COMPREHENSIVE ANALYSIS OF VEGETATION INDICES USING MULTITEMPORAL DRONE IMAGES

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Abstract

The use of drones (UAVs) has been showing an increasing trend in recent years. The available aerial vehicles and the cameras or camera systems mounted on them significantly influence—and in some cases may even limit—their effective and reliable application in surveying agricultural areas, while also meeting data security requirements. The extractable information content of the produced visual and non-visual data is not only determined by the data itself but is also greatly affected by the methods used for processing and analysis. This paper focused on the analysis and comparison of vegetation indices derived from multispectral drone imagery, specifically for monitoring corn growth and health. The introduction outlines the significance of using these indices in agriculture and environmental protection, aiming to enhance sustainable and cost-effective farming practices. The study emphasizes the potential benefits of the precise and timely monitoring of vegetation indices contributes to improved crop yields, optimized nutrient and water usage, and minimized environmental impacts. The research involves capturing images at different times and altitudes using both RGB and multispectral drones to gather reliable data about plant health during various growth stages. The methodology section describes the study area, the drone and imaging systems used, and the software applied for data processing. It details the specific vegetation indices calculated, both discrete and non-discrete, and the statistical methods employed to analyse their correlations. The results section discusses findings related to the discrete and non-discrete indices, how they reflect the phenological phases of vegetation throughout the growing season and might replace to complement.

Keywords: vegetation index, UAV, multitemporal, drone images

1. Introduction

The utilization of vegetation indices calculated from multitemporal drone imagery has garnered significant attention in the domains of agriculture and environmental management [1,2,3,4,]. These indices are pivotal for assessing plant health and growth, particularly for crops like corn, where accurate and timely information can substantially impact yield and environmental sustainability [5].

Accurate vegetation indices enable precision agriculture, allowing farmers to monitor crop conditions, optimize input usage (like water and fertilizers), and increase productivity. By utilizing drone technology, this study endeavours to make such advanced techniques accessible and cost-effective, especially for smaller farms.

The main goal of vegetation indices collected through remote sensing is to analyse and monitor vegetation changes over time on a seasonal or annual scale [6]. Data collection is carried out using satellite and/or aerial platforms, in which unmanned aerial vehicles (UAVs) are playing an increasingly important role [7,8], all of which can be supplemented by additional laboratory measurements [9]. Analyses include information-theoretic entropy [10,11] or spectral structure-based measurements [12,13,14,15]. These indices are optimized with specialized algorithms based on the characteristics of the study area and vegetation, most commonly utilizing the red and near-infrared spectral domains [16,17].

The study makes a case for integrating drone-based assessments into routine agricultural practices to support sustainability. This approach aligns with global efforts to minimize the adverse environmental impact of farming activities while maximizing resource efficiencies. The primary objective of this research is to determine the viability and effectiveness of using expanded and alternative (non-discrete) vegetation indices to monitor corn growth.

Comparative Analysis: A critical comparison between traditional discrete vegetation indices (such as NDVI [18]) and potential non-discrete indices is carried out to discover alternatives that might provide more nuanced insights or replace traditional measures in certain conditions [19,20].

Through meticulous analysis, the study aims to enhance crop monitoring techniques, providing data-driven insights for optimizing farming operations, enhancing yield, and implementing sustainable agricultural practices.

Data Collection via Drone Technology: Multitemporal imaging flights conducted at altitudes of 80 m and 120 m capture the dynamic growth phases of corn, providing comprehensive data sets. This dual-altitude approach assures depth and accuracy in monitoring various stages of crop development.

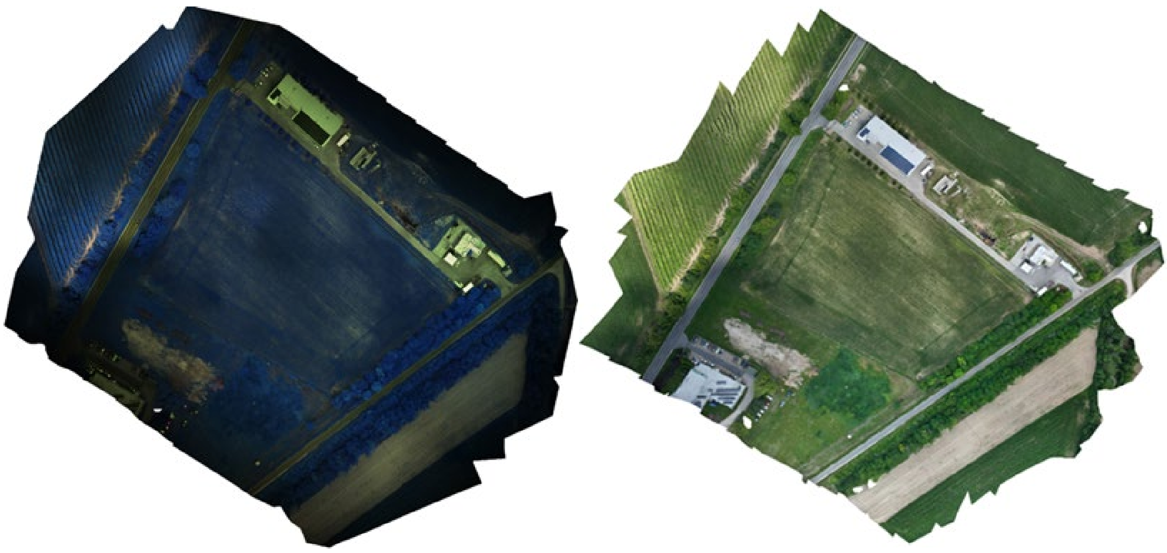
Analysis of Indices Correlations: By establishing relationships between discrete and non-discrete indices, the research attempts to unlock potential new avenues for effective crop monitoring. The goal is to ascertain if and how non-discrete indices can serve as adequate surrogates for more conventional metrics.

