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Original Article

A Comparative Analysis of RG-NIR and Multispectral Camera Imagery Acquired via Unmanned Aerial Vehicles for Sugarcane Crop Detection

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ABSTRACT
This study compares of two types of multispectral cameras, DJI Mavic 3M and MAPIR RGN, in assessing sugarcane health through reflectance analysis and vegetation indices. The research was conducted in a sugarcane plantation in Sidoarjo, East Java, using multispectral data captured by drones. The analysis evaluated the relationship between reflectance values, vegetation indices, and chlorophyll content in sugarcane. Results indicate that the MAPIR RGN camera outperformed the DJI Mavic 3M in measuring chlorophyll content. The Near Infrared (NIR) channel of MAPIR RGN showed the highest correlation with chlorophyll ($r = 0.2166$). Additionally, the Ratio Vegetation Index (RVI) from MAPIR RGN had the strongest correlation ($r = 0.2716$) among all vegetation indices. Conversely, the DJI Mavic 3M camera demonstrated weaker correlations across all reflectance channels and vegetation indices. These differences may stem from sensor sensitivity and the quality of data produced by each camera. Based on these findings, the MAPIR RGN camera is recommended for precision agriculture applications in sugarcane plantations, as it provides more accurate spectral data reflecting vegetation health. This study underscores the relevance of drone technology in enhancing the efficiency of sugarcane plantation management.

KEYWORDS
Remote Sensing; Multispectral Camera; Drone/UAV; Precision Farming; Vegetation Index

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INTRODUCTION

Precision agriculture has become a key strategy in achieving food sovereignty (Amarasingam et al., 2022). Remote sensing technology plays a significant role in supporting more efficient and effective agricultural land management (Wang et al., 2025). This technological advancement offers potential solutions for improving the management of agricultural areas (Mpakairi et al., 2025; van der Velden et al., 2025). Among agricultural commodities, sugarcane holds substantial importance as a primary source of sugar (Dimov et al., 2022). Sugar is considered a staple food component crucial to human livelihood, and most countries regulate its availability to meet national consumption demands. In Indonesia, the total area allocated to sugarcane plantations has shown a consistent upward trend over the past decade. However, this expansion has not been accompanied by a proportional increase in productivity. Several factors contribute to this discrepancy, including limited implementation of modern management technologies in sugarcane plantations, labor shortages, climatic constraints, and the outdated infrastructure of most sugar mills in the country.

According to data presented at the National Summit on Sugar held on December 13, 2023, the area of sugarcane plantations has continued to grow over the past ten years. By 2022, sugarcane plantations in Indonesia spanned approximately 490,000 hectares, and the area was projected to increase to 505,000 hectares by 2023. Ironically, this increase in plantation area has not resulted in a corresponding rise in sugar production, which is largely attributed to the declining quality of harvested sugarcane. This quality deterioration is believed to stem from suboptimal plantation management practices.

Remote sensing technology has been proven to assist in land management (Sharma et al., 2024; Xu et al., 2024), including the monitoring of sugarcane agricultural fields. Remote sensing enables spatial distribution mapping and reduces the need for labor-intensive and time-consuming field data collection, which typically requires greater financial and human resources (Karongo et al., 2025; Orynbaikyzy et al., 2019; Sørensen et al., 2025). Satellite imagery, the most commonly used remote sensing data, provides a combination of various spatial and spectral resolutions and allows for computational data extraction and analysis (Damm et al., 2022). However, satellite imagery often lacks the spatial resolution required to capture fine-scale variations in sugarcane fields, particularly those with small plot sizes. Therefore, higher-resolution remote sensing data with rich spectral information suitable for digital processing are needed (Xiao et al., 2025).

