ISSN 2682-681X (Paper), ISSN 2705-4241 (Online) | http://unilorinjoger.com | https://doi.org/10.63745/joger.2025.12.30.010

JOURNAL OF GEOMATICS AND ENVIRONMENTAL RESEARCH
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RESEARCH ARTICLE

UAV-Based Multispectral Imaging for Precision Crop Health Assessment in Oil Palm Plantations

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Abstract

Unmanned Aerial Vehicles (UAVs) have become integral tools in precision agriculture, offering high-resolution remote sensing capabilities for effective crop health monitoring. This study evaluates the application of UAV-based multispectral and RGB imagery to assess crop health and enhance agricultural productivity in an oil palm plantation. Data acquisition was performed using DJI Matrice 210 RTK and Phantom 4 drones equipped with multispectral sensors, capturing images at 2 cm spatial resolution. Subsequent data processing using Pix4D Mapper and ArcGIS 10.8 produced orthomosaic maps and vegetation indices, including RGBVI, MGRVI, and NDVI. Tree geolocation and enumeration were conducted manually to leverage the distinct visual characteristics of palm trees. Health status classification using the Natural Break Jenks method indicated that over 96% of trees were healthy. Findings confirm the effectiveness of UAV imaging combined with advanced analytics for dynamic crop monitoring, recommending future integration of primary data and automated analysis to further optimize precision agriculture practices.

ARTICLE HISTORY
Received: 29th August, 2025
Accepted: 12th December, 2025
Published: 13th December, 2025

KEYWORDS
UAV
Crop health
Orthomosaic
Natural Break Jenks method
Tree health
NDVI

Citation: Abiodun O. E., Lawal A. B., Egbeyemi L. O., Adeyemi A. A., Victor M. A., (2025). UAV Based Multispectral Imaging for Precision Crop Health Assessment in Oil Palm Plantations. *Journal of Geomatics and Environmental Research, 8(2). Pp 99-110*

1. INTRODUCTION

Unmanned Aerial Systems (UAS) have become increasingly prevalent in remote sensing applications within the field of Precision Agriculture. Equipped with diverse types of sensors, UAVs enable the identification of specific zones within crop fields that require differential management interventions, such as targeted inputs. This capability allows farmers to respond promptly and effectively to emerging issues, ensuring better crop management (El Metwally, 2021). UAV technology finds applications across a wide spectrum in Precision Agriculture, including crop health monitoring, disease detection, growth tracking, yield estimation, and weed management. Due to their growing adoption and promising prospects, UAVs represent the future of remote sensing in agriculture, attracting considerable research interest. Several comprehensive reviews have documented their multifaceted applications in crop and environmental monitoring (Tsouros, 2019; Nyaga *et al*., 2021).

The global demand for agricultural products consistently surpasses supply, necessitating improved management of agricultural production. Traditional approaches are often inadequate to meet this challenge without integrating modern technologies (Wang & Meng, 2025). Among innovative solutions, remote sensing stands out as a rapid, non-invasive, and effective technique capable of acquiring and analyzing spectral properties of terrestrial surfaces from various platforms, ranging from satellites to ground-based systems (Abdulraheem *et al*., 2024; Kazanskiy *et al.,* 2025). UAVs play an instrumental role by capturing high-resolution images over farmlands, which, combined with vegetation indices computation, enable the generation of vegetation maps vital for crop monitoring. Their primary advantage lies in producing high-resolution data critical for precise crop parameter estimation while supporting frequent, in-season assessments due to their flexible flight capabilities (Makanza *et al*., 2018). Precision Farming strategies often rely on within-field yield potential estimates derived from remotely sensed products such as Vegetation Index (VI) maps (Rebouh *et al*., 2023; Longchamps *et al*., 2022). This study applies remote sensing methods to effectively monitor canopy cover and crop health.

Remotely sensed information on vegetation growth and vigor offers valuable insights for diverse domains, including environmental monitoring, biodiversity conservation, agriculture, forestry, and urban green infrastructure management (Qazi, *et al.*, 2021). In agriculture, such data provide an objective basis for both macro and micro agricultural management and are often essential for accurate crop yield estimation (Moomen *et al*., 2024; Kumar *et al*., 2024). Monitoring land conditions and especially green vegetation cover is critical for understanding ecosystem dynamics. The fraction of vegetation cover (FVC) is a key indicator used to observe temporal trends in vegetation cover across landscapes (Gogoi, *et al.*, 2018).