2. Materials and Methods

The experiments were conducted in a 1.7-hectare field in Lengyeltóti, bordered by a forest and a vineyard. The field, previously utilized for winter wheat cultivation, presents a typical environment for corn farming in the region.

The farming community here utilizes a cooperative model, pooling resources for machinery and labour to achieve better yield results. Despite achieving respectable productivity in the face of volatile weather patterns, challenges remain around adaptation and maximization of resource use.

Figure 1. Lengyeltóti crop field 17.06.2024. TIF (left), VIS (right) orthophoto



2.1. Drone and Imaging Systems

A DJI Mavic 3 Multispectral drone was used for data acquisition. Its multispectral and RGB sensors are essential for calculating vegetation indices, providing comprehensive spectral data that reveals the physiological status of the corn throughout growth stages.

The drone's ability to capture high-resolution images along various spectral bands, including the critical near-infrared, facilitates the calculation and evaluation of indices like NDVI, among others.

Table 1. Mavic 3M camera specification [21]

Parameter	RGB Camera	Multispectral Camera	Notes
Sensor Type	4/3 CMOS	1/2.8" CMOS (per band)	
Effective Pixels	20 MP	5 MP (per band)	
Bands/Channels	RGB (Red,Green,Blue)	Green,Red,Red-Edge,NIR	
Aperture	f/2.8–f/11	f/2.8 (fixed)	
Shutter Speed	8–1/8000 s	8–1/8000 s	
ISO Range	100–6400	100–800	
FOV (Field of View)	84°	61.2° (per band)	
Focal Length (35mm equiv.)	24 mm	26 mm	
Image Size	5280×3956 px	1280×960 px (per band)	
Video Resolution	Up to 4K (3840×2160 @ 30fps)	1080p @ 30fps	
Photo Format	JPEG/DNG	JPEG	
Video Format	MP4 (H.264/H.265)	MP4 (H.264)	
Minimum Shooting Interval	0.7 s	2 s (simultaneous)	
Focus Modes	MF/AFC/AFS	Fixed Focus	
Zoom	Digital 1–56x	None	
Storage	microSD card	microSD card	Selectable for RGB
Exposure Modes	Auto/S/A/M	Auto/S/M	
Exposure Compensation	-3.0 to +3.0 EV	-3.0 to +3.0 EV	
Gimbal Control	3-axis	3-axis	Shared gimbal
Special Features	Adjustable aperture	Vegetation index/color map	NDVI and other indices from MS
Simultaneous Capture	Supported	Supported	Can capture RGB+MS together
App Support	DJI Pilot 2	DJI Pilot 2	
Side-by-side View	Supported	Supported	

2.2. Software and Processing Protocols

DJI Pro Software Used for flight planning, ensuring appropriate coverage and overlap of captured images necessary for precise data synthesis.

Figure 2. DJI Pro flight plan

DXO PhotoLab and Agisoft Metashape were employed for quality enhancement and orthophoto generation, respectively. QGIS served as the main platform for computing vegetation indices through standardized formulas. Applied noise reduction to VIS images using DXO PhotoLab 5, correcting vignetting, distortion, blurriness, and chromatic aberration. Only relevant images were retained. Agisoft Metashape 1.6.4 was used for alignment, point cloud generation, texture mapping, and orthophoto creation, requiring significant computational resources.

Vegetation indices (NDVI, GNDVI, VDVI [22]) were computed in QGIS 3.26.3, with the agricultural area extracted, normalized, and classified into ten groups. Results were rounded and saved as an HTML file.

Excel analysis determined peak values, spatial distribution, statistical parameters, and overlap. Python 3.11.4 (PIL, Image; skimage.measure, shannon_entropy) modules facilitated comparison between discrete and non-discrete indices [23,24,25,26].

