

Evaluating UAV Pansharpening for Soil Water Content Estimation Using Spectral Indices in Generative Sweet Maize

Mety Maryanti^{*1}, Muhammad Amir Solihin², Mahfud Arifin³

^{1,2,3}Faculty of Agriculture, Universitas Padjadjaran, Jl. Raya Bandung–Sumedang, Jatinangor, Sumedang Regency, West Java 45363, Indonesia

ABSTRACT

Published online: October 27, 2026

Soil water content monitoring during the generative phase of sweet maize is critical for irrigation decisions in precision agriculture, yet conventional destructive sampling is too slow and spatially limited for field-scale management. This study evaluated whether pansharpening improves or degrades the accuracy of eight spectral indices for estimating SWC through an index-by-index comparison. The study was conducted on a 720 m² field of fertilizer-dose treatment plots in Ciparanje, Jatinangor, Indonesia, with 15 purposively selected sampling points. Multispectral imagery was acquired with a DJI Matrice 350 RTK UAV and MicaSense Altum-PT sensor at 30 m altitude and 80% overlap, yielding 1.24 cm/pixel ground sample distance before and 0.62 cm/pixel after pansharpening. Eight indices were correlated with gravimetric SWC via Spearman correlation and linear regression, cross-checked with classical assumption tests. Pansharpening improved spatial resolution with generally preserved spectral quality, though the NIR and RedEdge bands showed the weakest fidelity. The effect on SWC estimation was index-dependent: NDVI was essentially preserved, whereas SAVI and MSAVI lost 25.0% and 22.7% of their explanatory power; red-edge and water-based indices remained unchanged, and TVDI was non-significant. Only the red-edge indices CI_{re} and NDRE satisfied all classical regression assumptions in both products; the pansharpened NDRE model ($R^2 = 0.4177$, RMSE = 1.5021, $p = 0.009$) was therefore used to generate a field-capacity-based SWC map of the 720 m² field, providing zone-specific irrigation guidance. Pansharpening thus benefits SWC estimation depending on index formulation, supporting an index-specific processing rule for irrigation scheduling in regenerative sweet maize.

Cite the Article: Maryanti, M., Solihin, M.A., Arifin, M. (2026). Evaluating UAV Pansharpening for Soil Water Content Estimation Using Spectral Indices in Generative Sweet Maize. International Journal of Life Science and Agriculture Research, 5(10), 756-767. <https://doi.org/10.55677/ijlsar/V05I10Y2026-07>

License: This is an open access article under the CC BY 4.0 license:

<https://creativecommons.org/licenses/by/4.0/>

KEYWORDS: Pansharpening, Soil Water Content, Sweet Maize, Spectral Indices, UAV.

Corresponding Author:
Mety Maryanti

INTRODUCTION

Soil water content (SWC) is a crucial limiting factor determining sweet maize productivity amidst current climate change. Soil drought has been shown to reduce ear weight by $\pm 76.7\%$, trigger plant morphological degradation, and disrupt nutrient availability as well as soil biogeochemical dynamics (Lestari et al., 2025; Viceli et al., 2025). These impacts can ultimately affect the efficiency of greenhouse gas emissions and sequestration (Hao et al., 2025). Therefore, continuous monitoring of soil water content is essential to support the implementation of precision agriculture and climate change adaptation strategies.

Compared to conventional methods (gravimetry and direct measurements) that are destructive, time-consuming, and inefficient for large areas, remote sensing technology offers the advantage of a broader observation scale (Cao et al., 2021). An effective approach is the utilization of spectral indices, such as the Soil-Adjusted Vegetation Index (SAVI), which has proven to

have a linear correlation with in-situ soil moisture (Cahyono et al., 2022). This flexibility and detailed resolution can be further optimized using multispectral Unmanned Aerial Vehicles (UAVs), which are typically equipped with RGB, NIR, and Red Edge band sensors (Jurišić et al., 2022; Lu et al., 2020).

Although hundreds of spectral indices are available for environmental monitoring (Chen et al., 2025), each index has characteristic limitations. Vegetation-based indices (such as NDVI, SAVI, MSAVI, CI_{re}, and NDRE) frequently experience saturation during the closed canopy phase, whereas water and thermal-based indices (such as NDWI, CWSI, and TVDI) exhibit varying sensitivities depending on plant phenological stages and soil conditions. To minimize the confounding effects of mixed soil-canopy signals during these stages, enhancing the spatial resolution of the imagery becomes crucial. In this context, pansharpening serves as a powerful image-fusion framework that merges multispectral and panchromatic datasets to yield enhanced imagery characterized by simultaneously high spatial and spectral resolutions (Sekrecka et al., 2019).

The application of pansharpening has been proven to improve land cover classification accuracy and clarify object details in satellite imagery (Alcaras & Parente, 2023; Rokni, 2023). However, the utilization of this technique on UAV imagery remains largely unexplored since most multispectral drones lack a built-in panchromatic band, and previous research has predominantly focused on data fusion or machine learning (Modak et al., 2024). Therefore, this study aims to evaluate the effect of pansharpening on multispectral drone imagery for estimating soil water content based on spectral indices during the generative phase of sweet maize, in order to improve the accuracy of sustainable land evaluation.

METHODS

Study Site

The study was conducted at a sweet maize (*Zea mays saccharata*) field during its generative phase in Ciparanje, Jatinangor, Sumedang Regency, West Java. Spanning an area of 720 m², the field comprises several experimental plots treated with varying fertilizer doses (organic and inorganic), thereby establishing canopy heterogeneity (Figure 1). A purposive sampling approach was employed to determine the locations and number of sampling points, aiming to achieve a uniform and systematic spatial representation of the study area. Fifteen sampling points were strategically selected to represent key biophysical characteristics, including variations in soil surface conditions, vegetation density, and topographical positions.

