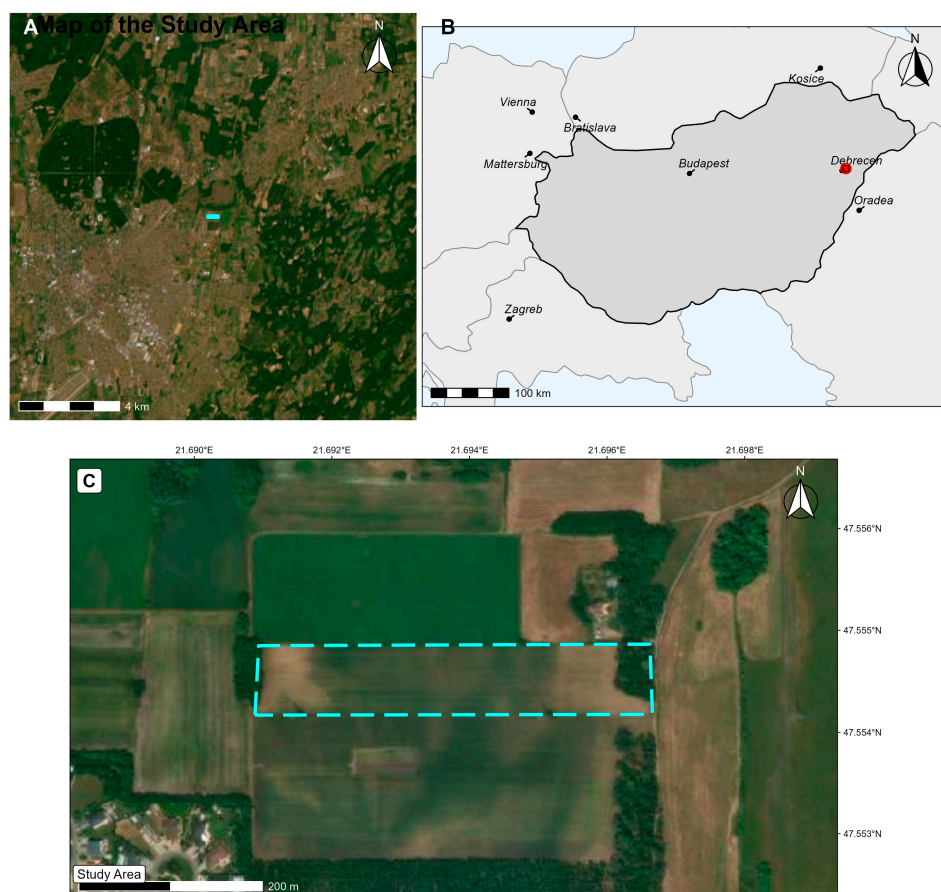


Figure 1. Geographic location and layout of the experimental site, Hungary, Hajdú-Bihar County, near the city of Debrecen. (A) Satellite overview of the broader study area; (B) location map of Hungary indicating the position of Debrecen relative to major regional cities; (C) detailed satellite image of the experimental field, with the study area boundary outlined by the cyan dashed rectangle.

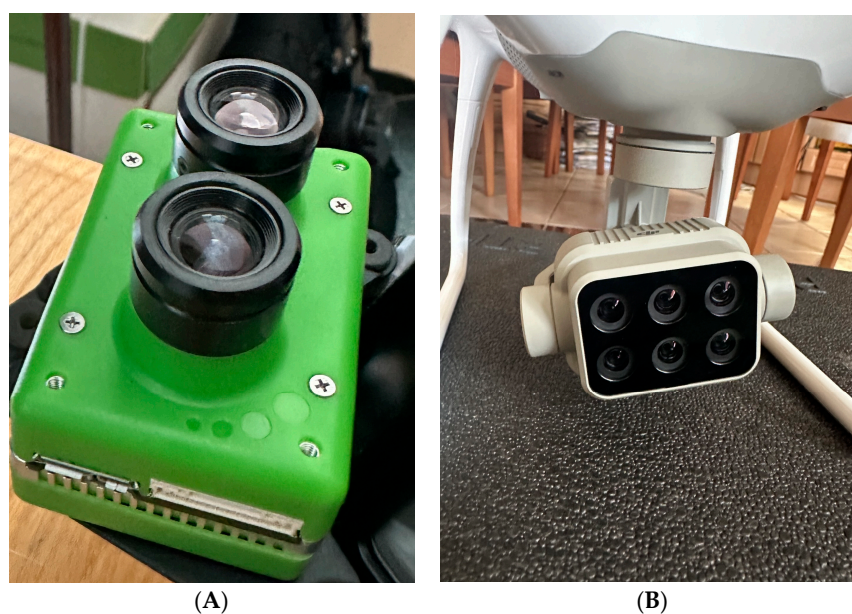


Figure 2. Optical sensors used in the study (A): Phantom 4 Multispectral CS, (B): Sentera Double 4K (P4 Pro kit). Authors' own images.

The remote sensing campaign was carried out on a commercial maize field (hybrid: DKC 4596, FAO 350–370, Bayer Crop Science Alfred-Nobel-Straße 50, 40789 Monheim

am Rhein, Germany). Sowing was performed in late April 2021 at a target density of $\sim 70,000$ plants ha^{-1} with a standard 75 cm inter-row spacing. Fertilization followed conventional local practices with an application of ~ 120 kg N/ha. Weed control was managed using a post-emergence herbicide treatment of Laudis (2.4 L/ha; tembotrione + isoxadifen-ethyl). No fungicides, insecticides, or seed treatments were applied during the growing season. The 2021 growing season was characterized by typical continental conditions with moderate drought stress during late summer (July–August).

2.2. Data Acquisition and Geospatial Processing

The aerial surveys were conducted on 16 September 2021, at a flight altitude of 35.5 m above the experimental site in the outskirts of Debrecen (Figure 1). The resulting Ground Sampling Distance (GSD) was 1.9 cm/pixel. Aerial surveys were conducted separately for each platform: the P4M in multispectral mode (1 RGB + 5 monochrome channels), and the Sentera Double 4K in its native dual-lens configuration (Table 1). Following the flights, the captured imagery was systematically organized and processed. Orthomosaics were generated using WebODM (version 3.2.7) software, with high-resolution output of 2 cm/pixel. The orthophotos were exported in .tiff format to ensure compatibility with Geographic Information Systems (GIS) environments. The subsequent raster analysis was performed using Quantum GIS (QGIS 3.20 (Odense)). NDRE was calculated using the 730 nm (P4M) and 720 nm (Sentera) Red Edge bands. Digital Surface Models (DSM) and Digital Terrain Models (DTM) were generated from the raw multispectral imagery using Structure from Motion (SfM) photogrammetry in WebODM (v3.2.7). The canopy height model (ALT) was derived as DSM–DTM for each platform. Vegetation indices (NDVI/NDRE) were calculated separately from the orthomosaics using the following formulas:

- $\text{NDVI} = (R_{\text{NIR}} - R_{\text{Red}}) / (R_{\text{NIR}} + R_{\text{Red}})$ [18,19]
- $\text{NDRE} = (R_{\text{NIR}} - R_{\text{RedEdge}}) / (R_{\text{NIR}} + R_{\text{RedEdge}})$ [21,22]

Table 1. Technical specifications and comparison of the P4M and Sentera 4K sensors.