3.3. Computed Indices

The study examined 7 discrete indices alongside 34 non-discrete indices. This extensive range enabled a detailed exploration of each indices's reliability and applicability in various growth phases.

Indices such as NDVI, GNDVI, OSAVI [27,28], and non-discrete formulas were assessed for their reflection of plant health. These computations were key to determining the potential replacements and supplements for traditional discrete indices.

Table 2. Non-Discrete indices [29,30,31] R: red band, G: green band, B: blue band, r: R/(R+G+B), g: G/(R+G+B), b: G/(R+G+B)

Index	Name	Formula	Range	Reference
BCC	Blue Chromatic Coordinate Index	B/(R+G+B)	0 1	De Swaef et al. 2021
BGI	Simple blue-green Ratio; Blue Green Pigment Index	B/G	0 <	Zarco-Tejada et al. 2005
BI	Brightness Index	sqrt((R2+B2+G2)/3)	0 - 256	Richardson & Wiegand 1977
BRVI	Blue Red Vegetation Index	(B-R)/(B+R)	-1 +1	De Swaef et al. 2021
CIVE	Color Index of Vegetation	0,441*R-0,881*G+0,385*B+18,78745	-∞ +∞	Kataoka et al. 2003
ExB	Excess Blue	1.4*b-g	-1 +2	Mao et al 2003
ExG	Excess Green	2g-r-b	-1 +2	Woebbecke et al. 1995
ExGR	Excess Green-Excess Red	(2*g-r-b)-1.4*r-g	-∞ 1	Meyer & Neto 2008
ExR	Excess Red	1.4r-g	-1 +2	Mao et al 2003
GCC	Green Percentage Index	G/(R+G+B)	0 1	Richardson et al. 2007
GLI	Green Leaf Index	(2G-R-B)/(2G+R+B)	-1 +1	Louhaichi et al., 2001
GR	Simple red-green Ratio	G/R	0 <	Gamon & Surfus 1999
GRVI	Green Red Vegetation Index	(G-R)/(G+R)	-1 +1	Motohka et al. 2010
HI	Primary Colors Hue Index	(2*R-G-B)/(G-B)	-∞ +∞	Escadafal et al. 1994
HUE	Overall Hue Index	atan(2*(B-G-R)/30.5*(G-R))	-∞ +∞	Escadafal et al. 1994
IKAW	Kawashima index	(R-B)/(R+B)	-1 +1	Kawashima & Nakatani 1998
IOR	Iron Oxide Ratio	R/B	0 <	Segal 1982
IPCA	Principal Component Analysis Index	0.994*|R − B| + 0.961*|G − B| + 0.914*|G − R|	-∞ +∞	Saberioon et al. 2014
MGRVI	Modified Green Red Vegetation Index	(G2-R2)/(G2+R2)	-1 +1	Bending, et al. 2015
MPRI	Modified Photochemical Reflectance Index	(G-R)/(G+R)	-1 +1	Yang et al. 2008
MVARI	Modified Visible Atmospherically Resistant Vegetation Index	(G-B)/(G+R-B)	-∞ +∞	Yang, et al. 2008
NDI	Normalized Difference Index	128*(((G-R)/(G+R))+1)	0 - 256	Mcnairn & Protz 1993
NGBDI	Normalised Green Blue Difference Index	(G-B)/(G+B)	-1 +1	Du & Noguchi 2017
NGRDI	Normalised Green Red Difference Index	(G-R)/(G+R)	-1 +1	Tucker 1979; Hunt et al. 2005
NGRVI	New Green-Red Vegetation Index	(G2+R2)/(G2-R2)	-256 +256	Xianlong et al. 2019
RCC	Red Chromatic Coordinate Index	R/(R+G+B)	0 1	De Swaef et al. 2021
RGBVI	Red Green Blue Vegetation Index	(G2-(B*R))/(G2+(B*R))	-1 +1	Bending et al. 2015
PRI	Photochemical Reflectance Index	R/G	0 <	Gamon et al. 1997
SAVI	Soil Adjusted Vegetation Index	(1.5*(G-R))/(G+R+0.5)	-∞ +∞	Li, et al. 2010
SCI	Soil Color Index	(R-G)/(R+G)	-1 +1	Mathieu et al. 1998
SI	Spectral Slope Saturation Index	(R-B)/(R+B)	-1 +1	Escadafal et al. 1994
TGI	Triangular Greenness Index	G-0.39*R-0.61*B	-∞ +∞	Hunt et al. 2013
VARI	Visible Atmospherically Resistant Vegetation Index	(G-R)/(G+R-B)	-∞ +∞	Gitelson et al. 2002
VDVI	Visible Band-Difference Vegetation Index	(2G-R-B)/(2G+R+B)	-1 +1	Wang et al., 2015
VEG	Vegetative Index	G/(R^0.667*B^0.334)	0 <	De Swaef et al. 2021
VIgreen	Vegetation Index Green	(G-R)/(G+R)	-1 +1	Gitelson, et al. 2002
vNDVI	Visible NDVI	0.5268*(R^-0.1294*G^0.3389*G^-0.3118)	0 <	Costa, et al. 2020
WI	Woebbecke Index	(G-B)/(R-G)	-∞ +∞	Woebbecke et al. 1995
IRGBVI	Improved-Red-Green-Blue Vegetation Index	(5*G^2-2*R^2-5*B^2)/(5*G^2+2*R^2+5*B^2)	-1 +1	Chen et al 2024