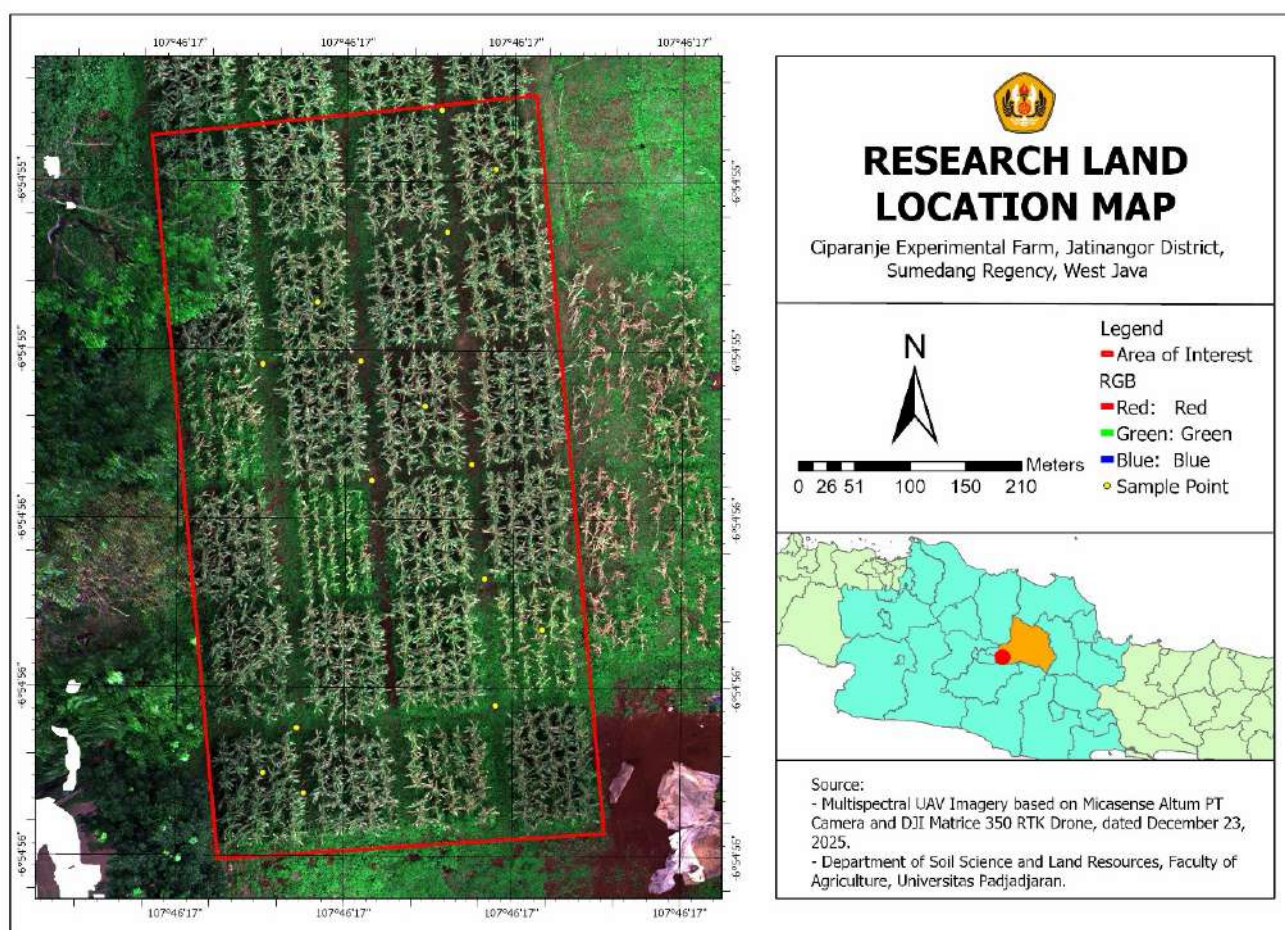


Figure 1. Map of the study area

Data Acquisition and Image Processing

Multispectral imagery was acquired using a DJI Matrice 350 RTK Unmanned Aerial Vehicle (UAV) equipped with a MicaSense Altum-PT sensor. Flight operations were conducted at an altitude of 30 meters with an 80% overlap. The resulting imagery yielded a Ground Sample Distance (GSD) of 0.62 cm/pixel for the pansharpened imagery and 1.24 cm/pixel for the non-pansharpened imagery.

Image acquisition took place under clear weather conditions; however, the soil was at field capacity due to rainfall on the day prior to the observation. The image processing workflow, comprising image stitching, radiometric correction, and pansharpening. Pansharpening was performed in Agisoft Metashape by utilizing the panchromatic band of multispectral camera to sharpen the multispectral bands during orthomosaic generation, following the pan-sharpening workflow described in the Micasense technical guide. Disturbed soil samples were collected in-situ at a depth of 5 cm to determine surface soil water content. Gravimetric water content analysis was conducted at the Soil Physics Laboratory, Faculty of Agriculture, Padjadjaran University, using the following formula:

$$SWC = \frac{W1 - W2}{W2 - W3} \times 100\%$$

Where:

SWC = Soil water content (%)

W1 = Weight of the container + initial wet soil (g)

W2 = Weight of the container + oven-dried soil (g)

W3 = Weight of the empty container (g)

Data Analysis

The calculation of eight selected spectral indices was performed using ArcGIS Pro based on the equations listed in Table 1. The performance of each index in estimating soil water content was evaluated through correlation and linear regression analyses. To ensure model validity, classical assumption tests (including normality, heteroscedasticity, and autocorrelation tests) were conducted using SPSS. A comparative evaluation was subsequently performed between the two types of imagery (pansharpened and non-pansharpened). Spatial data processing, such as the generation of Soil Water Content (SWC) estimation maps, was performed using RStudio.

Table 1. Mathematical formulas of the utilized spectral indices.

Group	Spectral Indices	Formula	Reference
Vegetation	NDVI (<i>Normalized Difference Vegetation Index</i>)	$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$	Rouse et al., 1973
	SAVI (<i>Soil Adjusted Vegetation Index</i>)	$SAVI = \frac{(NIR - RED)}{(NIR + RED + L)} \times (1 + L)$	Huete, 1988
	MSAVI (<i>Modified Soil Adjusted Vegetation Index</i>)	$MSAVI = \frac{2 \cdot NIR + 1 - \sqrt{(2 \cdot NIR + 1)^2 - 8(NIR - Red)}}{2}$	Qi et al., 1994
	CI _{re} (<i>Chlorophyll Index – Red Edge</i>)	$CI_{RedEdge} = \left(\frac{NIR}{RedEdge} \right) - 1$	Barnes et al., 2000
	NDRE (<i>Normalized Difference Red Edge</i>)	$NDRE = \frac{(NIR - RedEdge)}{(NIR + RedEdge)}$	Barnes et al., 2000
Water	NDWI (<i>Normalized Difference Water Index</i>)	$NDWI = \frac{(Green - NIR)}{(Green + NIR)}$	McFeeters, 1996
Thermal	CWSI (<i>Crop Water Stress Index</i>)	$CWSI = \frac{[(T_c - T_a) - (T_{wet} - T_a)]}{[(T_{dry} - T_a) - (T_{wet} - T_a)]}$	Jackson et al., 1981/ Idso et al., 1981
	TVDI (<i>Temperature Vegetation Dryness Indeks</i>)	$TVDI = \frac{T_s - T_{smin}}{T_{smax} - T_{smin}}$	Sandholt et al., 2002

Notes: NIR=Near-Infrared; L = Soil brightness correction factor; T_c = Crop canopy temperature; T_a = Air temperature; T_{wet} Canopy temperature under non-water-stressed conditions (lower baseline); T_{dry} = Canopy temperature under maximum water-stressed conditions (upper baseline); T_s = Actual land surface temperature retrieved from image pixels; T_{smin} = Minimum land surface temperature (wet edge); T_{smax} : Maximum land surface temperature (dry edge).