Unmanned aerial vehicles (UAVs), or drones, offer a viable solution by generating high spatial resolution imagery (digital aerial photography), capable of achieving resolutions at the millimeter scale (Sofonia et al., 2019). Currently, many UAV systems are equipped with advanced digital cameras capable of capturing multispectral imagery (Ebrahimy et al., 2025). Examples include the MAPIR RGN camera and the multispectral sensor integrated with the DJI Mavic 3M UAV, both of which are commonly utilized for mapping purposes. The diversity of drone-mounted cameras produces a range of imagery with different spectral bands and capture ranges, which may result in varied or sometimes overlapping datasets. Given this variability, it is essential to examine the specifications and characteristics of UAV imagery to provide users with informed recommendations regarding camera selection and field data acquisition strategies, ensuring optimal data utilization in subsequent applications.

Multispectral reflectance data captured by UAV-mounted cameras plays a crucial role in assessing chlorophyll content, a primary indicator of plant health (Das et al., 2023; Gao et al., 2024). Chlorophyll is an integral component of photosynthesis and has a direct influence on plant growth, vigor, and productivity (Woldemariam et al., 2024). Its presence is strongly correlated with leaf coloration, canopy density, and photosynthetic efficiency (Pierre Pott et al., 2022). Chlorophyll predominantly absorbs light in the red and blue wavelengths, while reflecting green and near-infrared (NIR) light (Bagheri & Kafashan, 2025). Multispectral cameras are capable of detecting this spectral variance, allowing for the estimation of chlorophyll content through vegetation indices (Ochiai et al., 2024) such as the Normalized Difference Vegetation Index (NDVI), Green NDVI (GNDVI), and the Modified Chlorophyll Absorption Ratio Index (MCARI) (Hofmann, 2023).

Chlorophyll monitoring is particularly critical in sugarcane cultivation, as it directly affects photosynthetic performance and serves as a proxy for plant health (Jay et al., 2017). Remote sensing data acquired via multispectral cameras enable efficient chlorophyll assessments using indices such as the

Chlorophyll Index–Red Edge (ClRE) and GNDVI. These indices have shown strong correlations with key sugarcane parameters such as biomass, yield, and disease resistance (Saengprachatanarug et al., 2022; Shendryk et al., 2020). Spectral vegetation indices such as the Ratio Vegetation Index (RVI) and the Difference Vegetation Index (DVI) have demonstrated high coefficients of determination (R^2), reaching values between 0.94 and 0.96, making them highly reliable for chlorophyll estimation in sugarcane (Narmilan et al., 2022).

This study aims to compare the spectral data output from two distinct UAV-compatible cameras—the multispectral sensor of the DJI Mavic 3M and the MAPIR RGN camera—to determine their respective capabilities in providing vegetation indices for supporting precision agriculture in sugarcane cultivation. Recent studies have highlighted that multispectral cameras, such as those integrated into the DJI Mavic 3M platform, can deliver high-accuracy vegetation data with notable efficiency for crop monitoring. In contrast, red-green-NIR cameras like the MAPIR RGN remain widely used due to their affordability and customizable spectral configurations. However, direct performance comparisons between these camera systems in the context of specific crops like sugarcane remain limited. Therefore, this research occupies a strategic position in addressing this knowledge gap within the field of remote sensing-based precision agriculture.

METHOD

The method of collecting aerial photo data used in this study is to conduct aerial photography directly on sugarcane plantation land, using 2 different cameras (MAPIR RGN Camera and DJI Mavic 3M Multispectral Camera) which are transported using unmanned aerial vehicles.

Research Location

The location of the research was carried out in a sugarcane plantation in the Sidoarjo Regency area, East Java Province, precisely in Urangagung Village, Sidoarjo District. Sidoarjo is an area that has a fairly large sugarcane plantation on the island of Java, so it is considered to be able to present sugarcane plantations in the Java Island area. The location can be seen in detail in the following map image, where the research area is focused on sugarcane plantation plots with an area of +1 Ha. The research area was adjusted to the capabilities of the camera for photography and the diversity of sugarcane plants with several different treatment plots in terms of fertilization. With different treatments, it is expected to provide a diversity of diverse spectral responses to be covered through unmanned aircraft cameras.