UAV Platform	DJI Phantom 4 Multispectral (P4M RTK)	Sentera Double 4K (P4 Pro V2 kit)
Sensor Configuration	6 separate sensors (1 RGB + 5 monochrome)	Integrated dual-sensor system for agricultural surveying
Sensor Type	1/2.9" CMOS	Sony Exmor R TM IMX 377 CMOS
Resolution	2.08 MP (effective)/2.12 MP (total)	12.3 MP
Focal length	5.74 mm (35 mm equiv.: 40 mm)	4.14 mm
Field of View (FOV)	62.7°	60° horizontal/47° vertical
Aperture	f/2.2	not specified
GSD Value	2 cm/px at 50 m altitude	3.5 cm/px at 80 m altitude
Video Capability	not specified	4K (H.264 encoding)
Blue Band	450 nm $\pm$ 16 nm	446 nm $\pm$ 60 nm
Green Band	560 nm $\pm$ 16 nm	548 nm $\pm$ 45 nm
Red Band	650 nm $\pm$ 16 nm	625 nm (100 nm bandwidth)
Red Edge	730 nm $\pm$ 16 nm	720 nm (40 nm bandwidth)
Near Infrared (NIR)	840 nm $\pm$ 26 nm	850 nm (40 nm) and 840 nm (20 nm)
Data Source	[26]	[27]

Radiometric correction was performed using the built-in irradiance sensor (ILS) of the DJI Phantom 4 Multispectral (P4M) to account for light fluctuations within and between

images. No external reflectance panel was used. Since NDVI and NDRE are normalized vegetation indices, relative spectral data (rather than absolute reflectance) was deemed sufficient for identifying vegetation differences and establishing cross-sensor correlations. Consistent masking and filtering procedures were applied across all raster layers to ensure data integrity. To facilitate precise data extraction, a shapefile (.shp) was created using advanced digitizing tools. To ensure methodological consistency, identical processing settings were applied in WebODM for both platforms, including:

1. Default multispectral pipeline
2. Identical matching quality and resolution parameters
3. Consistent dense point cloud generation method

This ensured direct comparability of DSM and orthophoto outputs between the P4M and Sentra.

This layer consisted of 15 sampling parcels (sample plots), each measuring 7 m × 4 m (Figure 3).

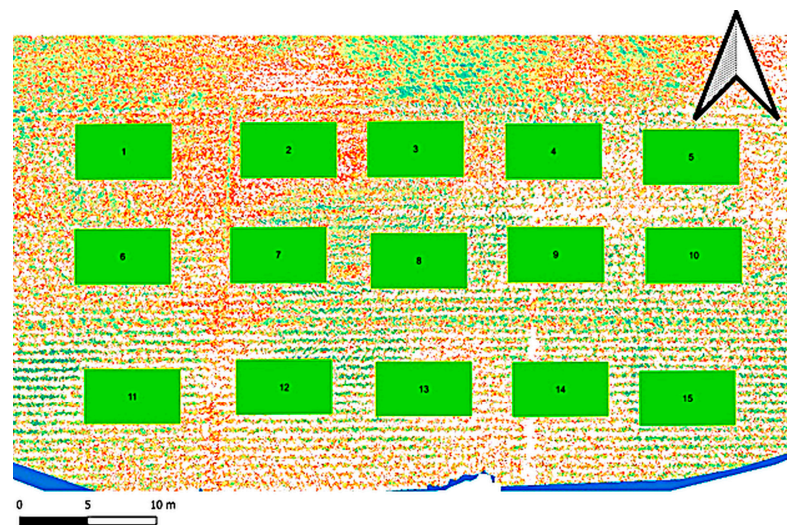


Figure 3. Spatial distribution of the sampling “boxes” overlaid on the baseline NDVI vegetation map of the study area. The 15 sampling plots were distributed using a stratified random layout (rather than a rigid grid) to avoid systematic bias along tractor tracks or single crop rows and to capture natural within-field heterogeneity.

The same shapefile was utilized across all compared datasets, ensuring that the extracted statistical values originated from the exact same spatial locations for every sensor platform. Following the spatial alignment, zonal statistics were used to calculate the mean values for each sampling box, which were then recorded in a unified database for subsequent statistical analysis.

Ground-Truth Measurements

In situ ground-truth canopy height measurements were collected on the day of the flight campaign (16 September 2021) using a standard graduated measuring rod. Within each of the 15 designated sampling plots, 10 representative maize plants were measured from the soil surface to the top of the canopy (tassel height), yielding a total of 150 ground-truth sampling points. The measured in situ plant height ranged between 180 cm and 230 cm across the field, with an overall field average of 205.4 ± 12.3 cm (mean $\pm$ SD).

The flights were conducted sequentially on September 16, 2021, between 10:45 and 11:30 local time, with minimal time separation (~15–20 min) between the P4M and Sentra missions. The solar elevation angle during this window was approximately 43–45° (calcu-

lated based on coordinates and date for the Debrecen area). Stable, clear-sky conditions ensured consistent illumination across both flights.

2.3. Statistical Analysis and Software Environment

The vegetation index (VI) maps were generated from the processed orthophotos using QGIS 3.20 (Odense). Data extraction was performed using a standardized shapefile containing 15 uniform sampling plots. The zonal statistics plugin was utilized to calculate mean values for each plot, which served as the primary dataset for the statistical evaluations. For data manipulation and the visualization of canopy height (ALT), The R statistical computing environment (Version 4.1.2) was employed. The analysis utilized the tidyverse [28–31] ecosystem, specifically the dplyr and ggplot2 for the creation of graphics.

The core comparative statistical analysis, including Pearson correlation and Bland–Altman analysis, was conducted using Jamovi (version 2.6) [32]. The analytical capabilities of jamovi were extended through specialized modules: seolmatrix for comprehensive correlation [33]; ClinicoPath for diagnostic metrics [34]; snowCluster for multivariate data exploration [35,36]; and ggstatsplot to integrate statistical details directly into visualization.

Multivariate relationships were visualized using network analysis tools such as qgraph and multidimensional scaling via jMDS and the SMACOF approach. All statistical tests were performed at a significance level of $\alpha = 0.05$.

3. Results

To ensure data consistency across different remote sensing platforms, a comparative analysis of the spectral outputs from the DJI P4 Multispectral and the Sentra D4K sensors was conducted. The results, based on Figure 4, illustrate that the Sentra sensor systematically produced higher values for both vegetation indices (NDVI/NDRE) compared to the P4M. Regarding the NDVI, the P4M recorded a mean of 0.238, whereas the Sentra reached 0.324. The relative difference is a significant 36%. The discrepancy for the NDRE is less significant. The data also reveal a difference in variability: the Sentra had a standard deviation of 0.053 compared to the P4M's 0.036.