RESULT AND DISCUSSION

1. Visual and Spectral Quality Evaluation of Pansharpened Images

Pansharpener reduced the ground sample distance (GSD) of the MicaSense Altum-PT stack from 1.24 cm/pixel to 0.62 cm/pixel, a fourfold increase in pixel density (Table 2). The visual impact is seen in Figure 2, where canopy boundaries and inter-row gaps between soil are more contrast and vibrant in pansharpened composite. The band count dropped from 7 to 6, as the panchromatic channel is no longer an output band but is instead consumed as the detail source, and the radiometric encoding shifted from 16-bit unsigned integer to 32-bit floating point, since detail injection introduces fractional adjustments that an integer format would clip. File size increased only 1.7-fold, from 5.16 to 9 GB, despite the fourfold rise in pixel count, a gap best explained by the reduced band count and the export compression applied to the fused product, which together offset most of the expected size growth. No dedicated spatial-domain metric accompanies this dataset, so the sharpening assessment presented here for the spatial dimension remains qualitative rather than the more objective spectral-fidelity metrics discussed below.

Table 2. Technical specifications of the raw and processed drone imagery

Parameter	Non-Pansharpened Imagery	Pansharpened Imagery
UAV Platform	DJI Matrice 350 RTK	DJI Matrice 350 RTK
Camera Sensor	MicaSense Altum-PT	MicaSense Altum-PT
Flight Altitude	30 m	30 m
Forward/Side Overlap	80% / 80%	80% / 80%
Ground Sample Distance (GSD)	1.24 cm/pixel (Native)	0.62 cm/pixel
Number of Bands	7 Bands	6 Bands
Bit Depth	16-bit Unsigned	32-bit Floating Point
File Size	5,16 GB	9 GB

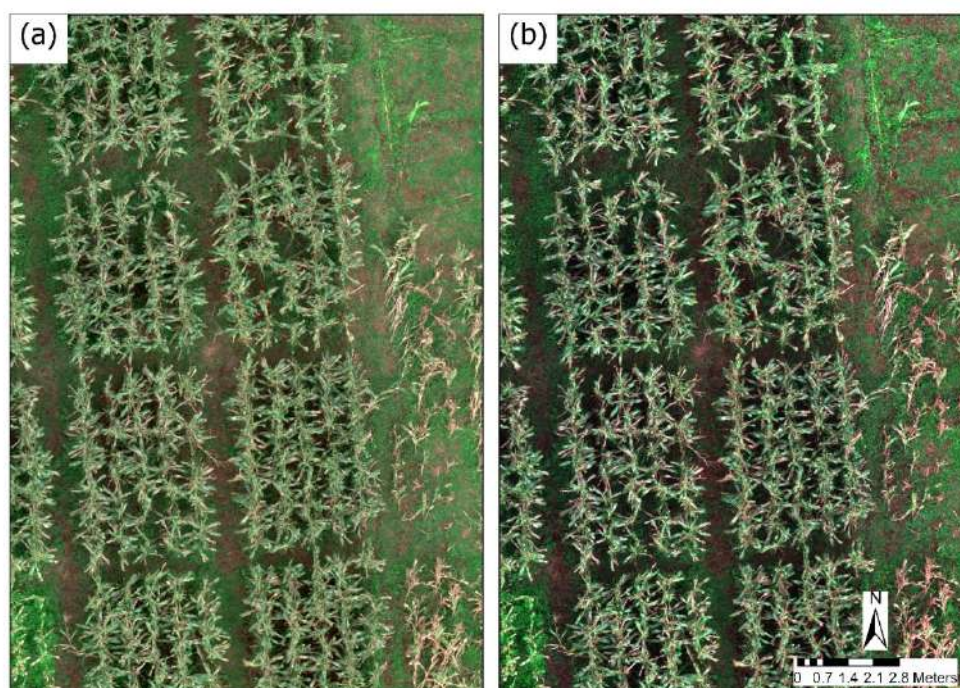


Figure 2. Visual comparison of UAV imagery: (a) non-pansharpened multispectral bands; (b) pansharpened imagery

Table 3 shows that fidelity varies noticeably across bands. Blue achieves the closest agreement with the reference ($CC = 0.9835$, $RMSE = 0.0020$), followed closely by Red ($CC = 0.9792$, $RMSE = 0.0039$). Green sits at an intermediate level ($CC = 0.9542$, $RMSE = 0.0059$), while RedEdge and NIR show the weakest correlation of the set ($CC = 0.9187$ and 0.9129 , respectively); NIR also carries the highest RMSE among the optical bands (0.0397), despite its CC remaining fairly close to RedEdge's. The optical average lands at $CC = 0.9497$, $RMSE = 0.0133$, $SAM = 0.1391^\circ$. LWIR, by contrast, reaches a near-perfect CC of 1.0000 , with an $RMSE$ (0.0174) in the same range as the optical bands; it is excluded from the optical average because it belongs to a different sensing domain altogether. The low average SAM value is a favorable sign on its own, since it reflects how closely the

angular shape of the spectral signature was preserved during fusion, and it lines up with the generally strong CC and low RMSE recorded across most bands. It particularly reinforces that, even where a band such as NIR shows an elevated RMSE, the underlying spectral shape was not meaningfully distorted.

The built-in pansharpening module in Metashape follows a component-substitution (CS) fusion approach, injecting spatial detail from the panchromatic channel into every band while controlling how strongly that detail correlates with the panchromatic signal. This class of algorithms carries a well-documented trade-off: strong spatial sharpening comes at the cost of spectral distortion that grows with how poorly a band's spectral response is represented within the broadband panchromatic channel (Ciotola et al., 2025; Dadrass Javan et al., 2021). The comparatively lower CC for RedEdge and NIR likely traces back to this mismatch.

Table 3. Quality evaluation results of the pan-sharpened image against the reference multispectral image (optical bands)

Band	CC	RMSE	SAM (°)
Blue	0.9835	0.0020	
Green	0.9542	0.0059	
Red	0.9792	0.0039	
RedEdge	0.9187	0.0148	
NIR	0.9129	0.0397	
Average	0.9497	0.0133	0.1391
LWIR	1.0000	0.0174	

Note: Correlation Coefficient (CC), Root Mean Square Error (RMSE), Spectral Angle Mapper (SAM)

According to MicaSense's own documentation for the Altum-PT panchromatic sensor, the five discrete multispectral bands leave gaps in the spectral range the panchromatic imager covers, meaning some of the information the panchromatic sensor captures falls between the narrower multispectral bands (MicaSense, 2026). RedEdge sits in the region of steepest reflectance change for vegetation and occupies a narrow spectral window, which a broadband panchromatic signal struggles to represent faithfully, offering a weaker structural cue for detail injection in that band.