2.0 MATERIALS AND METHODS

2.1 Study Area

The study was conducted along the Benin-Sagamu Expressway in Odogbolu, Ogun State, located in southwestern Nigeria. Ogun State is bounded by Lagos State to the south, Oyo and Osun states to the north, Ondo State to the east, and the Republic of Benin to the west. The state's capital is Abeokuta, a major urban center. Known as the "Gateway to Nigeria," Ogun State hosts several industrial and manufacturing hubs, including Dangote Cement Factory at Ibese, Nestle, Lafarge Cement Factory at Ewekoro, and Procter & Gamble in Agbara. The area selected for this research encompasses an oil palm tree plantation, providing a representative site for precision agriculture studies.

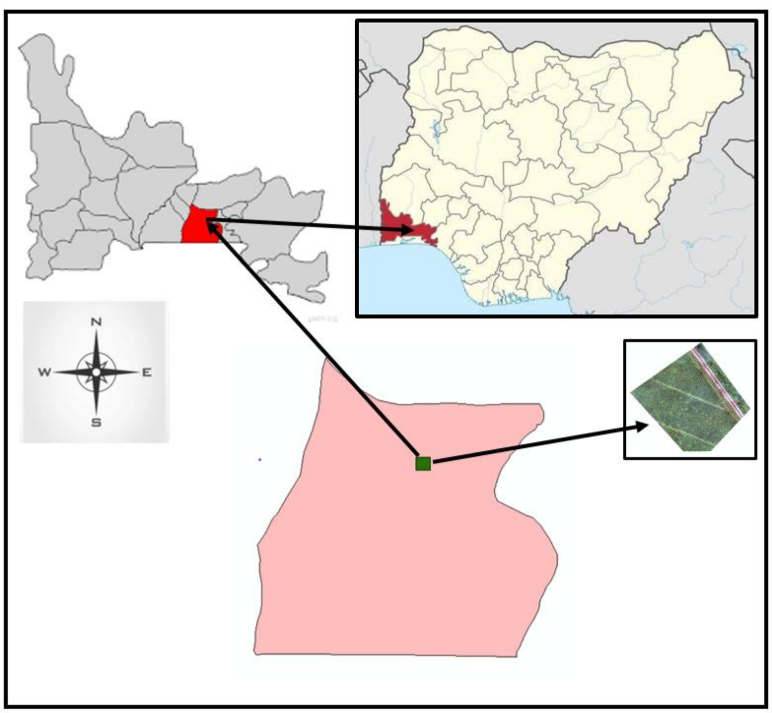

Figure 1: Study area

2.2 Instrumentation

Aerial image data acquisition was performed using two Unmanned Aerial Vehicles (UAVs): the DJI Matrice 210 RTK equipped with a Multispectral Sensor capturing near-infrared, Red Edge, and RGB bands, and the DJI Phantom 4 drone. The multispectral sensor comprised five cameras capturing distinct wavelength bands, including blue, green, red, red-edge, and near-infrared, enabling comprehensive spectral analysis (Figures 2 and 3).

Figure 2: DJI Matrices 210 RTK and DJI Phantom 4 drone.