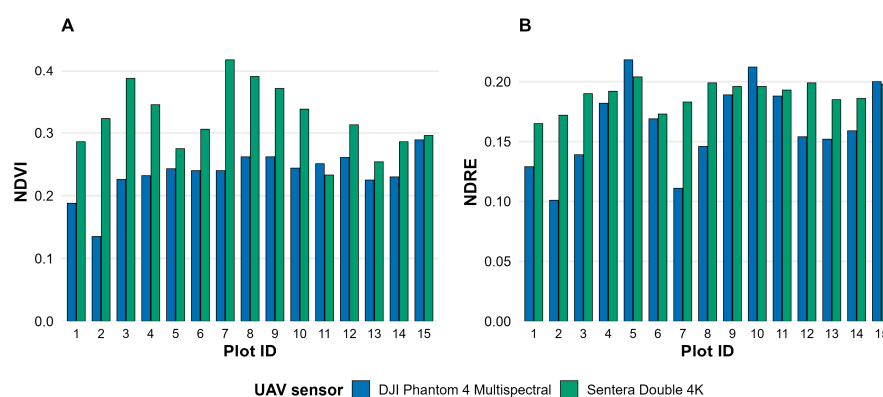


Figure 4. Comparing the calculated Normalized Difference Vegetation Index (NDVI, (A)) and Normalized Difference Red Edge index (NDRE, (B)) values across 15 parcels (parc_id) using the Phantom 4 Multispectral (p4multi) and Sentra sensor platforms (parcel mean values).

While absolute NDVI values differed systematically between platforms (Sentra: 36% higher mean than P4M), NDRE demonstrated stronger cross-platform agreement ($r = 0.66$, $p = 0.007$), suggesting that Red Edge-based indices are more robust to spectral response differences. Spatial patterns of both NDVI and NDRE were visually consistent between platforms (see Supplementary Figures S1–S5), indicating that relative variability (e.g., for management zones) may still be comparable despite absolute offsets.

The analysis of vegetation index correlations provided some critical information regarding the comparability of the sensors. In terms of NDVI ($r = 0.07$, p -value = 0.79), there is practically no linear correlation between the NDVI values generated by the P4M and the Sentera D4K. In contrast, the NDRE results ($r = 0.66$, p -value = 0.007) demonstrate a moderately strong and statistically significant relationship (Figure 5).

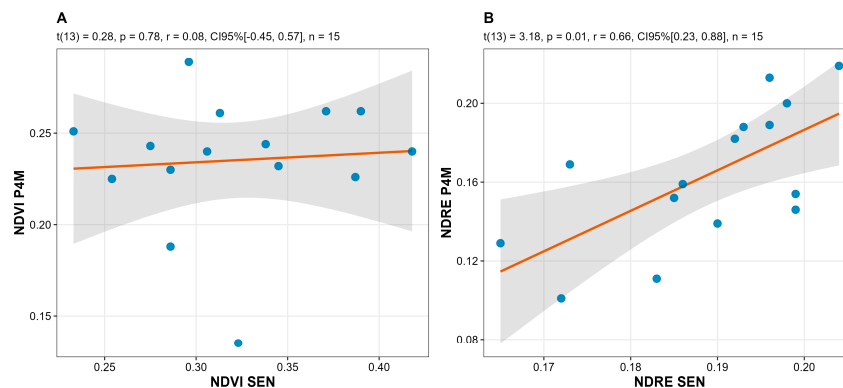


Figure 5. Correlation and Regression Analysis Between Phantom 4 Multispectral (P4M) and Sentera (SEN) Vegetation Indices. The scatter plots with marginal histograms illustrate the statistical relationship between the two UAV sensor platforms. (A) shows the correlation for NDVI; (B) shows the correlation for NDRE. The blue lines represent the linear regression fits surrounded by 95% confidence intervals (grey shaded areas).

Based on the Bland–Altman analysis, on Figure 6, it can be concluded that the NDVI values obtained from the DJI P4M and the S4K are not technically interchangeable. The statistical analysis reveals a significant systematic bias between the two sensors. The P4M consistently records lower NDVI values compared to the Sentera sensor (Figure 6B), with a mean bias of 0.0860, since the 95% CI (0.0517 to 0.1202) represents real divergence rather than random noise. On the NDVI scale, a 0.086-unit difference is substantial, approximately 15–20% relative deviation at plot level. In addition (Table 2), the limits of agreement (LoA) are notably wide ranging from -0.0352 to 0.2072 . This broad range indicates high variability between the two instruments. In contrast, the NDRE index demonstrates a higher degree of agreement between the two sensors. The analysis indicated a mean bias of 0.0255, which is lower than the bias observed in the NDVI measurements. The 95% CI (0.0094 to 0.0416) confirms a systematic underestimation by the P4M sensor. However, a 0.025-unit difference in NDRE is manageable. The LoA is much narrower for the NDRE index: -0.0315 to 0.0825 .

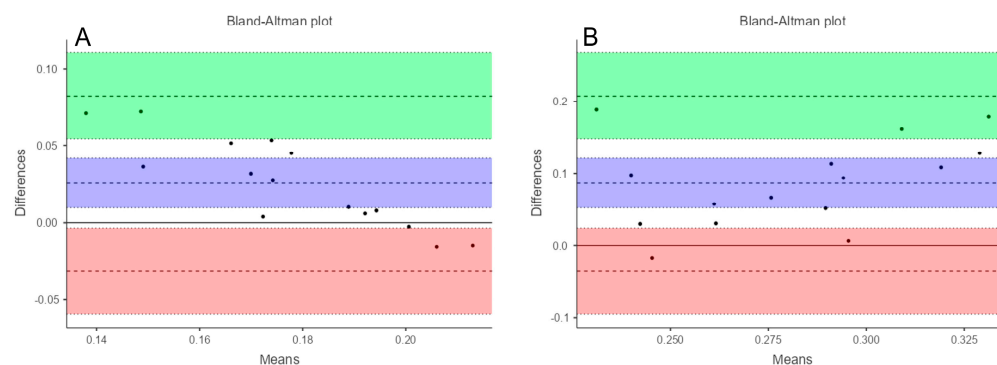


Figure 6. Bland–Altman analysis comparing the NDRE (A) and NDVI (B) index values obtained from the location and layout of the experimental site. The central blue represents systematic bias, while the green and lower red shaded regions represent the 95% LoA.

Table 2. Summary of Bland–Altman agreement statistics for NDRE (A) and NDVI (B) indices between P4M and Sentera sensors.

Comparison (Vegetation Index)	Bias [95% CI]	Lower LoA [95% CI]	Upper LoA [95% CI]
NDRE (A)	0.0255 [0.0094, 0.0416]	−0.0315 [−0.0596, −0.0033]	0.0825 [0.0543, −0.1106]
NDVI (B)	0.086 [0.0517, −0.1202]	−0.0352 [−0.0951, −0.0247]	0.2072 [0.1473, −0.2671]

Note: Bias represents the mean difference; LoA (Limits of Agreement) indicates the range within which 95% of the differences fall; CI: 95% Confidence Interval.

3.1. DSM Results

The statistical comparison of Digital Surface Model (DSM) values, expressed in meters (m), is summarized in Table 3. The analysis focuses on the Bias and 95% LoA to evaluate systematic offsets between sensor configurations. The data suggest that the Sentera D4K platform provides the most reliable elevation data relative to the actual surface elevation. The SEN NDVI and SEN NDRE showed the highest level of consistency, at 2.15 [95% CI: 2.07, 2.24]. This minor discrepancy confirms the Sentera system maintained stable altitude and surface reconstruction regardless of which VI was used. In contrast, the DJI P4M demonstrated a consistent trend of overestimating surface height. For example, P4M and SEN-NDRE revealed a positive bias of 51.4 m [51.0, 51.8]. The largest deviation was observed between the multispectral sensor and the RGB on the P4 platform (Figure 7A). SEN NDVI–SEN NDRE had the narrowest LoA range (1.86 to 2.45 m), which highlights high precision and low noise for Sentera-derived DSM. The data reveals substantial systematic errors (bias) in several comparisons, indicating that the elevation models are not aligned to the same vertical datum or have significant processing-induced offsets (Table 3).