The elevated RMSE for NIR, despite its CC remaining reasonably high, is explained more simply by the fact that RMSE is magnitude-dependent: NIR reflectance from healthy vegetation runs several times higher than in the visible bands, so the same proportional error translates into a much larger absolute error (Wu et al., 2023). The near-unity CC recorded for LWIR is best read as a resampling artifact rather than genuine spectral agreement, since the thermal radiance signal and the panchromatic signal occupy entirely different physical domains and offer no real basis for CS-style detail injection between the two.

These results carry a direct implication for the remainder of the paper. Agisoft's own documentation for the pansharpening module advises against computing vegetation indices from its output, since the fusion process alters per-band pixel values in ways that can compromise index accuracy (Agisoft, 2026), and the CC/RMSE figures obtained here do point to non-trivial per-band distortion, particularly in RedEdge and NIR. Independent multi-sensor evaluations of pansharpened reflectance data, however, indicate that ratio-based indices such as NDVI are largely preserved even where individual bands carry measurable error, because much of that error cancels out in the ratio calculation (Procházka et al., 2026). The low SAM value obtained here (0.1391°) supports this expectation rather than casting doubt on it, since it confirms that the spectral shape relationship between Red and NIR (the two bands NDVI depends on) was well maintained through the fusion process.

2. Performance of Spectral Indices in Soil Water Content (SWC) Estimation

Spearman correlation analysis confirms that all eight spectral indices remain significantly correlated with SWC after pansharpening, though the direction and magnitude of change differ among index types (Table 4, Figure 3). NDVI strengthens modestly ($r_s = -0.821$ to -0.836 , $\alpha < 0.01$), while SAVI and MSAVI weaken ($r_s = -0.718$ to -0.593 and -0.704 to -0.593), with significance dropping from $\alpha < 0.01$ to $\alpha < 0.05$. These data were collected during the late generative phase of maize, when the canopy typically thins and weed cover increases, and it is possible this background heterogeneity contributes to the SAVI/MSAVI decline. CI_{re}, NDRE, NDWI, CWSI, and TVDI, by contrast, show no change at all ($\Delta = 0.000$ for all). This is broadly consistent with earlier fusion studies finding that water and atmosphere resistant indices such as GNDVI and ARVI are among the least disturbed by pansharpening (Ghimire et al., 2020), and with reviews describing red-edge and water-based indices as comparatively stable formulations across varying conditions (Haque et al., 2024).

Table 4. Spearman Correlation Matrix between Spectral Indices and Soil Water Content (SWC)

Analysis	Statistic	NDVI	SAVI	MSAVI	CIre	NDRE	NDWI	CWSI	TVDI
Non-pansharpened	rs	-0.821**	-0.718**	-0.704**	-0.739**	-0.739**	0.789**	0.639*	0.564*
	p-value	<0.001	0.003	0.003	0.002	0.002	<0.001	0.010	0.028
Pansharpened	rs	-0.836**	-0.593*	-0.593*	-0.739**	-0.739**	0.789**	0.639*	0.564*
	p-value	<0.001	0.020	0.020	0.002	0.002	<0.001	0.010	0.028

Note: * significant at the $\alpha = 0.01$ level (2-tailed); significant at the $\alpha = 0.05$ level (2-tailed); ns = not significant. Positive values indicate a positive correlation, whereas negative values indicate an inverse (negative) correlation with SWC

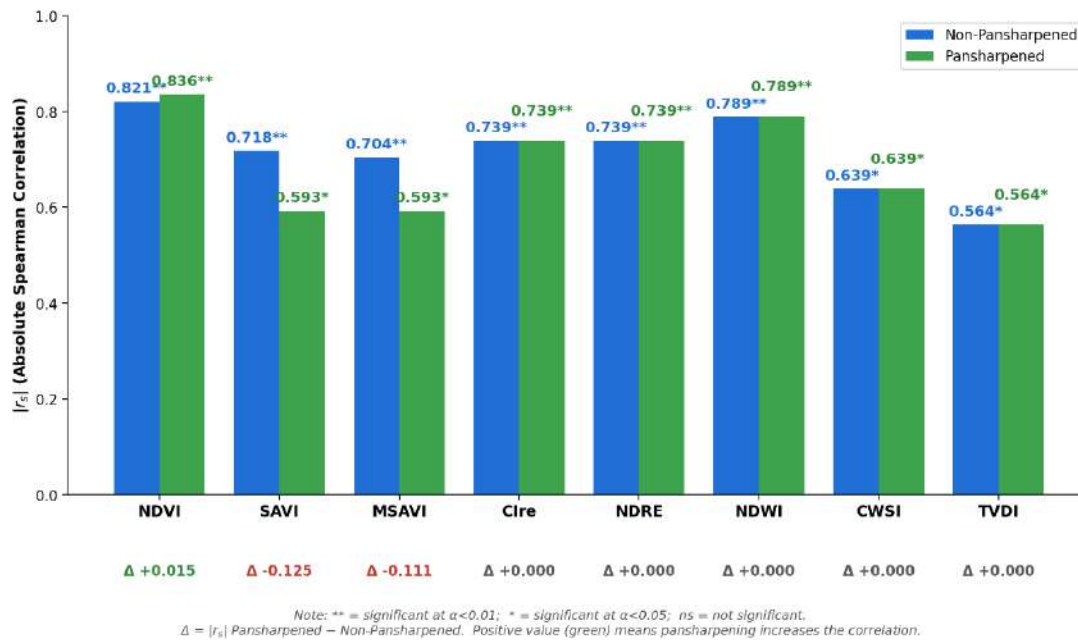


Figure 3. Comparison of Spearman correlation between soil water content and spectral indices

Table 5 shows that pansharpening did not act as a uniformly beneficial preprocessing step; its effect on linear regression performance was strongly index-dependent. Six of the eight indices remained essentially unchanged ($\Delta R^2 \leq +0.0004$), NDVI gained marginally (+0.0009, +0.2%), and the two soil-adjusted indices suffered pronounced declines: SAVI lost 25.0% of its explanatory power ($R^2 = 0.4414 \rightarrow 0.3312$) and MSAVI 22.7% ($R^2 = 0.4195 \rightarrow 0.3241$). Both remained statistically significant, but their p-values weakened (SAVI: 0.007 $\rightarrow$ 0.025; MSAVI: 0.009 $\rightarrow$ 0.027), while TVDI stayed weak and non-significant in both products ($p = 0.077$). This index dependence is consistent with the broader pansharpening literature: the degree of distortion introduced by fusion depends on the imaging sensor, the pan-sharpening algorithm, and the context of the scene analyzed (Beene et al., 2022), the impact of pansharpening being most evident at the highest spatial resolution tested (Jovanović et al., 2016), while the vegetation index formula itself determines how much of the injected spatial information survives the index calculation (Johnson, 2014).