Table 3. Discrete indices [32,33,34,35,36,37,38,39]

Index	Name	Formula	Range	Reference
NDVI	Normalized Difference Vegetation Index	(NIR-R)/(NIR+R)	-1 +1	Rouse et al. 1973
GNDVI	Green Normalized Difference Vegetation Index	(NIR-G)/(NIR+G)	-1 +1	Gitelson et al. 1996
NDRE	Normalized Difference Red Edge Index	(NIR-RE)/(NIR+RE)	-1 +1	Barnes et al. 2000
TNDVI	Transformed Normalized Difference Vegetation Index	1,5*(NIR–RED)/(NIR+RED)+0.5	-1 +1	Pervaiz et al. 2019
NDWI	Normalized Difference Water Index	(GREEN-NIR)/(GREEN+NIR)	-1 +1	McFeeters et al. 1996
SAVI	Soil-Adjusted Vegetation Index	((NIR - RED) / (NIR + RED + L)) x (1 + L)	-1 +1	Huete et al. 1988
OSAVI	Optimizes Soil-Adjusted Vegetation Index	(NIR-RED) / (NIR+RED+0,16)	-1 +1	Rondeaux et al. 1996

3. Results

3.1. Performance of Discrete Indices

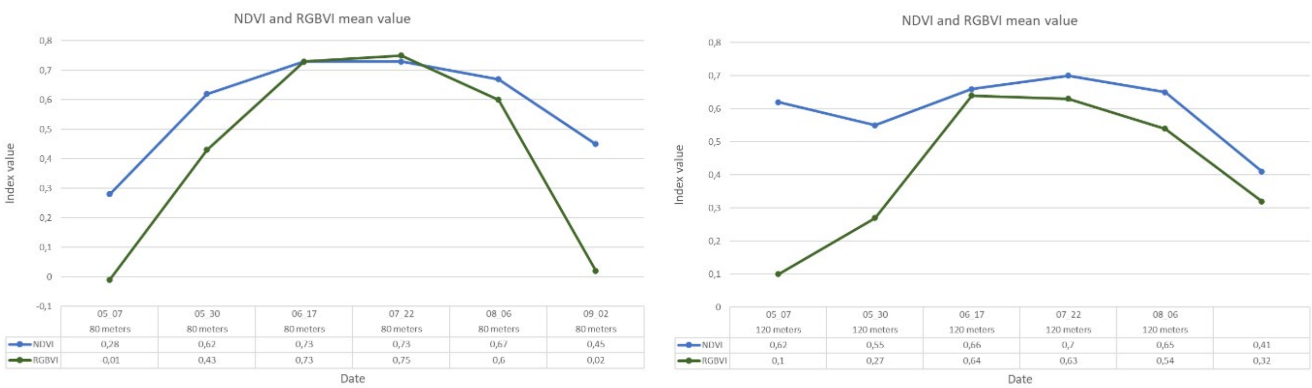
The research categorized vegetation indices into discrete and non-discrete groups. Discrete indices are derived from predefined spectral bands, whereas non-discrete indices are generated through various spectral combinations, allowing for greater adaptability to environmental changes. The evaluation of indices performance was based on imagery taken at different times and two distinct altitude levels (80m and 120m).

Among the discrete indices, NDVI, GNDVI, NDRE, SAVI, OSAVI, TNDVI [40,41], and NDWI were selected as they effectively reflected the growth status of maize. NDVI and GNDVI demonstrated the most stability, reliably tracking phenological phases, while NDRE showed greater sensitivity, resulting in more significant variations across different periods.