Table 3. Summary of Bland–Altman agreement statistics for DSM values between P4M and Sentera sensors.

Comparison (Method) DSM Values	Bias [95% CI]	Lower LoA [95% CI]	Upper LoA [95% CI]
SEN NDVI–P4M	−49.2 [−49.7, −48.8]	−50.7 [−51.5, −50.0]	−47.8 [−48.5, −47.0]
SEN NDVI–SEN NDRE	2.15 [2.07, 2.24]	1.86 [1.72, 2.01]	2.45 [2.30, 2.59]
SEN NDVI–SEN P4RGB	13.3 [13.1, 13.5]	12.6 [12.2, 12.9]	14.1 [13.7, 14.4]
P4M–SEN NDRE	51.4 [51.0, 51.8]	50.2 [49.5, 50.8]	52.6 [52.0, 53.3]
P4M–P4RGB	62.6 [62.1, 63.0]	61.1 [60.3, 61.8]	64.1 [63.3, 64.8]
SEN NDRE–SEN P4RGB	11.2 [10.9, 11.4]	10.4 [9.9, 10.8]	12.0 [11.6, 12.4]

Note: Bias represents the mean difference; LoA (Limits of Agreement) indicates the range within which 95% of the differences fall; CI: 95% Confidence Interval.

3.2. DTM Results

The statistical evaluation of Digital Terrain Model (DTM) values, expressed in meters (m) is summarized in Table 4. These results quantify the Bias and 95% LoA. The Sentera platform continues to demonstrate higher internal reliability in terrain modeling. SEN NDVI–NDRE yielded a low systematic bias of 2.17 m [95% CI: 2.03, 2.32]. Similar to the DSM results, P4M–SEN NDVI had a negative bias of −49.8 m, and P4M–SEN NDRE resulted in −51.9 m, indicating that the P4M-derived terrain models sit significantly higher than the Sentera NDVI/NDRE baselines. The highest deviation was observed in P4M vs. RGB with a positive bias of 62.8 m. This confirms that P4M-sensor terrain models are vertically inflated compared to standard RGB photogrammetric outputs. In comparison with RGB-based terrain models, the SEN NDVI–SEN P4RGB resulted in a bias of 13 m and

SEN NDRE–SEN4RGB showed a slightly lower 10.86 m. The 95% LoA numbers provide the random error and noise in the terrain models. According to those data, Sentra internal indices exhibited relatively tight LoA ranges. The P4M sensor displayed a wider LoA interval with higher variability (Figure 8).

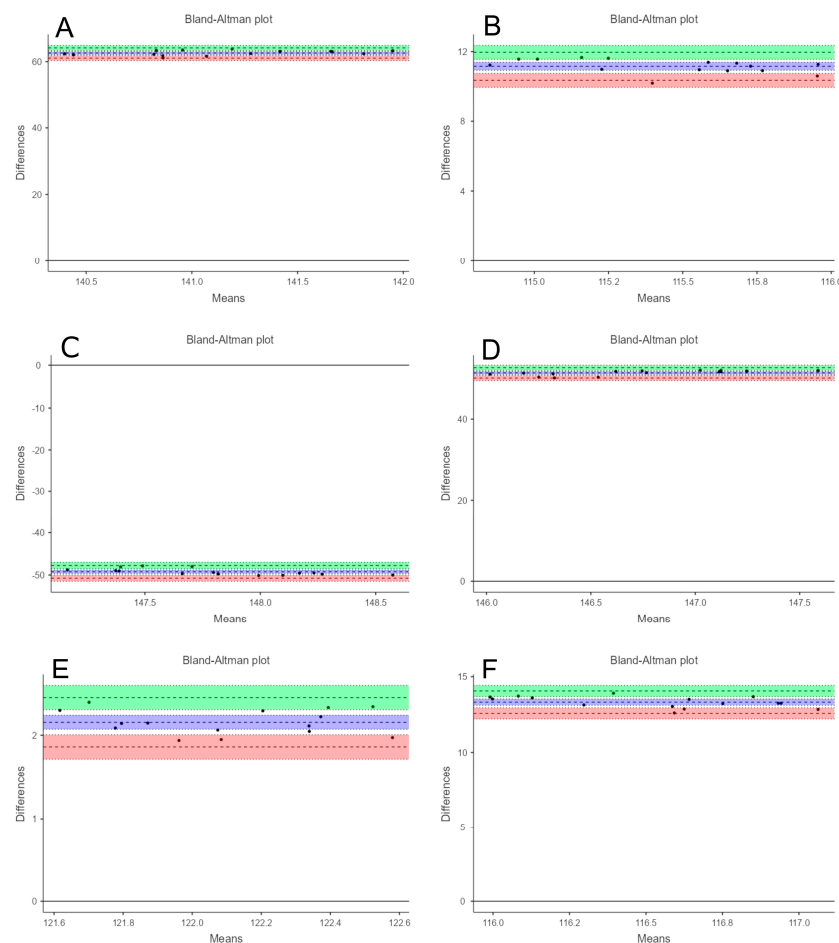


Figure 7. Bland–Altman plots assessing the agreement of DSM elevations across different sensors. The composite presents six Bland–Altman plots (A–F). The central blue represents systematic bias, the green and lower red shaded regions represent the 95% LoA. (A) P4M–P4RGB, (B) SEN NDRE–SEN4RGB, (C) SEN NDVI–P4M, (D) P4M–SEN NDRE (E) SEN NDVI–SEN NDRE and (F) SEN NDVI–SEN4RGB. Note: Vertical biases reflect datum differences (WGS84 ellipsoid vs. EGM96 geoid), not photogrammetric errors.

Table 4. Summary of Bland–Altman agreement statistics for DTM values between P4M and Sentra sensors.

Comparison (Method) DTM Values	Bias [95% CI]	Lower LoA [95% CI]	Upper LoA [95% CI]
SEN NDVI–P4M	−49.8 [−50.2, −49.4]	−51.2 [−51.9, −50.5]	−48.3 [−49.0, −47.6]
SEN NDVI–SEN NDRE	2.17 [2.03, 2.32]	1.66 [1.41, 1.92]	2.68 [2.43, 2.94]
SEN NDVI–SEN4RGB	13.0 [12.8, 13.3]	12.1 [11.7, 12.6]	13.9 [13.5, 14.4]
P4M–SEN NDRE	−51.9 [−52.3, −51.6]	−53.2 [−53.8, −52.6]	−50.7 [−51.3, −50.1]
P4M–P4RGB	62.8 [62.4, 63.2]	61.3 [60.6, 62.1]	64.3 [63.5, 65.0]
SEN NDRE–SEN4RGB	10.86 [10.57, 11.1]	9.85 [9.36, 10.3]	11.86 [11.36, 12.4]

Note: Bias represents the mean difference; LoA (Limits of Agreement) indicates the range within which 95% of the differences fall; CI: 95% Confidence Interval.