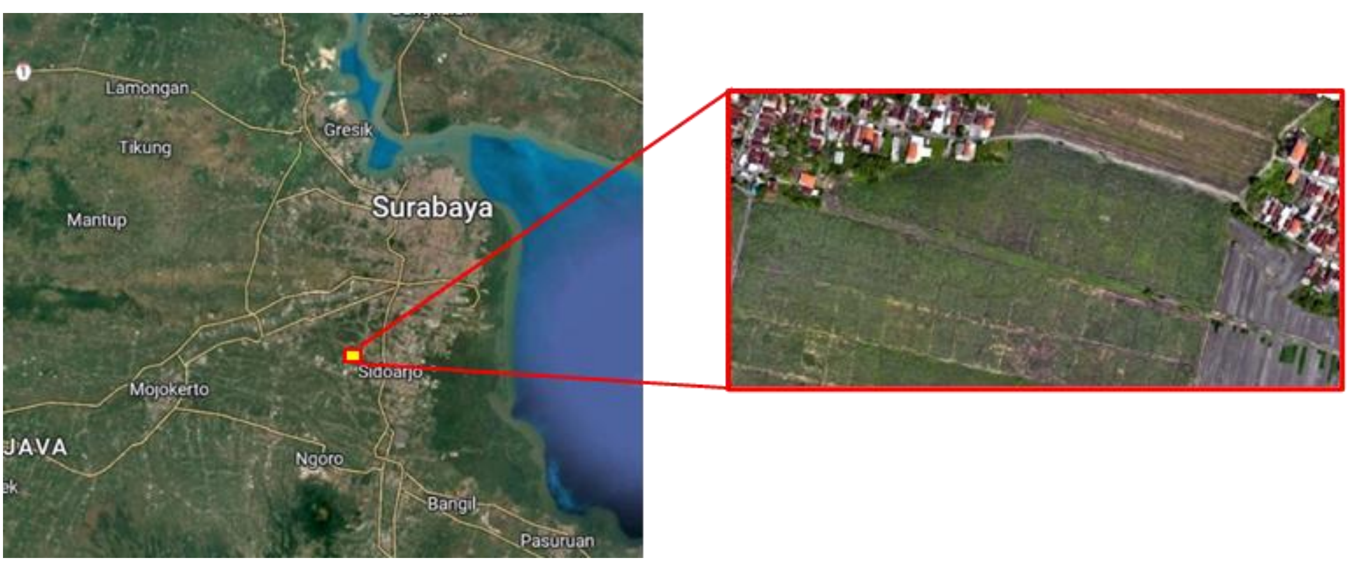

Figure 1. Research Location, Sugarcane Plantation, Urangagung, Sidoarjo, East Java Province (7°26'16.6"S 112°39'53.7"E)
Source: Analysis results

Figure 2. Unmanned Aircraft and Cameras

Table 1. Parameters of MAPIR RGN Camera and DJI Mavic 3M Multispectral Camera

Sensor Camera	Spectral Range (nm)/Middle Wavelength (channel width) (nm)	Resolution (pixels)	GSD@120(cm)
Mavic 3M (Multispectral Camera)	Green (G): 560 ± 16 nm; Red (R): 650 ± 16 nm; Red Edge (RE): 730 ± 16 nm; Near infrared (NIR): 860 ± 26 nm	2592 × 1944	6.4
MAPIR RGN	Green (G): 550±15nm; Red(R): 660±15nm; Near Infrared (NIR): 850±30nm	4,000 x 3,000	2.3

Source: www.mapir.camera dan www.ag.dji.com

Tools and Materials

The equipment used in this study is the DJI PHANTOM Drone used to transport the MAPIR RGN Camera and the DJI MAVIC 3M Unmanned Aircraft, as well as the Geodetic GNSS Receiver for the tying of the position of the Ground Control Point (GCP) in the field. Here are the parameters of the MAPIR RGN camera and the DJI Mavic 3M Multispectral Camera (see Table 1)

Field Data Acquisition

The MAPIR RGN camera is equipped with a mounting to be installed on the DJI Phantom. When shooting in the research area was carried out alternately with a flying altitude of +100 m, at first the DJI Mavic 3M was shot first, then continued with the MAPIR RGN camera shot carried by DJI Phantom. Before the shooting, a Ground Control Point was installed as a binding point to make geometry corrections on the aerial photos from the shooting.