3.2. Non-Discrete Indices and Their Potential

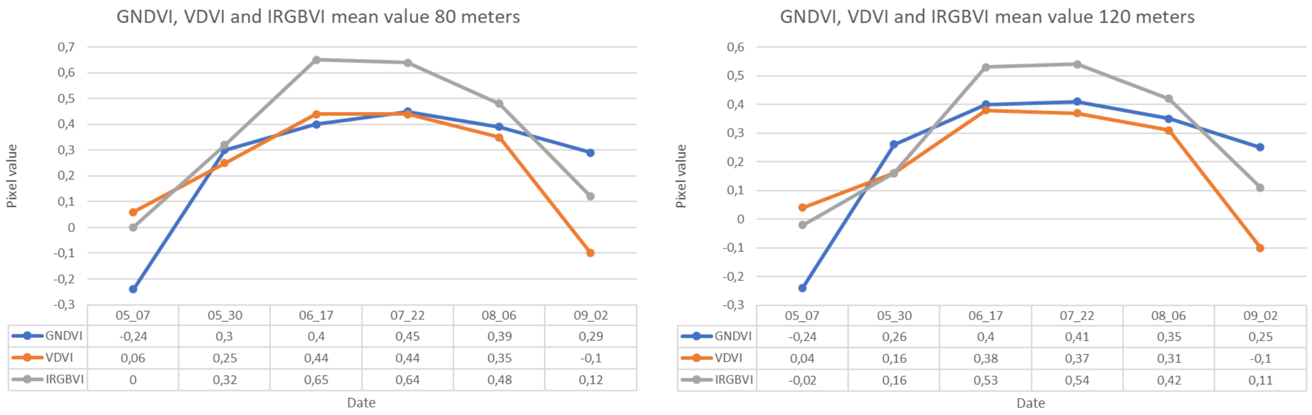
Among the non-discrete indices, 17 were selected from the original 39, as they showed the strongest correlation with discrete indices. IRGBVI performed particularly well in relation to GNDVI, while MVARI exhibited a strong association with OSAVI. Highlighted a subset of 17 promising non-discrete indices that demonstrated satisfactory correlation (above 65%) with key discrete indices across multiple growth stages. This highlights the potential for these indices in real-world agricultural applications.
Several non-discrete indices offered nuanced insights into crop health that discrete indices might have overlooked, revealing conditions pertinent to plant vigour and stress with potentially higher fidelity in certain contexts.
For the NDVI indices, the highest correlation values were observed with RGBVI and NGBDI indices. The RGBVI exhibited an average correlation of 84% at 80 meters and 82% at 120 meters, resulting in a minor -2% deviation. This indicates stable behaviour, suggesting that RGBVI demonstrates strong potential as an alternative to NDVI.

Figure 3. NDVI and RGBVI vegetation indices, full period on 80 (left) and 120 meters (right)



The IRGBVI indices showed the strongest correlation with GNDVI, with an average correlation of 85% at 80 meters and 81% at 120 meters, resulting in only a -4% deviation. These values indicate stability, and the trends of these indices are nearly identical, making IRGBVI a viable substitute.

Figure 4. GNDVI, IRGBVI and VDVI vegetation indices, full period on 80 (left) and 120 meters (right)



For the OSAVI indices, MVARI exhibited the highest correlation value, particularly in terms of stable trends. The average correlation was 68% at 80 meters and 70% at 120 meters, resulting in a +2% deviation, indicating that it remains stable at higher altitudes. The mean values of OSAVI and MVARI indices fall within the same range, suggesting that MVARI could potentially serve as a substitute.

Figure 5. OSAVI and MVARI vegetation indices, full period on 80 (left) and 120 meters (right)

3.3. Histograms and Distribution Observations

Histogram analysis provided clarity on the variability of responses across growth stages, highlighting which indices-maintained consistency despite growing conditions' dynamism.