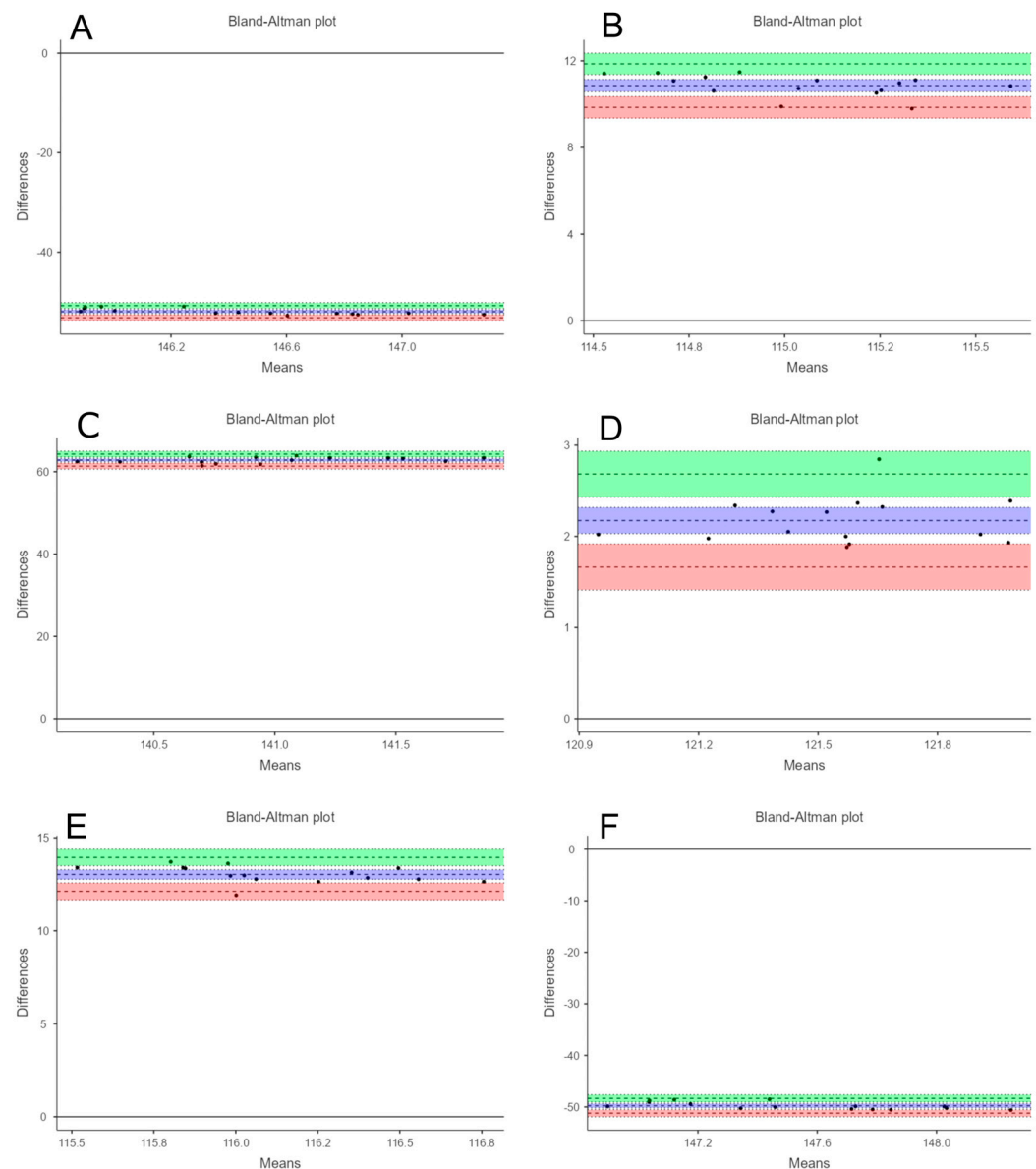


Figure 8. Bland–Altman plots assessing the agreement of DTM elevations across different sensors. The composite presents six Bland–Altman plots (A–F). The central blue represents systematic bias, the green and lower red shaded regions represents the 95% LoA. (A) SEN NDVI–P4M, (B) SEN NDRE–SEN P4RGB, (C) P4M–SEN P4RGB, (D) SEN NDVI–SEN NDRE (E) SEN NDVI–SEN P4RGB and (F) SEN NDVI–P4M.

3.3. DTM, DSM, ALT Correlation Results

NDVI–NDRE Pearson correlation coefficients were computed to assess the relationships between the different method pairs across three model types: Digital Surface Model (DSM), Digital Terrain Model (DTM), and Altitude (ALT) (Figure 9).

3.3.1. Digital Surface Model (DSM)

Within the DSM framework, a strong and highly significant positive correlation was observed between SEN NDVI and SEN NDRE ($r = 0.892^{***}$, $p < 0.001$, 95% CI [0.699, 0.964]). Additionally, SEN NDVI exhibited a moderate-to-strong positive correlation with P4RGB ($r = 0.620^{*}$, $p = 0.014$, 95% CI [0.157, 0.859]), and SEN NDRE demonstrated a significant moderate correlation with P4RGB ($r = 0.557^{*}$, $p = 0.031$, 95% CI [0.062, 0.832]). Conversely, the remaining comparisons did not reach statistical significance. The relationship between SEN NDRE and P4M was moderate but non-significant ($r = 0.472$, $p = 0.075$, 95% CI

$[-0.053, 0.793]$), while negligible and non-significant correlations were found for P4RGB vs. P4M ($r = 0.227, p = 0.416$) and SEN NDVI and P4M ($r = 0.094, p = 0.740$) (Table 5).

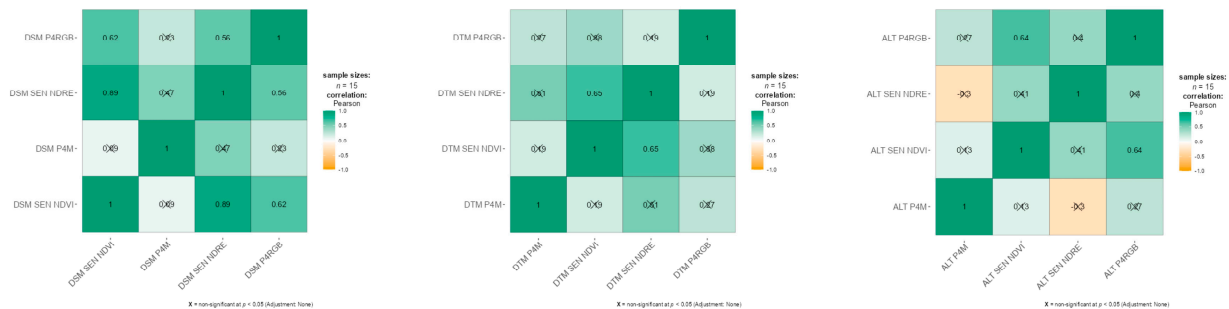


Figure 9. Pearson Correlation Coefficients, p -values, and confidence intervals for method pair comparisons across DSM, DTM and ALT model types.

Table 5. Pearson Correlation Coefficients, p -values, and confidence intervals for method pair comparisons across DSM, DTM and ALT model types.