The shooting process was carried out to make a flight path plan by determining the coverage area / Area of interest (AOI) which was then included in the Flight Mission on the control of the unmanned aircraft, along with other parameters such as Flight Path (waypoint and flight path), Altitude (flight altitude), Overlap (image overlap level), Gimbal Angles (camera angle), Speed: (flight speed), Return to Home and Method (RTK/PPK).

Before the flight, it is necessary to calibrate the platform and camera sensors. The most important thing related to this study is the calibration of reflections using the Micasense Calibrated Reflectance Panel (CRP) RP06-2123093-OB. Reflectance calibration helps to normalize the data so that the analysis results become consistent across various environmental conditions (Swaminathan et al., 2024). The calibration data using the reflectant calibration panel is used for the radiometric correction process on aerial photons during data processing after data acquisition in the field.

For the purpose of compiling an aerial photo mosaic into an orthophoto, it is necessary to make a geometry correction that requires field control point data in the form of Ground Control Point (GCP) and Independ Contorl Point (ICP) to assess the validation of the results of the orthorectification process. These points were measured using a Geodetic-type GNSS receiver, by pairing markers in the field.

The process of mosaic preparation and orthorectification uses agisoft metashape software, the orthorectification process is carried out by utilizing the Structure from Motion (SfM) technique to produce a digital surface model (DSM) used in geometric correction. Orthorectification corrects distortions due to differences in surface height and camera angles, allowing for more accurate analysis of geospatial maps (Sai et al., 2019). By integrating Ground Control Points (GCP) and SfM algorithms, Agisoft produces orthophoto mosaics with high resolution and geometric accuracy that meet standards (Pricope et al., 2019).

Figure 3. Micasense Calibrated Reflectance Panel (CRP) RP06-2123093-OB
Source: Analysis results

Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is a widely used formula in remote sensing to monitor vegetation health, growth, and density. This index is calculated using the reflectance values of the red channel (RED) and near-infrared (NIR) spectrum of the electromagnetic spectrum. NDVI is expressed by the following formula:

$$\text{NDVI} = \frac{NIR - R}{NIR + R}$$

This index effectively distinguishes between healthy vegetation, which is higher in the NIR and less in the RED, and areas that are not vegetated or unhealthy. NDVI values range from -1 to 1, where higher values (close to 1) indicate healthy, dense vegetation, and lower values indicate barren or sparsely overgrown lands.

NDVI is the most popular index for vegetation assessment due to its flexibility with any multispectral sensor. They discuss its widespread use in Unmanned Aerial System (UAS) applications while addressing potential limitations such as atmospheric effects and sensor inconsistencies (Huang et al., 2020). The application of NDVI in precision agriculture uses UAV-based multispectral cameras. has been conducted by Deng et al., 2018 in the study compared the accuracy of NDVI in various cameras and highlighted its role in monitoring plant health under various conditions [(Deng et al., 2018)]

Ratio Vegetation Index (RVI)

RVI is a vegetation index used in remote sensing to monitor vegetation health and density. This index calculates the ratio between reflections in the near-infrared (NIR) and red (RED) spectrum bands. The formula used is as follows:

$$\text{RVI} = \frac{NIR}{Red}$$

RVI is effective in distinguishing between vegetated and non-vegetated areas, as vegetation is more reflected in the NIR than in the red spectrum (RED). This simplicity makes RVI a practical tool, although it is less sensitive to high biomass areas compared to other indices such as NDVI. The correlation of RVI with SAR data, shows its potential in crop monitoring even under cloud cover conditions (Álvarez-Mozos et al., 2021)

Green Normalized Difference Vegetation Index (GNDVI)