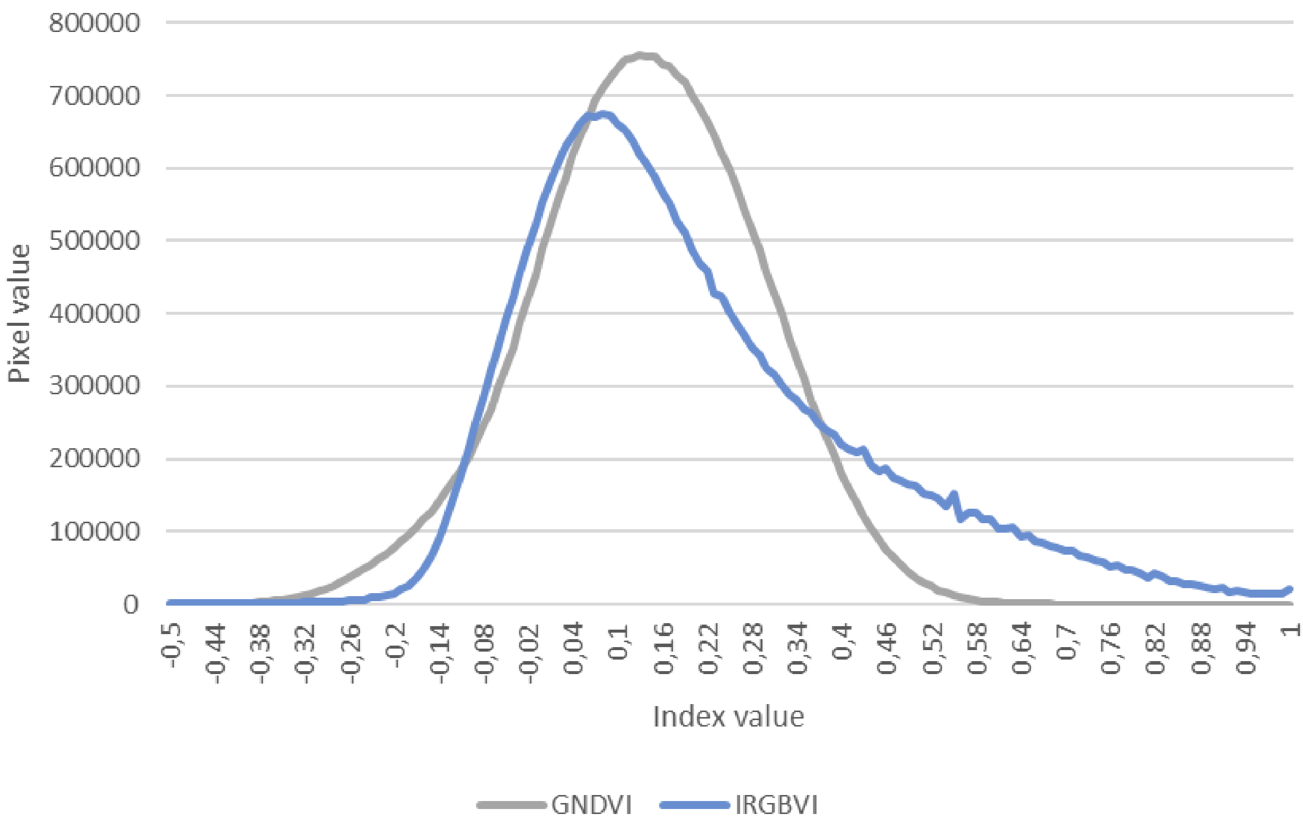
The histogram analyses revealed distribution patterns beneficial for identifying robust indices suitable for real-world applications, particularly in distinguishing health metrics across varied crop conditions.

The histogram analysis focused on two key indices pairs: GNDVI–IRGBVI and OSAVI–MVARI. During the evaluation, the distribution of these indices was examined across different time points and altitude levels to determine their stability and comparability.

3.4. Histogram Analysis of GNDVI and IRGBVI

The histograms clearly demonstrated that IRGBVI consistently follows the variations in GNDVI values, with a significant overlap in their distributions throughout the entire study period. At the lower altitude of 80 meters, the indices curves appeared more balanced, with fewer extreme values, indicating that IRGBVI effectively reflects the changes represented by GNDVI.

Figure 6. GNDVI and IRGBVI histogram comparison example (22 July)



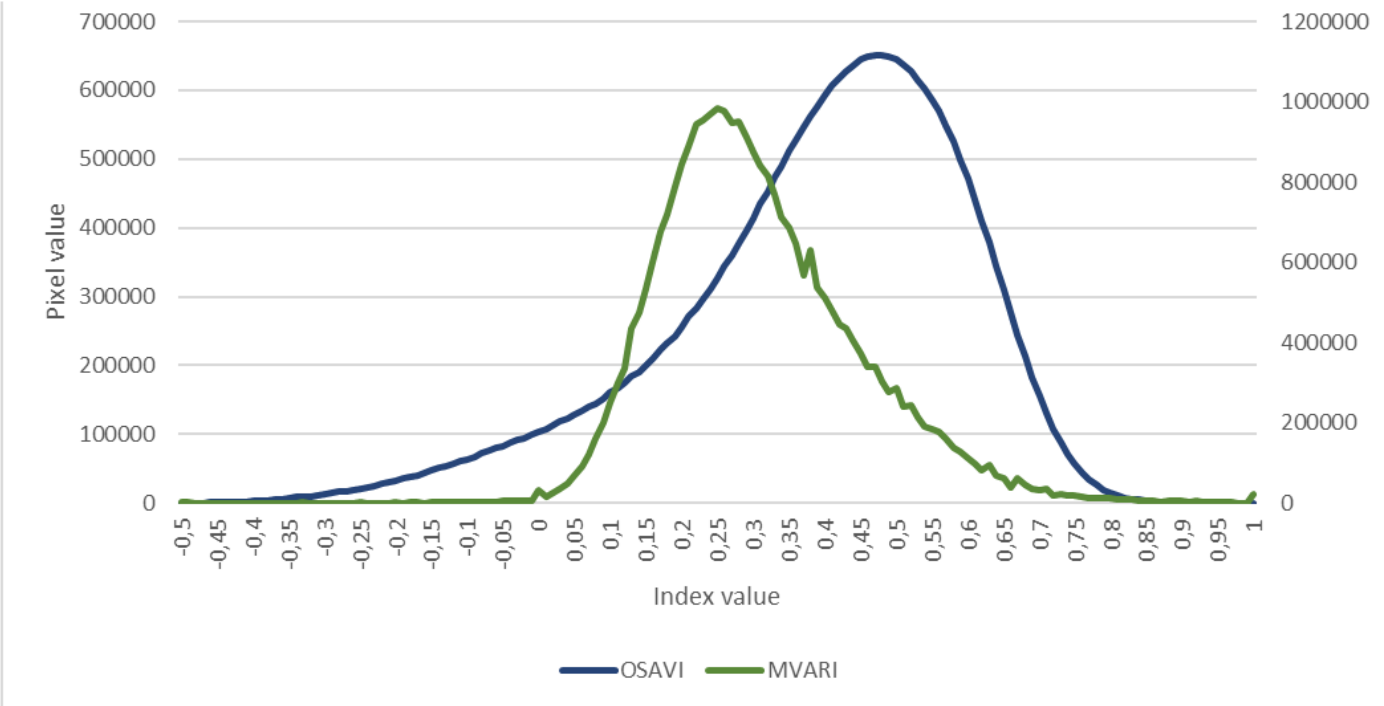
At 120 meters, minor deviations were observed: IRGBVI exhibited a slightly narrower distribution, suggesting that higher-altitude imaging may introduce greater variability. However, the mean values and overall characteristics of both indices remained closely aligned, reinforcing the conclusion that IRGBVI demonstrates strong potential as a suitable substitute for GNDVI, particularly at lower flight altitudes.