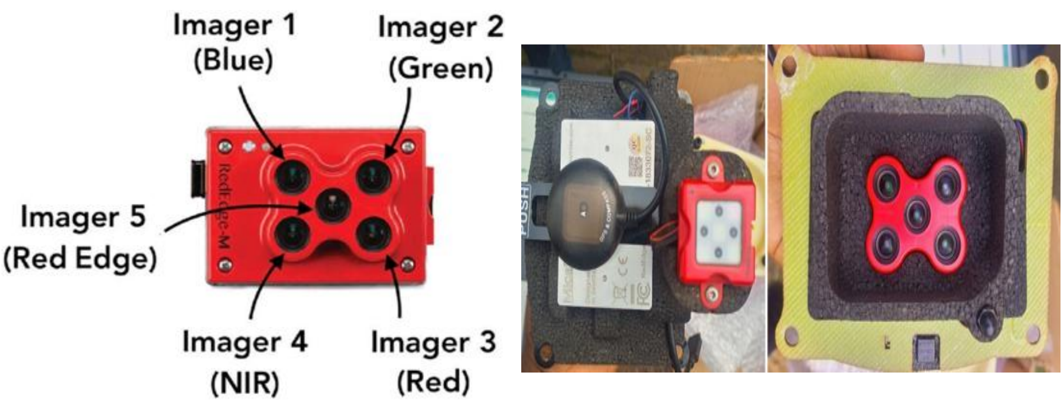

Figure 3: Multispectral Sensor

2.3 Software Used

Data processing and analysis were performed using a combination of specialized hardware and software. Ground control was managed by the D-RTK 2 Mobile Station, ensuring precise positional data during UAV flights. An HP EliteBook 840 G3 laptop served as the main computing platform for executing image processing and analysis tasks. Pix4D Mapper Enterprise Edition was used to process the UAV images, generate orthomosaic maps, and calculate vegetation indices. UAV flight missions were planned and coordinated using DJI Ground Station Pro (GS Pro) software. For geospatial analysis and visualization, ArcGIS 10.8 provided the tools needed to interpret and map the data. On-site control and monitoring of UAV operations were conducted through an iPad Mini-4, allowing real-time adjustments during data collection.

2.4 Data Acquisition

Multispectral images were captured on-site on November 18, 2023, with an impressive spatial resolution of 2 cm. The Micasense multispectral camera, with a removable 32GB memory card, was mounted as a payload on the DJI Matrice 210 RTK UAV. Care was taken to ensure that the GPS device and sensors had unobstructed signals. Flight parameters observed included an altitude of 50 meters, 75% front overlap, 70% side overlap, flight direction of 149 degrees, mapping speed of 6 m/s, gimbal angle at -90 degrees, and use of three batteries (Table 1).

Mission planning and camera configuration involved setting the Micasense camera's auto-capture mode enabled with overlap settings, target altitude at 50 meters above ground level, along-track overlap at 65%, and selecting TIFF (16-bit) raw format for image capture.

Table 1: UAV Pre-Flight Parameters

S/N	PARAMETERS	
1	Flight altitude	50m
2	Front overlap	75%
3	Side overlap	70%
4	Flight direction	149 degree
5	Mapping flight speed	6m/s
6	Starting waypoint	1
7	Gimbal angle	-90degree
8	Batteries	3

2.5 Data Processing

2.5.1 Multispectral Data Processing

The multispectral image dataset, consisting of approximately 3,030 images across blue, green, red, red-edge, and near-infrared bands, was processed in Pix4D Mapper to generate vegetation indices maps, particularly the Normalized Difference Vegetation Index (NDVI). Radiometric Calibration was however not carried out in this study because the calibration results in a previous similar study produced results within acceptable margin. The processing workflow involved creating a new project, importing the multispectral images, setting the coordinate system to WGS 84 UTM zone 31 selecting the agricultural multispectral processing template, and configuring the indices calculator for NDVI mapping. The complete processing duration was approximately 1 hour and 8 minutes (Figure 4).

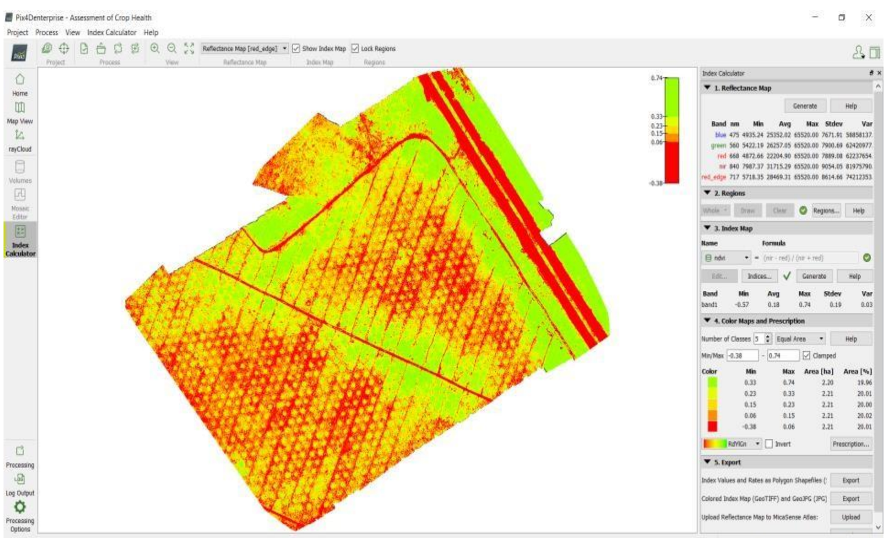

Figure 4: Interface of Pix4DMapper showing NDVI reflectance map

2.5.2 RGB Composite Dataset

The RGB composite dataset, comprising 144 image tiles stored in JPEG format, was processed to facilitate tree geolocation and enumeration. Pix4D Mapper's point cloud densification and orthomosaic generation tools were employed, complemented by automatic georeferencing through Real-Time Kinematic (RTK) GPS onboard the UAV.