The Green Normalized Difference Vegetation Index (GNDVI) is a vegetation index used in remote sensing to assess plant health and chlorophyll content. This index is a modification of the Normalized Difference Vegetation Index (NDVI), which replaces the red ribbon with the green ribbon in its calculation. The formula used is as follows:

$$\text{GNDVI} = \frac{NIR - Green}{NIR + Green}$$

Candiago et al. (2015) explored the application of GNDVI using multispectral imagery obtained by UAVs for precision agriculture. This study emphasizes the effectiveness of GNDVI in analyzing the health, strength, and productivity levels of vegetation or plants (Candiago et al., 2015)

Comparison through Correlation Analysis

Correlation analysis is a statistical method used to measure the strength and direction of the relationship between two variables. In the context of this study, correlation analysis was used to evaluate the relationship between the reflectance values of the multispectral cameras (MAPIR RGN and DJI Mavic 3M) and also their derivatives (Vegetation Index) with chlorophyll levels measured directly in the field. The correlation between reflectance values and chlorophyll levels allows validation of whether data from multispectral cameras can be used to accurately predict/detect plant health (Zhang et al., 2022). Through a comparison study of two multispectral cameras it is possible to determine which sensor is more effective for a particular application (Olivetti et al., 2023).

RESULTS AND DISCUSSION

Based on table 1. The parameter data of the MAPIR RGN Camera and the Multispectral Camera on the DJI Mavic 3M, has a difference where the Mavic 3M has 4 channels, namely Green Channel, Red Channel, RedEdge Channel, and Near Infra Red Channel while MAPIR RGN has 3 Channels, namely Green Channel, Red Channel and Near Infra Red Channel. Related to the spectral range on each of the same channels is 10 nm adrift on each channel and the range is 1 nm apart. The difference in pixel resolution on the camera also causes a difference in Ground Sampling Distance (GSD), where in the example at a flying altitude of 120 m, the DJI Mavic 3M has a GSD of 6.4 cm and the MAPIR RGN has a GSD of 2.3.cm, thus the MAPIR RGN camera has a better spatial resolution compared to the DJI Mavic 3M Multispectral camera.
The results of the mosaic and orthorectification process from the shooting of both types of cameras, are presented in the following image:

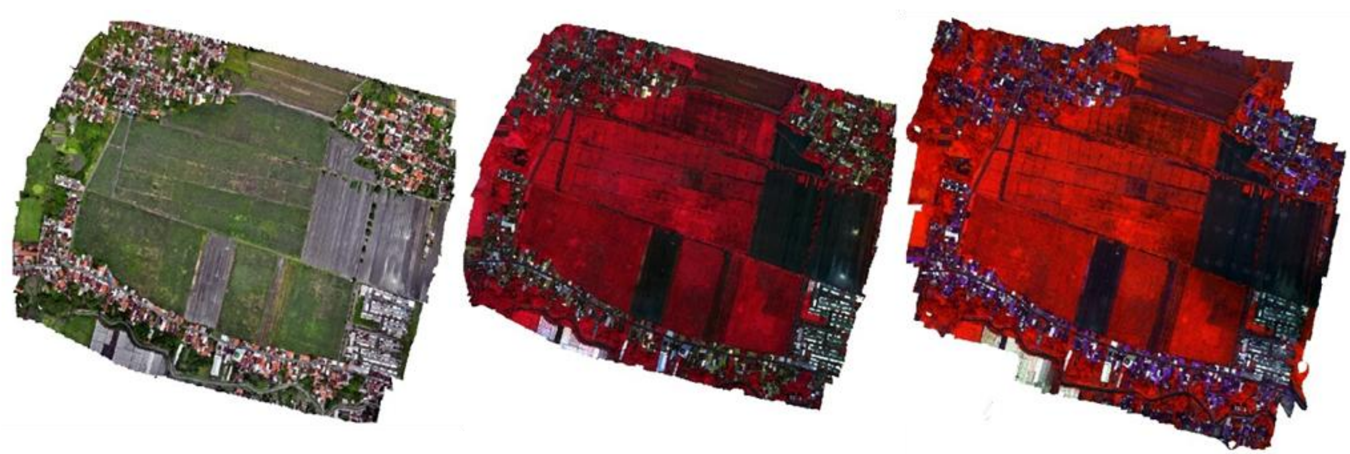

Figure 4. Orthophoto on multispectral camera compared to RGB Photo (left) DJI RGB Camera Color Aerial Photo; (Middle) Color Infrared Aerial Photo of DJI Mavic 3M Multispectral Camera and (right) Color Infrared Aerial Photo of MAPIR RGN Camera.

In addition to taking pictures, sample data was also taken in the field to be used as a calculation of chlorophyll. Field samples were carried out in a total of 15 sample points, with the distribution of sample points as shown in figure 5. The sampling method is Stratified Random Sampling according to the treatment class on sugarcane plants. The retrieval of reflectant pixel values on Orthophoto is based on sampling points in the field whose location is measured using a Geodetic GNSS Receiver. The samples taken are in the form of leaves on sugarcane plants, which will then be measured in the laboratory.

Figure 4. Map of Distribution of samples in the field

From the results of orthophoto, reflective data was collected for each channel contained in the two types of cameras, namely the GREEN, RED, NIR channels. The RedEdge channel on the DJI Mavic 3M multispectral camera is not used as a comparison because the MAPIR RGN camera does not produce the same channel. This is done in order to have equality in the comparison of the reflection of each channel, as well as the derivatives in the vegetation index used. The reflective sample data used was in accordance with the sample distribution in the measurement of chlorophyll samples in the layer. The following is the data for each type of camera.

Chlorophyll comes from the MAPIR RGN camera, which is an NIR (Near Infrared) channel, with a correlation value of 0.2166. These channels show a positive relationship between the reflectance values at the near-infrared wavelength and the chlorophyll values measured in the field. This correlation indicates that increased reflectance in NIR channels is related to increased chlorophyll levels, although the correlation is not very strong. The reflections of the Green Channel and the Red channel of the two cameras showed a weaker correlation. This is in line with the theory that NIR channels are more sensitive to light reflections from healthy leaves because chlorophyll absorbs more light in the green and red channels. The DJI Mavic 3M's multispectral camera, despite having high sensitivity, does not show significant correlation across all its reflection channels, including NIR. This may be due to differences in sensor quality or data processing settings in the camera.

Based on the correlation analysis between chlorophyll values and vegetation index, the vegetation index with the highest correlation was RVI (Ratio Vegetation Index) from the MAPIR RGN camera, with a correlation value of 0.2716. This shows that the RVI from MAPIR RGN has the strongest relationship compared to other vegetation indices, both from MAPIR RGN and DJI Mavic 3M.

RVI is a simple index that calculates the ratio between NIR reflectance and red reflectance. This index has a high sensitivity to changes in plant conditions, especially in health levels and chlorophyll levels. The positive correlation showed that the higher the RRI value, the higher the chlorophyll level measured.

Meanwhile, other vegetation indices such as NDVI (Normalized Difference Vegetation Index) and GNDVI (Green NDVI) from MAPIR RGN show a slightly lower correlation than RVI, although still significant. For the DJI Mavic 3M camera, all vegetation indices showed a weaker correlation compared to the MAPIR RGN, which is most likely due to different sensor sensitivities or the influence of environmental conditions during shooting.

Based on the comprehensive analysis of the data, a pronounced and noteworthy difference was observed between the DJI Mavic 3M multispectral camera and the MAPIR RGN camera in terms of their respective capabilities in capturing the relationship between spectral reflectance and vegetation indices with chlorophyll content in sugarcane crops. These differences are manifested in several key aspects, including the sensitivity and spectral responsiveness of specific reflectance channels, the precision and reliability of the derived vegetation indices, as well as the overall strength of the statistical correlation with measured chlorophyll concentrations. This suggests that each camera exhibits distinct performance characteristics that may influence their suitability and effectiveness for chlorophyll estimation and broader applications in precision agriculture monitoring for sugarcane.