Table 5. Comparison of linear regression performance (R^2) and statistical validity between non-pansharpened and pansharpened spectral indices for soil water content estimation

Index	R^2 Non-PAN	R^2 PAN	ΔR^2	$\Delta \%$	Significance (Sig. F)	Remarks
NDVI	0.5564	0.5573	+0.0009	+0.2%	Sig. (p=0.001 / 0.001)	≈ stable
SAVI	0.4414	0.3312	-0.1102	-25.0%	Sig. (p=0.007 / 0.025)	▼ decrease
MSAVI	0.4195	0.3241	-0.0954	-22.7%	Sig. (p=0.009 / 0.027)	▼ decrease
CIre	0.3512	0.3514	+0.0002	+0.1%	Sig. (p=0.020 / 0.020)	≈ stable
NDRE	0.4175	0.4177	+0.0002	+0.1%	Sig. (p=0.009 / 0.009)	≈ stable

Index	R^2 PAN	Non-PAN	R^2 PAN	ΔR^2	$\Delta \%$	Significance (Sig. F)	Remarks
NDWI	0.4443		0.4446	+0.0003	+0.1%	Sig. (p=0.007 / 0.007)	≈ stable
CWSI	0.2992		0.2997	+0.0004	+0.1%	Sig. (p=0.035 / 0.035)	≈ stable
TVDI	0.2215		0.2211	-0.0004	-0.2%	Not sig. (p=0.077 / 0.077)	≈ stable

Note: $\Delta R^2 = R^2(PAN) - R^2(Non-PAN)$. p-values in the Significance column are written as (Non-PAN / PAN)

Table 6 confirms the Table 5 pattern from the error side and strengthens the conclusion that the SAVI/MSAVI decline is real rather than an artifact of a single metric. RMSE moved in exact opposition to R^2 : SAVI and MSAVI were the only indices whose prediction error increased after fusion (1.4712 → 1.6098, +9.4%; and 1.4998 → 1.6183, +7.9%), whereas NDVI improved by a negligible 0.1% (1.3111 → 1.3097) and the remaining five indices changed by no more than 0.0005 percentage points of SWC. In gravimetric units, the SAVI/MSAVI deterioration corresponds to roughly 0.12–0.14 percentage points of soil water content, approximately two orders of magnitude larger than the fluctuations of the stable indices — two independent metrics therefore converge on the same verdict for the same two indices. Figure 4 visualizes this bimodal outcome: the bars for six indices overlap almost completely between the non-pansharpened and pansharpened products, while SAVI and MSAVI diverge clearly in both panels, R^2 dropping and RMSE rising simultaneously. The figure also makes the cross-index hierarchy explicit: NDVI occupies the top position on both metrics (highest $R^2 = 0.5573$, lowest RMSE = 1.3097) and TVDI the bottom ($R^2 = 0.2211$, RMSE = 1.7373), with the remaining indices arrayed consistently between them.

The degradation of SAVI and MSAVI is best understood from their mathematical structure combined with the band-level quality assessment in Table 3. Unlike NDVI, these indices are not pure ratios: SAVI incorporates the additive soil-brightness correction factor L, and MSAVI contains a nonlinear square-root term, so per-band perturbations introduced by detail injection are not cancelled by the ratio and may instead be amplified, particularly in the NIR band, which both indices weight heavily and which displayed the weakest fidelity among the optical bands (CC = 0.9129, RMSE = 0.0397). The low SAM value (0.1391°) shows that the spectral-shape relationship between Red and NIR survived fusion, which is consistent with the finding that NDVI itself is not materially distorted by pansharpening (Procházka et al., 2026). At the same time, the sharper 0.62 cm/pixel product resolves more of the background mixture typical of the late generative phase (thinning canopy and weed cover) and soil background interference is a recognized disturbance for soil moisture estimation from vegetation indices (Jin-xi et al., 2025); higher-spatial-resolution imagery is moreover more susceptible to spectral distortions upon pansharpening (Beene et al., 2022). Notably, the decline is corroborated by the rank-based evidence in Table 4: SAVI and MSAVI were the only indices whose Spearman correlations weakened after fusion (rs = −0.718 → −0.593 and −0.704 → −0.593, significance dropping from $\alpha < 0.01$ to $\alpha < 0.05$), so the R^2 loss is not a regression artifact.

Table 6. Comparison of Root Mean Square Error (RMSE) for soil water content estimation between non-pansharpened and pansharpened spectral indices

Index	RMSE PAN	Non-PAN	RMSE PAN	Δ RMSE	$\Delta \%$	Remarks
NDVI	1.3111		1.3097	-0.0014	-0.1%	≈ stable
SAVI	1.4712		1.6098	+0.1387	+9.4%	▲ worse
MSAVI	1.4998		1.6183	+0.1185	+7.9%	▲ worse
CIre	1.5856		1.5854	-0.0002	-0.0%	≈ stable
NDRE	1.5024		1.5021	-0.0003	-0.0%	≈ stable
NDWI	1.4674		1.4670	-0.0004	-0.0%	≈ stable
CWSI	1.6478		1.6473	-0.0005	-0.0%	≈ stable
TVDI	1.7368		1.7373	+0.0005	+0.0%	≈ stable

Note: Δ RMSE = RMSE(PAN) − RMSE(Non-PAN)

By contrast, the red-edge and water-based indices were remarkably stable: CI_{re}, NDRE, NDWI, and CWSI changed by no more than +0.1% in R^2 and −0.0% in RMSE. Their normalized-difference or ratio formulations evidently offset band-level distortion, notably even though RedEdge recorded the second-lowest correlation coefficient among the optical bands ($CC = 0.9187$, Table 3), CI_{re} and NDRE barely moved after fusion. NDWI and CWSI behaved similarly, while TVDI remained unchanged but poor; pansharpening cannot rescue an index whose signal domain (thermal) has no meaningful correspondent in the panchromatic channel, the near-perfect LWIR CC (1.0000, Table 3) is best read as a resampling artifact rather than genuine spectral agreement.

The classical assumption tests in Table 7 add a critical third layer of evidence and substantially refine the interpretation of the R^2 ranking. Although NDVI achieved the highest R^2 , its residuals were heteroscedastic in both datasets (Breusch-Pagan $p = 0.011^*$), so its inference validity is compromised. SAVI and MSAVI violated the independence assumption in both products (Durbin-Watson $d = 0.933$ – 0.942^* , indicating strong positive autocorrelation of residuals), and pansharpened MSAVI additionally failed the normality test (Shapiro-Wilk $p = 0.038^*$). These violations have a substantive explanation: spatial patterns within field trials violate the assumption of independence of observations (Hawinkel et al., 2022), and when the errors of a regression model are spatially dependent, the resulting estimate of the error standard deviation is biased downwards, which can lead to a false conclusion that the regression is statistically significant (Lark, 2000). The fact that SAVI and MSAVI (precisely the indices whose predictive fit collapsed after fusion) show the strongest residual autocorrelation suggests that the fusion-degraded models leave systematic spatial structure unmodeled. NDWI also failed the independence test ($d = 2.883$ – 2.885^* , negative autocorrelation), and CWSI failed homoscedasticity ($p = 0.035^*$).