3.5. Histogram Analysis of OSAVI and MVARI

The comparison between OSAVI and MVARI indices revealed a strong similarity in their behaviour. The OSAVI curve followed a well-defined structure, clearly representing vegetation characteristics. In contrast, the MVARI histogram exhibited less concentrated peaks, yet the overall distribution of both indices maintained a close relationship.

When examining the effect of altitude, the distribution differences between OSAVI and MVARI remained minimal, particularly in the 120-meter imagery. Interestingly, MVARI demonstrated greater stability at higher altitudes, suggesting that this index is less sensitive to altitude variations. This stability further reinforces the conclusion that MVARI can serve as a reliable alternative to OSAVI.

Figure 7. OSAVI and MVARI histogram comparison example (22 July)



In summary, the analysis indicates that IRGBVI and MVARI indices effectively represent the behaviour of GNDVI and OSAVI indices, particularly at lower altitude levels. IRGBVI performed exceptionally well at 80 meters, while MVARI remained reliable even at 120 meters. Based on the data, these non-discrete indices provide a viable alternative to discrete indices, making their application particularly advantageous under certain conditions.

3.6. Evaluating Data Quality through Entropy

The entropy-based analysis aims to provide deeper insights into the information content and variability of indices images. Entropy is a statistical measure that expresses the degree of order or uncertainty in data. Higher entropy values indicate greater information content and complexity, while lower values suggest more homogeneous and less variable areas.

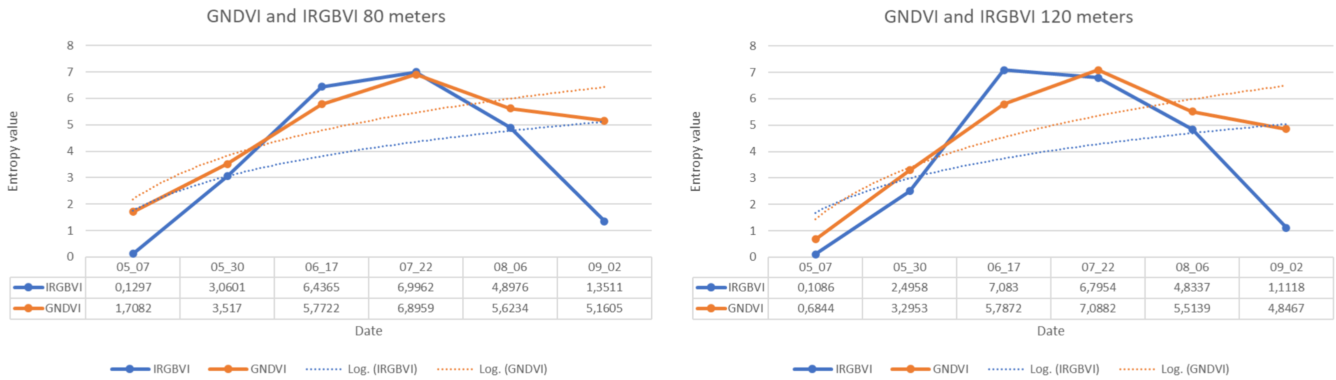
The entropy analysis underscored the disparities in data integrity and noise among different indices, with the quality of the green spectral value significantly influencing the overall interpretive reliability.

Insights from entropy evaluations pointed toward the necessity of careful indices selection in pragmatic agricultural settings, underscoring the interconnections between data quality and actionable agronomic insights.