Model Type	Comparison (Method Pairs)	Pearson's r	p -Value	95% CI [Lower, Upper]
DSM	SEN NDVI vs. SEN NDRE	0.892 ***	<0.001	[0.699, 0.964]
	SEN NDVI vs. P4RGB	0.620 *	0.014	[0.157, 0.859]
	SEN NDRE vs. P4RGB	0.557 *	0.031	[0.062, 0.832]
	SEN NDVI vs. P4M	0.094	0.740	[−0.440, 0.578]
	SEN NDRE vs. P4M	0.472	0.075	[−0.053, 0.793]
	P4RGB vs. P4M	0.227	0.416	[−0.323, 0.662]
DTM	SEN NDVI vs. SEN NDRE	0.649 **	0.009	[0.206, 0.872]
	SEN NDRE vs. P4M	0.513	0.051	[0.000, 0.812]
	SEN NDVI vs. P4RGB	0.379	0.164	[−0.166, 0.746]
	P4M vs. P4RGB	0.273	0.326	[−0.279, 0.689]
	P4M vs. SEN NDVI	0.193	0.491	[−0.355, 0.642]
	SEN NDRE vs. P4RGB	0.187	0.504	[−0.360, 0.638]
ALT	SEN NDVI vs. P4RGB	0.644 **	0.010	[0.196, 0.869]
	SEN NDVI vs. SEN NDRE	0.408	0.131	[−0.132, 0.761]
	SEN NDRE vs. P4RGB	0.403	0.136	[−0.137, 0.759]
	SEN NDVI vs. P4M	0.129	0.647	[−0.410, 0.601]
	P4M vs. P4RGB	0.272	0.327	[−0.279, 0.688]
	P4M vs. SEN NDRE	−0.299	0.278	[−0.704, 0.251]

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3.3.2. Digital Terrain Model (DTM)

For the DTM type, the only statistically significant relationship was a moderate-to-strong positive correlation between SEN NDVI and SEN NDRE ($r = 0.649$ **, $p = 0.009$, 95% CI [0.206, 0.872]). The correlation between SEN NDRE and P4M approached statistical significance, demonstrating a moderate positive relationship ($r = 0.513, p = 0.051$, 95% CI [0.000, 0.812]). None of the remaining method pairs displayed significant correlations, including SEN NDVI vs. P4RGB ($r = 0.379, p = 0.164$), P4M vs. P4RGB ($r = 0.273, p = 0.326$), P4M vs. SEN NDVI ($r = 0.193, p = 0.491$), and SEN NDRE vs. P4RGB ($r = 0.187, p = 0.504$) (Table 5).

3.3.3. Altitude (ALT)

Analysis of the ALT model type revealed a single statistically significant, moderate-to-strong positive correlation between SEN NDVI and P4RGB ($r = 0.644$ **, $p = 0.010$, 95%

CI [0.196, 0.869]). No other comparisons demonstrated statistical significance. Weak-to-moderate, non-significant positive relationships were observed for SEN NDVI vs. SEN NDRE ($r = 0.408$, $p = 0.131$), SEN NDRE vs. P4RGB ($r = 0.403$, $p = 0.136$), and P4M vs. P4RGB ($r = 0.272$, $p = 0.327$). The correlation between SEN NDVI and P4M was weak and non-significant ($r = 0.129$, $p = 0.647$), whereas P4M and SEN NDRE exhibited a weak, non-significant negative correlation ($r = -0.299$, $p = 0.278$, 95% CI $[-0.704, 0.251]$) (Table 5).

3.4. Canopy Height (ALT) Estimations Obtained via Different Unmanned Aerial Vehicle (UAV)

The canopy height (ALT) estimations obtained via photogrammetry were validated against in situ ground-truth measurements (see Section Ground-Truth Measurements). The average in-situ canopy height measured across the 15 plots was 205.4 ± 12.3 cm (mean $\pm$ SD), ranging from 180 to 230 cm. While absolute canopy-height estimates from both platforms were substantially underestimated (Sentera: $\sim 50\%$ of ground-truth; P4M: near-zero), the relative spatial patterns were more reliably captured by the Sentera platform due to its higher resolution (12.3 MP vs. 2.08 MP). This suggests that within-field variability (rather than absolute height) may still be useful for management zone delineation, provided users account for systematic underestimation.

The canopy height (ALT) estimations obtained via different unmanned aerial vehicle (UAV) platform and sensor configurations—specifically the Phantom 4 Multispectral (P4M), Phantom 4 RGB (P4RGB), and Sentera-based sensors using NDVI and NDRE indices—demonstrated substantial variations across the 15 monitored parcels (Parc ID 1 to 15) (Figure 10). The actual ground truth height of the crop canopy was approximately 180 to 230 cm (1.8 to 2.3 m) during the measurements. Comparing the remote sensing data against this actual ground truth reveals critical insights into which configurations managed to capture the real canopy dynamics relatively well and which ones proved to be completely unusable for practical field evaluation.

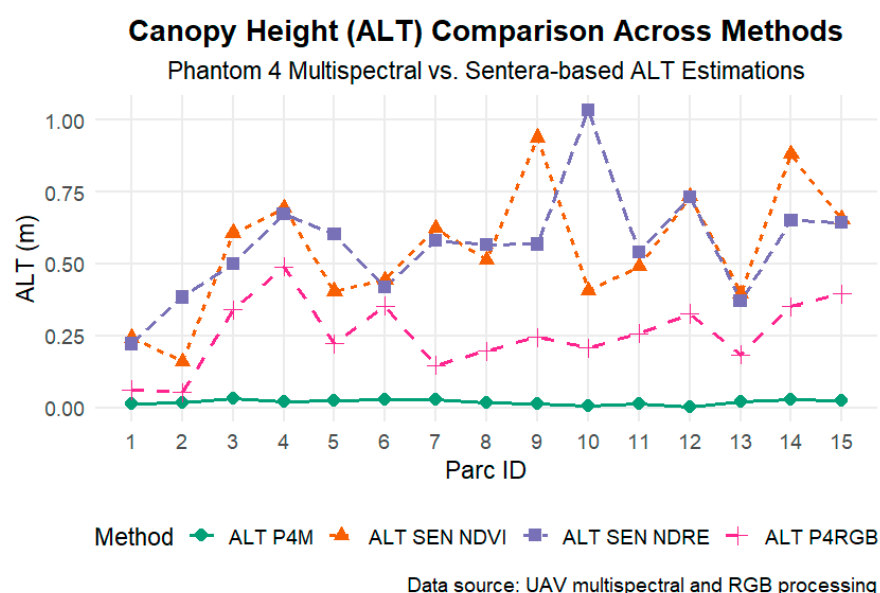


Figure 10. Canopy Height (ALT) comparison across methods. The line plot illustrates the variation in canopy height estimations (in meters) across 15 agricultural parcels (Parc ID) using four distinct methodological approaches: Phantom 4 Multispectral (ALT P4M), Sentera NDVI (ALT SEN NDVI), Sentera NDRE (ALT SEN NDRE), and Phantom 4 RGB (ALT P4RGB). The solid line represents Phantom 4 Multispectral (ALT P4M), while dashed lines show the Sentera NDVI (ALT SEN NDVI), Sentera NDRE (ALT SEN NDRE), and Phantom 4 RGB (ALT P4RGB) trends. Markers indicate parcel-specific ALT values. The data visualization and statistical tracking were generated using RStudio [Version 4.1.2].