The only indices whose linear models satisfied all three classical assumptions simultaneously in both image products were the red-edge indices, CI_{re} (Shapiro-Wilk 0.469; Durbin-Watson 2.112–2.113; Breusch-Pagan 0.090) and NDRE (0.257; 2.128–2.130; 0.058), both with significant regressions ($p = 0.020$ and $p = 0.009$), while TVDI also passed all three assumptions but remained non-significant ($p = 0.077$). From a strictly statistical standpoint, then, CI_{re} and NDRE (not NDVI, despite its higher R^2) are the most defensible linear models for SWC estimation, and the decision to generate the SWC map from pansharpened NDRE ($R^2 = 0.4177$, $p = 0.009$, RMSE = 1.5021, all assumptions satisfied; Figure 6) is fully consistent with this evidence.

Finally, the moderate R^2 values observed here (0.22–0.56) must be read in the context of the wider literature. When indices are derived from a crop canopy, linear regression achieves only moderate accuracy, e.g., $R^2 = 0.533$ for oats under water deficit (Feng et al., 2025), whereas markedly higher performance has been reported for bare-soil scenes where the index–soil moisture signal is more direct ($R^2 = 0.89$, RMSE = 2.80%) (Khose & Mailapalli, 2024). Because canopy leaf moisture content can be used as a proxy to predict surface soil moisture (Qu et al., 2024), and because nonlinear algorithms consistently outperform linear regression in such settings, back-propagation neural networks reduced the RMSE of soil moisture estimation by 20.9% relative to multiple linear regression at 0–20 cm ($0.0110 \rightarrow 0.0087$) (Wang et al., 2024), the Table 5 results should be treated as a baseline rather than a ceiling. In practical terms, the three tables together support an index-specific processing rule: retain the non-pansharpened product when using SAVI or MSAVI, while the pansharpened product is safe for NDVI, CI_{re}, NDRE, NDWI, and CWSI; among all linear models tested, red-edge NDRE on the pansharpened product is the most statistically dependable choice for SWC mapping in the generative phase of sweet maize.

Table 7. Summary of classical assumption test results for linear regression models across non-pansharpened and pansharpened spectral indices

Index	Dataset	Normality (Shapiro-Wilk p)	Autocorrelation (Durbin-Watson d)	Heteroscedasticity (Breusch-Pagan p)
NDVI	Non-PAN	0.149	2.459	0.011*
NDVI	PAN	0.149	2.458	0.011*
SAVI	Non-PAN	0.107	0.933*	0.370
SAVI	PAN	0.052	0.942*	0.823
MSAVI	Non-PAN	0.066	0.925*	0.477
MSAVI	PAN	0.038*	0.938*	0.929
CI _{re}	Non-PAN	0.469	2.112	0.090
CI _{re}	PAN	0.469	2.113	0.090
NDRE	Non-PAN	0.257	2.128	0.058

Index	Dataset	Normality (Shapiro-Wilk p)	Autocorrelation (Durbin-Watson d)	Heteroscedasticity (Breusch-Pagan p)
NDRE	PAN	0.257	2.130	0.058
NDWI	Non-PAN	0.077	2.883*	0.074
NDWI	PAN	0.075	2.885*	0.075
CWSI	Non-PAN	0.441	2.277	0.035*
CWSI	PAN	0.439	2.279	0.035*
TVDI	Non-PAN	0.377	2.099	0.054
TVDI	PAN	0.379	2.099	0.054

Note: Normality was assessed using the Shapiro-Wilk test (H_0 : residuals are normally distributed; rejected when $p < 0.05$, marked *). Autocorrelation was assessed using the Durbin-Watson statistic (d), evaluated against the critical values dL and dU for $n = 15$ and $k = 1$; values falling outside the non-autocorrelation range ($dU < d < 4 - dU$) are marked *. Heteroscedasticity was assessed using the Breusch-Pagan test (H_0 : residuals are homoscedastic; rejected when $p < 0.05$, marked *).

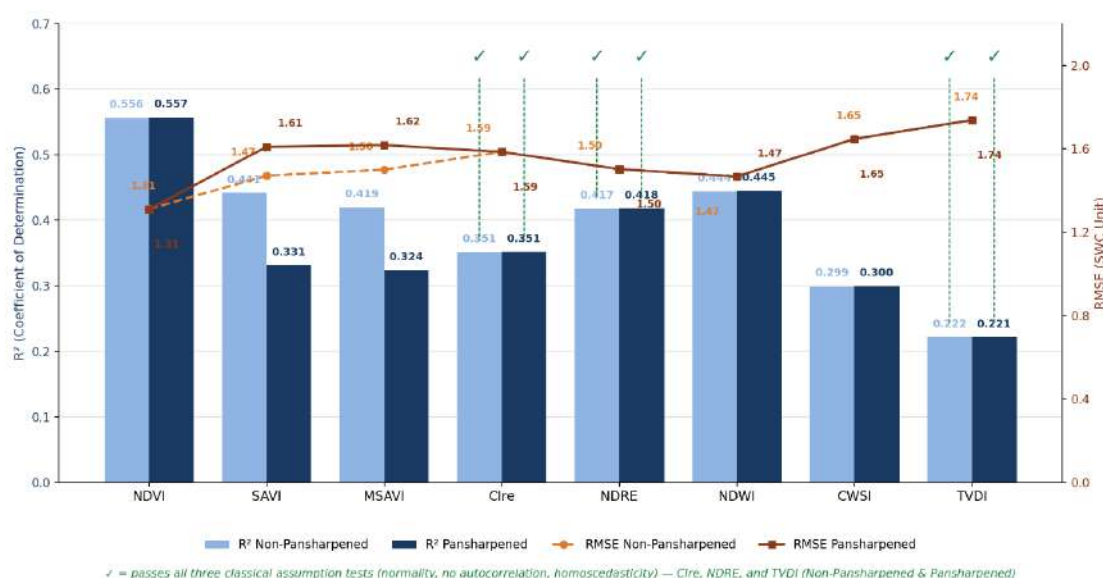


Figure 4. Comparison of linear regression model performance for non-pansharpener and pansharpener imagery (R^2 and RMSE)