1. Reflectan

MAPIR RGN cameras show better performance in terms of reflection correlation with chlorophyll, especially in NIR (Near Infrared) channels with a correlation of 0.2166. NIR has a high sensitivity to vegetation health due to its strong reflective properties on leaves with high chlorophyll content. In contrast, the reflections from the DJI Mavic 3M's multispectral camera, including its NIR channels, show a weak correlation with chlorophyll. This can be due to differences in sensor quality or data processing levels between the two cameras.

2. Vegetation Index

The vegetation index of the MAPIR RGN camera, such as RVI (0.2716), has the highest correlation with chlorophyll compared to all other indices, including those derived from the DJI Mavic 3M multispectral camera. This indicates that the MAPIR RGN camera is superior in producing spectral data that is relevant for vegetation analysis.

Table 2. Chlorophyll, Reflectance, and Vegetation Index Data on DJI Mavic 3M multispectral camera

Sample	CHLOROPHYLL	Green_DJI	Red_DJI	RedEdge_DJI	NIR_DJI	NDVI_DJI	RVI_DJI	GNDVI_DJI
1	1.138	0.0691	0.0349	0.3086	0.3652	0.8256	10.4689	0.6817
2	1.159	0.0671	0.0571	0.1685	0.2047	0.5640	3.5866	0.5060
3	1.227	0.0542	0.0378	0.1626	0.2802	0.7623	7.4152	0.6759
4	1.081	0.1429	0.0799	0.3322	0.4034	0.6693	5.0473	0.4767
5	1.232	0.0560	0.0378	0.1610	0.1757	0.6458	4.6473	0.5167
6	1.130	0.0272	0.0163	0.0859	0.1436	0.7958	8.7925	0.6812
7	1.193	0.0823	0.0483	0.2418	0.2832	0.7087	5.8660	0.5495
8	1.070	0.0692	0.0400	0.2093	0.2639	0.7367	6.5950	0.5845
9	1.090	0.1329	0.0731	0.3550	0.5384	0.7608	7.3627	0.6039
10	1.141	0.0732	0.0501	0.2217	0.2659	0.6827	5.3037	0.5681
11	1.129	0.0601	0.0327	0.1404	0.1883	0.7041	5.7600	0.5159
12	1.156	0.0478	0.0224	0.1786	0.3107	0.8657	13.8909	0.7333
13	1.045	0.0656	0.0371	0.2355	0.2882	0.7719	7.7673	0.6290
14	1.160	0.0935	0.0454	0.2456	0.2713	0.7131	5.9711	0.4873
15	1.203	0.1217	0.0708	0.3198	0.4684	0.7375	6.6192	0.5875

Source : Research results, 2024

Table 3. Chlorophyll, Reflectance, and Vegetation Index Data on Mair RGN multispectral cameras

Sample	CHLOROPHYLL	MAPIR_NIR	MAPIR_Red	MAPIR_Green	NDVI_MAPIR	RVI_MAPIR	GNDVI_MAPIR
1	1.138	1.29736	0.21945	0.09335	0.71064	5.91183	0.86575
2	1.159	1.14850	0.21472	0.04703	0.68498	5.34878	0.92133
3	1.227	1.53769	0.17578	0.08151	0.79482	8.74774	0.89932
4	1.081	1.09351	0.22659	0.11996	0.65670	4.82586	0.80228
5	1.232	1.16562	0.22867	0.07724	0.67199	5.09742	0.87571
6	1.130	1.46701	0.21225	0.06265	0.74721	6.91172	0.91808
7	1.193	1.22296	0.23230	0.09277	0.68074	5.26458	0.85898
8	1.070	1.18665	0.21378	0.07532	0.69470	5.55089	0.88063
9	1.090	1.48486	0.20764	0.09656	0.75463	7.15109	0.87788
10	1.141	1.27164	0.26184	0.10565	0.65850	4.85653	0.84658
11	1.129	1.06268	0.19510	0.10434	0.68977	5.44690	0.82119
12	1.156	1.45633	0.17926	0.08188	0.78080	8.12411	0.89354
13	1.045	1.22919	0.22202	0.06430	0.69403	5.53649	0.90058
14	1.160	0.92554	0.20633	0.07492	0.63542	4.48573	0.85023
15	1.203	1.54388	0.21066	0.08771	0.75987	7.32870	0.89249