The ALT P4M (p4multi) method consistently yielded the lowest canopy height estimations across all experimental units, with values remaining nearly flat and extremely close to zero, fluctuating within a narrow range between 0.03 m at Parc 15 and 0.0299 m at Parc 4. Because it completely failed to reflect the true height of the 1.8 to 2.3 m canopy and showed virtually zero correlation with actual crop growth, this specific Phantom 4 Multispectral processing approach proved unreliable for canopy height estimation under these parameters. Similarly, the standard RGB-based processing (p4rgb), while capturing relative variations between parcels more effectively than the P4M method, remained drastically underestimated compared to the real field conditions. With values ranging from a minimum of 0.0522 m at Parc 2 to a maximum of 0.4899 m at Parc 5, the P4RGB method captured less than a quarter of the actual crop height, making it unsuitable for precise absolute height tracking.

In contrast, the ALT values derived from the Sentera sensor configurations (SEN-NDVI and SEN-NDRE) performed remarkably better, proving to be the only methods that caught the actual standing crop volume and structural trends relatively well. Although they still presented an underestimation compared to the maximum ground truth height of 2.3 m, they came significantly closer to the real-world scale and effectively mapped the true spatial variability across the field. In general, the NDVI and NDRE vegetation index-based terrain and canopy modeling methods followed a highly synchronized pattern across most parcels, albeit with localized deviations.

Overall, only the Sentera-derived index models captured within-field height variability with useful sensitivity; both Phantom 4 workflows failed to represent crop structure reliably.

4. Discussion

The comparative analysis of the digital surface models (DSM), digital terrain models (DTM), and vegetation indices reveals significant discrepancies rooted in the technical architecture of the evaluated sensor platforms. The Sentera Double 4K system features a superior effective resolution of 12.3 MP (Sony Exmor R™ IMX377) compared to the 2.08 MP of the DJI Phantom 4 Multispectral (P4M). This difference in pixel density directly impacts the Ground Sampling Distance (GSD): per the manufacturer's specifications, the Sentera platform is rated for a high-fidelity 3.5 cm/pixel GSD from a reference altitude of 80 m (Table 1), whereas in the present study both platforms were flown at 35.5 m, yielding an actual GSD of 1.9 cm/pixel for both sensors (Section 2.2). This increased spatial resolution may partly explain the higher internal consistency observed in Sentera-derived models (software-based calculations), since UAV multispectral outputs are known to be affected by sensor-specific noise, lens distortion, band alignment, and post-processing limitations (Kelcey and Lucieer, 2012) [37]. Correlation matrices show that DSM accuracy is relatively stable across platforms, particularly between Sentera NDVI and NDRE models ($r = 0.892$, $p < 0.001$). Previous UAV-based maize studies have demonstrated that DSM-derived products can be effectively used for plant-height estimation, although their reliability depends on the quality and resolution of the reconstructed surface model (Oehme et al., 2022) [38]. However, once the vegetation is filtered to produce DTMs, the correlation weakens significantly. This agrees with maize-specific UAV studies showing that plant-height estimation is strongly influenced by the method used to derive ground altitude or DTM, as well as by RTK/GCP configuration and image acquisition geometry (Fujiwara et al., 2022) [39]. The lack of significant correlation between DTM P4M and SEN NDVI ($r = 0.193$, $p = 0.491$) highlights the sensitivity of terrain estimation to sensor-specific point cloud generation algorithms.

Bland–Altman analysis identified a systematic vertical bias of approximately 50–60 m between the P4M and P4RGB platforms. This is not a geometric distortion but a result

of different vertical datum definitions: the P4M recorded height relative to the WGS84 ellipsoid, while the P4RGB software applied a geoid (EGM96) correction to provide orthometric heights [40,41]. Such discrepancies are a known source of vertical offsets in GNSS- and UAV-based mapping workflows when ellipsoidal and orthometric heights are not handled consistently [42,43]. Despite this large offset, the narrow Limits of Agreement (LoA range < 3 m) suggest that the terrain's relative geometry remains consistent, allowing for effective vertical co-registration. Therefore, the observed bias should be treated as a correctable datum-related vertical shift rather than as evidence of poor photogrammetric reconstruction quality.

The spectral band configurations further differentiate the performance of the two systems. While the Red Edge (RE) bands are relatively similar, the DJI P4M uses a narrower red band ($650 \text{ nm} \pm 16 \text{ nm}$) compared to the Sentera sensor platform ($625 \text{ nm} \pm 100 \text{ nm}$). Such differences in central wavelength and bandwidth can lead to sensor-dependent reflectance and vegetation index values, particularly for indices relying on the red band, such as NDVI [44,45]. In contrast, the more comparable RE band configuration may partly explain the stronger agreement observed for NDRE between the two platforms.

Bland–Altman results for vegetation indices show that NDRE is the more stable index across platforms, with a minimal bias of 0.0255 and a narrow 95% CI [0.009, 0.041]. In contrast, NDVI exhibited a much larger systematic bias of 0.0860 and a wide LoA (up to 0.2072). This indicates that NDVI is highly sensitive to the physical sensor construction and band-width differences [44,45], whereas NDRE (using the Red Edge band) provides a more consistent representation of canopy physiological status across different hardware configurations [46].

The observed data suggests that the lower sensor resolution of the P4M correlates with higher noise in both terrain modeling (DSM $r = 0.094$) and spectral index calculation (higher NDVI bias). This is consistent with previous studies showing that UAV multispectral outputs are affected by sensor-specific noise, lens distortion, radiometric correction procedures, and sensor-to-sensor variability [37,44]. The Sentera platform's internal consistency across DSM, DTM, and spectral outputs makes it a more robust solution for precision agriculture. For cross-platform data fusion involving the P4M, rigorous Ground Control Point (GCP) calibration is recommended to reduce geometric inconsistencies in UAV-SfM products [47] and a standardized normalization process for NDVI to account for the observed spectral bias.

A detailed examination of the Canopy Height (ALT) results (derived from DSM–DTM) reveals that while the Sentera Double 4K provided more dynamic values than the DJI P4M, both systems significantly underestimated the actual field conditions. In situ measurements indicated a crop height exceeding 2.0 m across most plots, yet the Sentera estimations peaked only around 1.0 m, with even lower values in the weaker parcel edges. Similar discrepancies have been reported in UAV-SfM crop height studies, where DSM-derived canopy height estimates depend strongly on the quality of the reconstructed surface model and the underlying terrain reference [39,48].

This discrepancy highlights a shared limitation in UAV photogrammetry: as canopy density increases, the software's ability to identify the true ground surface (DTM) through the biomass diminishes, leading to an “inflated” DTM and a consequently “compressed” canopy height. Similar limitations have been observed in dense maize canopies, where accurate plant height retrieval depends on reliable ground or micro-terrain estimation below the canopy [39,49]. Even with the Sentera's superior 12.3 MP resolution, the sensors primarily captured the upper leaf layers, failing to penetrate to the soil level in the dense central areas of the parcels. While ground-truth canopy height was rigorously mea-

sured (Section 2.2), the lack of LiDAR or independent terrain survey data limited absolute validation of DTM/DSM accuracy under dense canopy conditions.