3. Field Capacity-Based SWC Estimation for Regenerative Sweet Maize Farming

The SWC map in Figure 6 is operationally meaningful because it is anchored to a laboratory reference standard: the 15 in-situ samples collected at 5 cm depth were analyzed gravimetrically. The pansharpener NDRE model ($R^2 = 0.4177$, $RMSE = 1.5021$, $p = 0.009$) then extrapolates these point measurements across the entire 720 m² field at 0.62 cm/pixel, converting sparse point data into a continuous spatial map (Khose & Mailapalli, 2024) and overcoming the time-consuming, labor-intensive, and spatially discontinuous nature of conventional sampling (Qu et al., 2024). Because acquisition took place one day after heavy rainfall at the site, the soil was at field capacity, and the map can be read against this drained upper limit using the allowable-depletion framework: soil water depletion levels of 30%, 40%, and 50% reflect commonly used allowable depletion levels in irrigation scheduling (Darikandeh et al., 2026), and full irrigation is conventionally triggered at 50% depletion of soil available water (Ding et al., 2020). Zones still near field capacity therefore indicate where water can be withheld, while zones approaching the depletion threshold indicate where irrigation should be triggered, turning a bare moisture reading into a field-capacity-based irrigation decision.

The map supports site-specific rather than uniform irrigation, with well-documented economic and environmental gains: reviews report VRI water savings of 25–30% (Yaqoob et al., 2026), with water savings of up to 50% achievable (Alomari & Alfatlawi, 2024); in a corn study in Alabama, soil-sensor-based VRI applied 26% less irrigation water than uniform irrigation on the zones covering 55% of the field, with no statistically significant yield differences (Bondesan et al., 2022). Environmentally, VRI reduces nutrient loss, runoff, and groundwater contamination by limiting nitrate leaching (Yaqoob et al., 2026), and integrated

variable-rate irrigation with precision nitrogen management reduced nitrate leaching by 80% while adding an extra US\$1,900 ha⁻¹ in profit at a consistent yield level in Minnesota corn (Kechchour et al., 2025). The regenerative framework of this study amplifies these benefits: restoration of soil organic matter increases water retention more at field capacity than at the permanent wilting point, thereby enlarging the plant-available water capacity itself (Lal, 2020); regenerative management seeks soil conditions in which a greater proportion of soil moisture is readily available and infiltration is higher (Lankford & Orr, 2022); and regeneratively managed orchards have shown higher gravimetric soil moisture and faster water infiltration than their conventional counterparts (Fenster et al., 2021). Because the SWC map renders these moisture differences visible plot by plot, it can serve as a monitoring tool for how organic amendments improve water retention across the treatment plots.

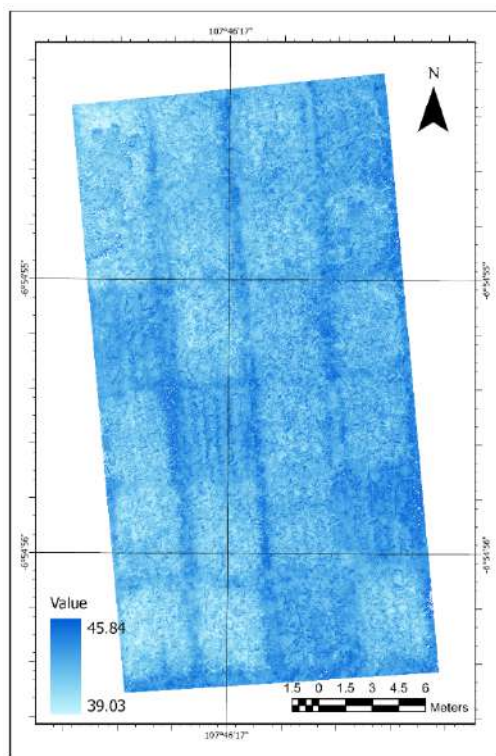


Figure 6. Spatial Distribution of Estimated Soil Water Content (SWC) in the Generative Phase of Sweet Maize, Derived from Pansharpener NDRE

The workflow is also timed to the most water-sensitive phase of the crop. Skipping irrigation at tasseling or silking reduced maize yield by 18–20% compared with full irrigation, and skipping both stages reduced yield by 47.7% (Kiranmai et al., 2025); yield losses can reach 50% when stress occurs at silking (Sah et al., 2020), and soil moisture during the tasseling stage has been shown to exert the greatest direct effect on maize grain yield (path coefficient 0.999) (Zhang et al., 2024). Because the workflow relies only on UAV imagery and gravimetric sampling, it can be repeated within the season at the moments when irrigation decisions carry the highest marginal value. Its limits should nevertheless be stated: the model was calibrated on a single 720 m² field at a single observation time when the soil was near field capacity, so transfer to other soils, moisture regimes, or seasons requires recalibration against fresh gravimetric samples, and the map is a snapshot that should be combined with weather and evapotranspiration information. Within these boundaries, Figure 6 demonstrates the core value proposition of this study, an index-specific pansharpener rule, validated against a gravimetric reference standard, that produces spatially explicit SWC information for field-capacity-based irrigation scheduling in regenerative sweet maize farming. Future research should nevertheless extend the proposed workflow to larger areas and more diverse agro-environmental conditions by increasing the number of sampling points and varying their distribution across soil types, moisture regimes, and crop growth stages, in order to strengthen the robustness, transferability, and statistical power of the calibrated regression models.

CONCLUSION

This study evaluated the effect of pansharpener on UAV-based multispectral imagery for estimating soil water content during the generative phase of sweet maize under regenerative farming practices. Pansharpener successfully enhanced spatial resolution to 0.62 cm/pixel while generally preserving spectral quality, as indicated by the low SAM value (0.1391°); nevertheless, the NIR and RedEdge bands exhibited the weakest band-level fidelity (CC = 0.9129 and 0.9187, respectively), and the near-perfect LWIR correlation (CC = 1.0000) was attributed to resampling rather than genuine spectral agreement. The effect of pansharpener

on SWC estimation was strongly index-dependent: the pure-ratio NDVI was essentially preserved ($R^2 = 0.5564 \rightarrow 0.5573$), whereas the soil-adjusted SAVI and MSAVI lost 25.0% and 22.7% of their explanatory power ($R^2 = 0.4414 \rightarrow 0.3312$ and $0.4195 \rightarrow 0.3241$), with corresponding increases in RMSE (+9.4% and +7.9%) — a deterioration corroborated by the weakening of their Spearman correlations and reflected in their residual autocorrelation; among all linear models, the red-edge indices CI_{re} and NDRE were the most statistically defensible, being the only models satisfying all classical assumptions in both image products, and the pansharpened NDRE model ($R^2 = 0.4177$, RMSE = 1.5021, $p = 0.009$) was therefore used to generate the SWC map. Interpreted against field capacity — the soil being at field capacity one day after heavy rainfall — the resulting map provides spatially explicit, zone-specific irrigation guidance across the 720 m² field, supporting the water-saving and nutrient-leaching reduction goals of variable-rate irrigation while enabling plot-level monitoring of how organic amendments improve soil water retention, consistent with the water-conservation objectives of regenerative sweet maize farming. Future research should extend this workflow to larger areas with more numerous and more diverse sampling points across soil types, moisture regimes, and growth stages in order to strengthen the robustness, transferability, and statistical power of the calibrated models.