Source: Research results, 2024

Table 4. Analysis of correlation results

No	Variable	Correlation	Regression Equation	R-squared
1	DJI_Green	-0.21715977	KLOROFIL = 1.1727 + -0.3754 * DJI_Green	0.047158
2	DJI_Red	-0.110050839	KLOROFIL = 1.1590 + -0.3391 * DJI_Red	0.012111
3	DJI_NIR	-0.200309179	KLOROFIL = 1.1742 + -0.1032 * DJI_NIR	0.040124
4	DJI_NDVI	-0.167657805	KLOROFIL = 1.2356 + -0.1261 * DJI_NDVI	0.028109
5	DJI_RVI	-0.097883004	KLOROFIL = 1.1586 + -0.0021 * DJI_RVI	0.009581
6	DJI_GNDVI	-0.004990562	KLOROFIL = 1.1456 + -0.0035 * DJI_GNDVI	2.49E-05
7	MAPIR_Green	-0.090770334	KLOROFIL = 1.1664 + -0.2710 * MAPIR_Green	0.008239
8	MAPIR_Red	-0.172202404	KLOROFIL = 1.2414 + -0.4576 * MAPIR_Red	0.029654
9	MAPIR_NIR	0.216581501	KLOROFIL = 1.0615 + 0.0645 * MAPIR_NIR	0.046908
10	MAPIR_NDVI	0.214652567	KLOROFIL = 0.9678 + 0.2483 * MAPIR_NDVI	0.046076
11	MAPIR_RVI	0.271581826	KLOROFIL = 1.0725 + 0.0118 * MAPIR_RVI	0.073757
12	MAPIR_GNDVI	0.176362202	KLOROFIL = 0.8870 + 0.2937 * MAPIR_GNDVI	0.031104

Source: Research results, 2024

CONCLUSION

Based on data analysis in reflection and vegetation index research, the MAPIR RGN camera is proven to be superior to the DJI Mavic 3M multispectral camera for detecting sugarcane vegetation. This is based on the higher correlation values between reflectant values, vegetation index, and chlorophyll in the MAPIR RGN camera. The NIR channel of MAPIR RGN has the highest correlation with chlorophyll (0.2166), while in terms of vegetation index, RVI MAPIR RGN shows the best correlation (0.2716). These two results confirm that the MAPIR RGN camera has a better sensitivity to spectral variations that reflect chlorophyll levels and plant health.

In contrast, the DJI Mavic 3M camera showed a lower correlation for all reflectance channels and vegetation index. This shows that the MAPIR RGN sensor is more optimal in detecting spectral reflections, particularly in NIR channels, which is very relevant for plant health analysis. The MAPIR RGN camera is more recommended for research on detecting sugarcane plants because it shows a stronger relationship with chlorophyll variables, both through reflection and vegetation index. However, this study has a number of limitations that need to be considered. Limited coverage of the observation area as well as a relatively small sample count can affect the generalization of results. In addition, external factors such as lighting conditions, shooting angles, and sensor calibration can affect the quality of the data obtained. Further research is suggested to conduct comparative tests with a wider spatial and temporal scope, and involve different types of plants and different environmental conditions to obtain more comprehensive results. In addition, the integration of data with other environmental parameters such as soil moisture, soil characteristics, and climate information, as well as the use of artificial intelligence-based image analysis methods or machine learning, can improve the accuracy and relevance of findings in supporting the implementation of precision agriculture.

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