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2.5.3 Vegetation Indices Calculation

Subsequently, vegetation indices including RGBVI (Red Green Blue Vegetation Index) and MGRVI (Modified Green Red Vegetation Index) were computed using ArcGIS 10.8's Raster Calculator tool, applying map algebra expressions to the orthomosaic data (Figures 5 and 6).

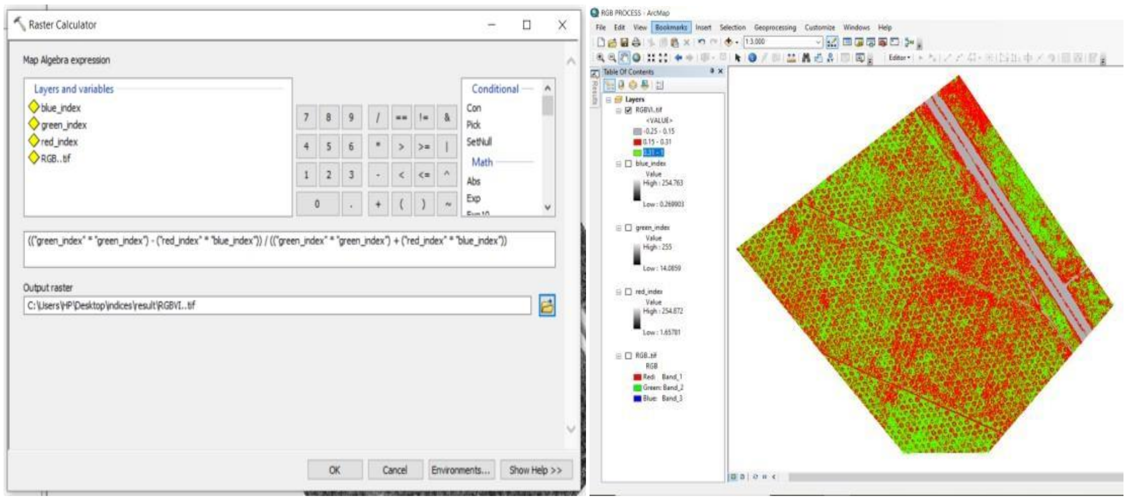

Figure 5: Appearance of orthomosaic after applying RGBVI and colour scheme

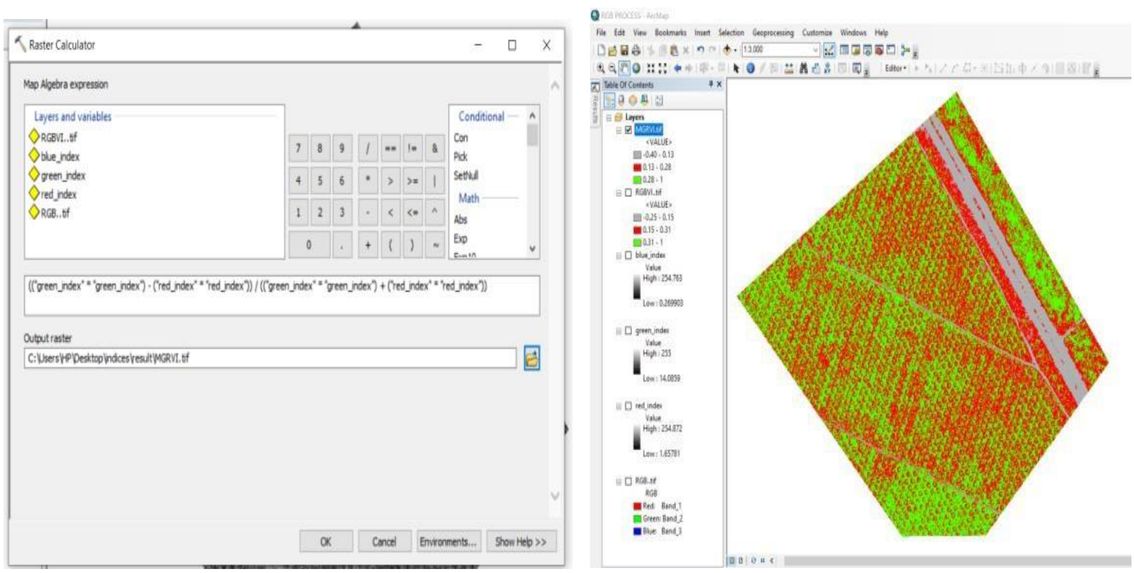

Figure 6: Appearance of orthomosaic after applying MGRVI and colour scheme

2.5.4 Tree Crop Geolocation and Enumeration

To accurately locate each oil palm tree and quantify their total number within the study area, manual digitizing techniques were applied within the ArcGIS 10.8 environment using tree shape and pattern as criteria for digitizing. Point feature shapefiles were created, and individual trees were manually digitized on the true-color RGB orthomosaic to ensure precision in enumeration and geolocation.

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2.6 Assessment of Tree Health Status