ACKNOWLEDGEMENT

The author thanks the Ministry of Agriculture of the Republic of Indonesia for the financial support provided through the Master's Scholarship program (Beasiswa S2 Tugas Belajar Kementan), which made it possible to pursue this master's degree and carry out this research.

REFERENCES

1. D. Lestari, A. M. Firmansyah, R. P. CNAWP, M. Andriani, T. M. Syahniar, and P. R. Ratri, “Morpho-Physiological Response of Sweet Corn (*Zea mays* L. Var *saccharata* Sturt) Bonanza F1 Variety to Drought Stress and Potassium Fertilizer Application,” *JURNAL AGRONOMI TANAMAN TROPIKA (JUATIKA)*, vol. 7, no. 2, May 2025, doi: 10.36378/juatika.v7i2.4620.
2. J. M. Viceli, A. C. B. Acosta, E. Pocojeski, C. A. Casali, N. C. H. Kessler, and D. Tessaro, “Influence of soil water content on chemical and microbiological characteristics of selected riparian forests in southern Brazil,” *Wetl. Ecol. Manag.*, vol. 33, no. 2, Apr. 2025, doi: 10.1007/s11273-025-10041-8.
3. Y. Hao *et al.*, “Soil moisture controls over carbon sequestration and greenhouse gas emissions: a review,” Dec. 01, 2025, *Nature Research*. doi: 10.1038/s41612-024-00888-8.
4. Z. Cao, H. Gao, Z. Nan, Y. Zhao, and Z. Yin, “A semi-physical approach for downscaling satellite soil moisture data in a typical cold alpine area, Northwest China,” *Remote Sens. (Basel)*, vol. 13, no. 3, pp. 1–26, Feb. 2021, doi: 10.3390/rs13030509.
5. B. E. Cahyono, P. O. Putri, A. Subekti, A. T. Nugroho, and K. Nishi, “Analysis of soil moisture as an indicator of land quality using vegetation index (SAVI and NDMI) retrieved from remote sensing data in Jember - Indonesia,” in *AIP Conference Proceedings*, American Institute of Physics Inc., Mar. 2022. doi: 10.1063/5.0078761.
6. F. Lu, Y. Sun, and F. Hou, “Using UAV visible images to estimate the soil moisture of steppe,” *Water (Switzerland)*, vol. 12, no. 9, Sep. 2020, doi: 10.3390/W12092334.
7. M. Jurišić, D. Radočaj, I. Plaščak, S. D. Galić, and D. Petrović, “THE EVALUATION OF THE RGB AND MULTISPECTRAL CAMERA ON THE UNMANNED AERIAL VEHICLE (UAV) FOR THE MACHINE LEARNING CLASSIFICATION OF MAIZE,” *Poljoprivreda*, vol. 28, no. 2, pp. 74–80, 2022, doi: 10.18047/poljo.28.2.10.
8. Q. Chen, E. Vaudour, A. C. Richer-de-Forges, and D. Arrouays, “Spectral indices in remote sensing of soil: definition, popularity, and issues. A critical overview,” *Remote Sens. Environ.*, vol. 329, p. 114918, 2025, doi: <https://doi.org/10.1016/j.rse.2025.114918>.
9. A. Sekrecka, M. Kedzierski, and D. Wierzbicki, “Pre-processing of panchromatic images to improve object detection in pansharpened images,” *Sensors (Switzerland)*, vol. 19, no. 23, Dec. 2019, doi: 10.3390/s19235146.
10. E. Alcaras and C. Parente, “The Effectiveness of Pan-Sharpener Algorithms on Different Land Cover Types in GeoEye-1 Satellite Images,” *J. Imaging*, vol. 9, no. 5, May 2023, doi: 10.3390/jimaging9050093.
11. K. Rokni, “INVESTIGATING THE IMPACT OF PAN SHARPENING ON THE ACCURACY OF LAND COVER MAPPING IN LANDSAT OLI IMAGERY,” *Geodesy and Cartography (Vilnius)*, vol. 49, no. 1, pp. 12–18, Mar. 2023, doi: 10.3846/gac.2023.15308.
12. S. Modak, J. Heil, and A. Stein, “Pansharpening Low-Altitude Multispectral Images of Potato Plants Using a Generative Adversarial Network,” *Remote Sens. (Basel)*, vol. 16, no. 5, Mar. 2024, doi: 10.3390/rs16050874.
13. F. Dadrass Javan, F. Samadzadegan, S. Mehravar, A. Toosi, R. Khatami, and A. Stein, “A review of image fusion techniques for pan-sharpening of high-resolution satellite imagery,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 171, pp. 101–117, Jan. 2021, doi: 10.1016/j.isprsjprs.2020.11.001.

14. M. Ciotola *et al.*, “Hyperspectral Pansharpening: Critical review, tools, and future perspectives,” *IEEE Geosci. Remote Sens. Mag.*, vol. 13, no. 1, pp. 311–338, Mar. 2025, doi: 10.1109/MGRS.2024.3509139.
15. MicaSense, “‘Panchromatic Band – FAQs,’ MicaSense Knowledge Base.”
16. L. Wu, X. Jiang, J. Peng, G. Wu, and X. Xiong, “A spectral preserved model based on spectral contribution and dependence with detail injection for pansharpening,” *Sci. Rep.*, vol. 13, no. 1, p. 6882, Apr. 2023, doi: 10.1038/s41598-023-33574-5.
17. Agisoft, “‘Orthomosaic Pansharpening,’ Agisoft Helpdesk.”
18. J. Procházka, J. Komárek, D. Moravec, J. Rous, and T. Klouček, “Pansharpening largely preserves the normalized difference vegetation index: a multi-sensor comparison with PRISMA, Landsat 9, and field spectroscopy,” *Frontiers in Remote Sensing*, vol. 6, Jan. 2026, doi: 10.3389/frsen.2025.1713895.
19. P. Ghimire, D. Lei, and N. Juan, “Effect of Image Fusion on Vegetation Index Quality—A Comparative Study from Gaofen-1, Gaofen-2, Gaofen-4, Landsat-8 OLI and MODIS Imagery,” *Remote Sens. (Basel)*, vol. 12, no. 10, p. 1550, May 2020, doi: 10.3390/rs12101550.
20. M. A. Haque *et al.*, “Effects of Environmental Conditions on Vegetation Indices from Multispectral Images: A Review,” Aug. 01, 2024, *Korean Society of Remote Sensing*. doi: 10.7780/kjrs.2024.40.4.1.