The DJI Phantom 4 Multispectral (P4M) performed even more poorly in this regard, with ALT values remaining near zero. While the P4M's architecture—featuring six discrete lenses and five monochrome sensors—is designed for high spectral purity by eliminating “spectral crosstalk,” it proves disadvantageous for 3D structural reconstruction. The lower effective resolution (2.08 MP) and the slight parallax between the separate lenses make it difficult for photogrammetric algorithms to reconstruct the complex geometry of a 2-m-tall crop, effectively “smoothing out” the difference between the surface and the terrain models. Overall, these findings indicate that lower image resolution and sensor-specific geometric constraints may reduce point-cloud quality and compress DSM–DTM-derived canopy height estimates in structurally complex crop stands [37,48].

This study was limited to a single maize hybrid (DKC 4596) and one flight altitude (35.5 m), and a single phenological stage. The comparison was conducted on one flight date, so it reflects platform agreement at only one crop growth stage; because NDVI, NDRE, and canopy-height signals are known to vary with phenological development (e.g., canopy closure, leaf angle, senescence), the relative agreement between the P4M and Sentera platforms reported here should not be assumed to hold at earlier vegetative or later reproductive growth stages. Future work should test multiple altitudes, crops, growth stages, and sensor configurations to generalize findings. Additionally, lack of ground-truth LiDAR data prevented absolute validation of canopy height estimates. However, the relative performance between platforms (Sentera > P4M for spatial variability) aligns with expectations based on sensor resolution and architecture. Future studies should include GCPs, LiDAR validation, or manual height measurements to quantify absolute errors. While this study uses platforms that are no longer the newest available, the comparative methodology and key findings (e.g., NDRE's robustness for cross-platform fusion) are transferable to newer systems. Future work should validate these conclusions with current-generation sensors (e.g., DJI M3M, Sentera 6X) to assess whether improved spectral isolation and radiometric performance reduce the observed inconsistencies.

The inconsistencies observed between the DJI Phantom 4 Multispectral (P4M) and Sentera Double 4K platforms arise from radiometric, geometric, illumination, spatial sampling, and validation constraints. Radiometrically, the platforms' distinct spectral response functions (Table 1), including variations in central wavelengths and bandwidths for Red, NIR, and Red Edge bands, directly influence NDVI and NDRE computations, particularly for NDVI, which is highly sensitive to spectral mismatches in dense canopies [20,50]. Geometrically, the P4M's six separate sensors introduce parallax errors during Structure from Motion (SfM) processing, distorting 3D reconstructions, whereas the Sentera's dual-lens system minimizes such inconsistencies, likely explaining the P4M's poorer DSM and DTM performance under dense vegetation [10,23]. Illumination variability, though minimal, may also contribute, as the ~15–20 min interval between flights under stable, clear-sky conditions (solar elevation: ~43–45°) could introduce subtle reflectance differences [8]. Spatial sampling limitations further exacerbate discrepancies, as the P4M's lower effective resolution (2.08 MP vs. Sentera's 12.3 MP) reduces its ability to capture fine canopy details despite achieving the same 1.9 cm/pixel GSD [44]. Finally, validation constraints, such as the absence of LiDAR or GCPs, limit interpretability, relying instead on manual measurements (Section 2.2) for relative comparison [38]. To mitigate these issues, future work should use reflectance panels for radiometric calibration [18], co-register orthomosaics to quantify spatial misalignment [21], and incorporate GCPs or LiDAR for absolute validation [22].

5. Conclusions

This study demonstrated that NDVI values and structural models (DSM/DTM) from the P4M and Sentera platforms are not directly interchangeable without correction, while NDRE shows potential for cross-platform fusion. The Sentera Double 4K showed more consistent DSM, DTM, and canopy-height-related outputs, mainly due to its higher spatial resolution and more favorable sensor geometry, whereas the DJI Phantom 4 Multispectral showed considerable limitations in structural reconstruction under dense maize canopy conditions. Among the vegetation indices, NDRE proved to be more stable across platforms than NDVI, which was more strongly affected by sensor-specific spectral differences and systematic bias. Although vertical offsets between elevation models can be partly corrected through proper datum handling and ground control calibration, photogrammetric canopy height estimation remained compressed in dense crop stands. Relative to in-situ canopy-height measurements, absolute canopy height was consistently underestimated by both platforms, most severely by the P4M. Overall, NDRE is recommended for cross-platform spectral data fusion, while reliable canopy height monitoring in tall maize requires high-resolution imagery, rigorous georeferencing, and, where possible, complementary ground-based or LiDAR reference data. For spectral analysis, farmers should prioritize NDRE over NDVI when combining data from different sensors. For canopy height monitoring, high-resolution sensors (e.g., Sentera) with rigorous GCP calibration are recommended, and LiDAR integration should be considered for dense canopies.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/drones10100723/s1>, Figure S1. Digital surface model (DSM) point-cloud reconstructions of the maize trial plot generated from four UAV sensor/texture combinations. (A) Sentera Double 4K NDVI-textured DSM; (B) DJI Phantom 4 Multispectral (P4M) DSM; (C) P4M RGB-textured DSM; (D) Sentera Double 4K NDRE-textured DSM. All models were reconstructed in WebODM from imagery acquired at 35.5 m altitude over the DKC 4596 hybrid trial (Debrecen, Hungary). Figure S2. Digital surface model (DSM) of the maize trial plot reconstructed from DJI Phantom 4 Multispectral (P4M) imagery. The multi-lens, 2.08 MP-per-band sensor and associated lens parallax limited structural detail in the reconstructed canopy surface relative to the higher-resolution Sentera platform. Figure S3. RGB-textured digital surface model (DSM) of the maize trial plot, showing the transition between the maize canopy (left) and the mown grass headland (right) used for ground-control referencing. Figure S4. NDVI-textured digital surface model (DSM) of the maize trial plot derived from Sentera Double 4K imagery (12.3 MP), used to evaluate NDVI cross-platform agreement with the P4M sensor. Figure S5. NDRE-textured digital surface model (DSM) of the maize trial plot derived from Sentera Double 4K imagery, which showed a significant, moderately strong correlation with P4M NDRE outputs ($r = 0.66$, $p = 0.007$) and a narrower limit of agreement than the corresponding NDVI comparison.

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Abbreviations

The following abbreviations are used in this manuscript:

UAV	Unmanned Aerial Vehicle
PA	Precision Agriculture
RS	Remote Sensing
VI	Vegetation Index
NDVI	Normalized Difference Vegetation Index
NDRE	Normalized Difference Red Edge Index
RE	Red Edge
NIR	Near-Infrared
RGB	Red Green Blue
P4M	DJI Phantom 4 Multispectral
P4RGB	DJI Phantom 4 RGB
DSM	Digital Surface Model
DTM	Digital Terrain Model
CHM	Canopy Height Model
ALT	Altitude/relative canopy height derived from DSM–DTM
GSD	Ground Sampling Distance
GCP	Ground Control Point
RTK	Real-Time Kinematic
GNSS	Global Navigation Satellite System
SfM	Structure from Motion
LoA	Limits of Agreement
CI	Confidence Interval
WGS84	World Geodetic System 1984
EGM96	Earth Gravitational Model 1996
QGIS	Quantum Geographic Information System
GIS	Geographic Information System

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