During the study, entropy calculations were performed on each examined indices image, separately for each time point and altitude level. The results revealed significant differences in entropy values for IRGBVI and GNDVI, as well as OSAVI and MVARI, leading to important conclusions about their stability and applicability.

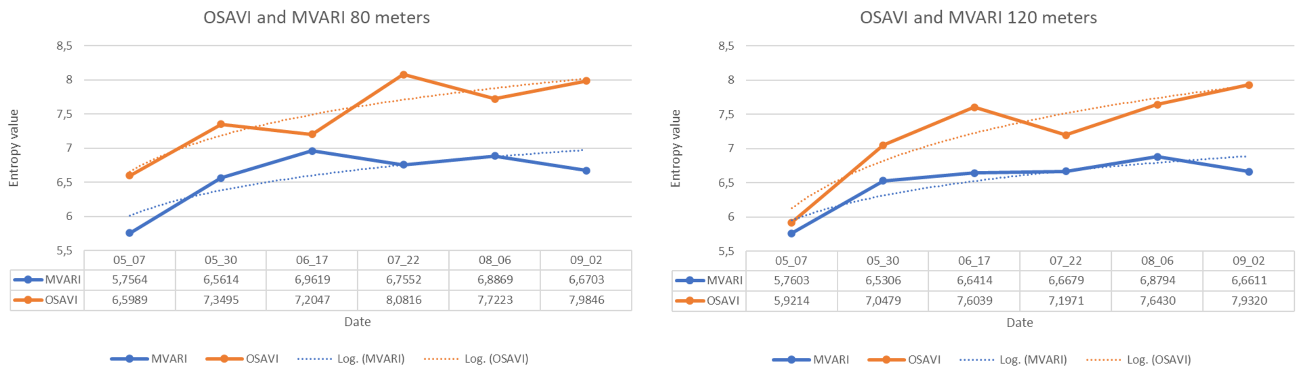
For the IRGBVI and GNDVI indices, entropy values were higher at 80 meters, indicating that images captured at lower altitudes contained more detail and exhibited greater variability. At 120 meters, entropy decreased, suggesting that images taken at higher altitudes were more homogeneous and less rich in detail. This aligns with the observation that IRGBVI consistently follows the variations in GNDVI values, but as altitude increases, the information content may diminish.

Figure 8. GNDVI and IRGBVI indices image entropy



For the OSAVI and MVARI indices, entropy values were more stable at 120 meters, whereas at 80 meters, they exhibited greater fluctuations. This suggests that MVARI is less sensitive to altitude variations and maintains reliable information content even at higher altitudes. In contrast, OSAVI showed significant entropy reductions at certain time points, likely due to soil effect compensation, indicating that this index may be more sensitive to environmental factors.

Figure 9. OSAVI and MVARI indices image entropy



Overall, the entropy-based analysis confirmed that IRGBVI and MVARI indices exhibit slightly lower but more stable information content, making them reliable alternatives to discrete indices under certain conditions. IRGBVI showed high entropy at 80 meters, while MVARI remained stable even at 120 meters, indicating that the applicability of these indices depends on flight altitude and environmental variations.

4. Conclusions

The research affirms the critical role of UAV-based multispectral data in offering precise vegetation metrics that effectively monitor corn growth and health. This empowers farmers with actionable information that facilitates sound decision-making in crop management.

Non-discrete indices like IRGBVI and MVARI displayed potential as substitutes or complements to traditional discrete indices. These alternatives could be particularly beneficial for specific phenological monitoring or when traditional metrics face limitations. The study encourages further validation and application of these findings across different crops and geographical locations to generalize the indices' effectiveness and reliability.

Research should focus on testing the efficacy of non-discrete indices under diverse environmental conditions and crop types, homing in on adaptive practices that bolster agricultural sustainability. Continuous technological improvements are expected to enhance data acquisition processes further, reinforcing agricultural ecosystems.

The outcomes pave the way for considering these indices in standard agricultural protocols, enhancing environmental stewardship, and innovation in farming methods.

By equipping farmers with enhanced tools for monitoring and managing crops, the findings support broader adoption of sustainable practices that conserve resources while maintaining or boosting productivity.

In summary, through an in-depth exploration of both established and new vegetation indices, the results highlighted the profound impact of integrating UAV technology and advanced analytics into agriculture. The detailed insights into various indices' strengths and applicability provide a vital foundation for improving practices and developing more environmentally conscious and efficient farming strategies globally. Through rigorous, continued exploration, agriculture can gradually adapt to modern challenges, ensuring long-term benefits for economies and ecosystems alike. Looking ahead, we intend to continue the investigations we have begun regarding non-discrete indices, across multiple plant cultures, throughout the entire vegetation period. This will include examining the effects of different times of day and irradiation conditions, which will ultimately provide further certainty about the possibilities for refining and utilizing non-discrete bands.

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