The health of the palm trees was assessed using NDVI values derived from the multispectral dataset. The NDVI scale ranges from -1 to 1. Values close to 1 indicate dense, healthy vegetation, while values near -1 represent sparse or no vegetation presence (Nagler, 2011). Vegetation density was classified as barren or sparse (0 to 0.2), low to medium (0.2 to 0.5), high (0.5 to 0.8), and very dense (above 0.8). The Natural Break Jenks classification method was employed in ArcGIS to categorize tree health status automatically with an appropriate color scheme, offering an objective and statistically significant segmentation of health classes (Figure 7).

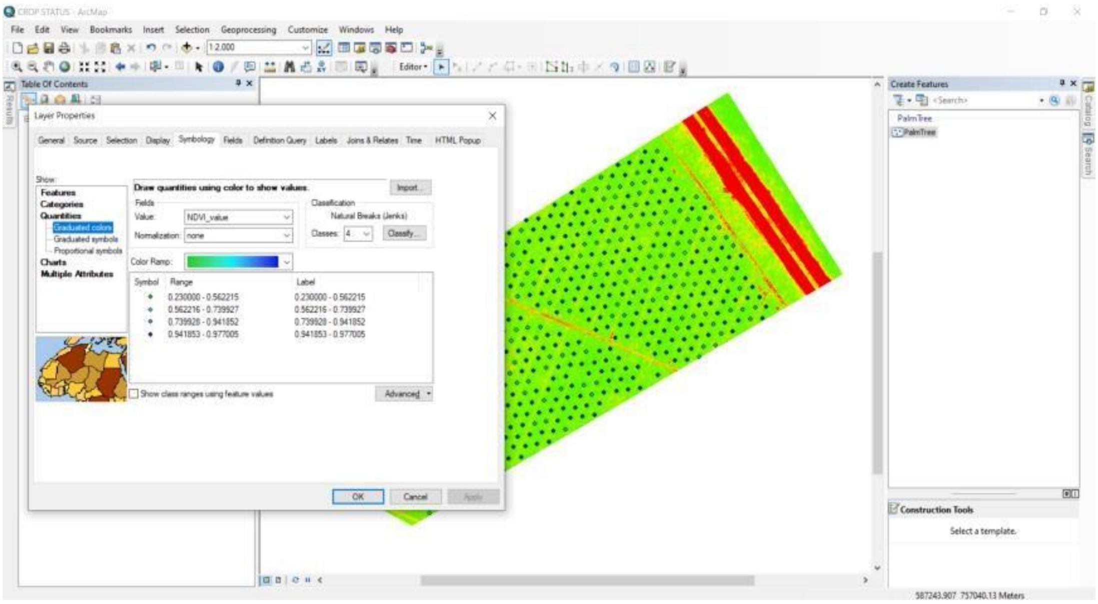

Figure 7: Natural break Jenks

3.0 RESULTS AND DISCUSSION

3.1 RGB Ortnomosaic Map

The RGB orthomosaic map generated from multiple high-resolution images of the oil palm plantation provides a detailed, visually intuitive representation of the study area. By integrating red, green, and blue spectral bands, the orthomosaic delineates farmland boundaries, tree distribution, and spatial arrangement succinctly. This RVG map (Figure 8) reveals the uniformity and spatial variability of vegetation cover, enabling observation of tree spacing patterns and potential areas needing management. Such comprehensive visualization supports informed decision-making by farmers and agronomists regarding land use, crop health status, and productivity optimization.

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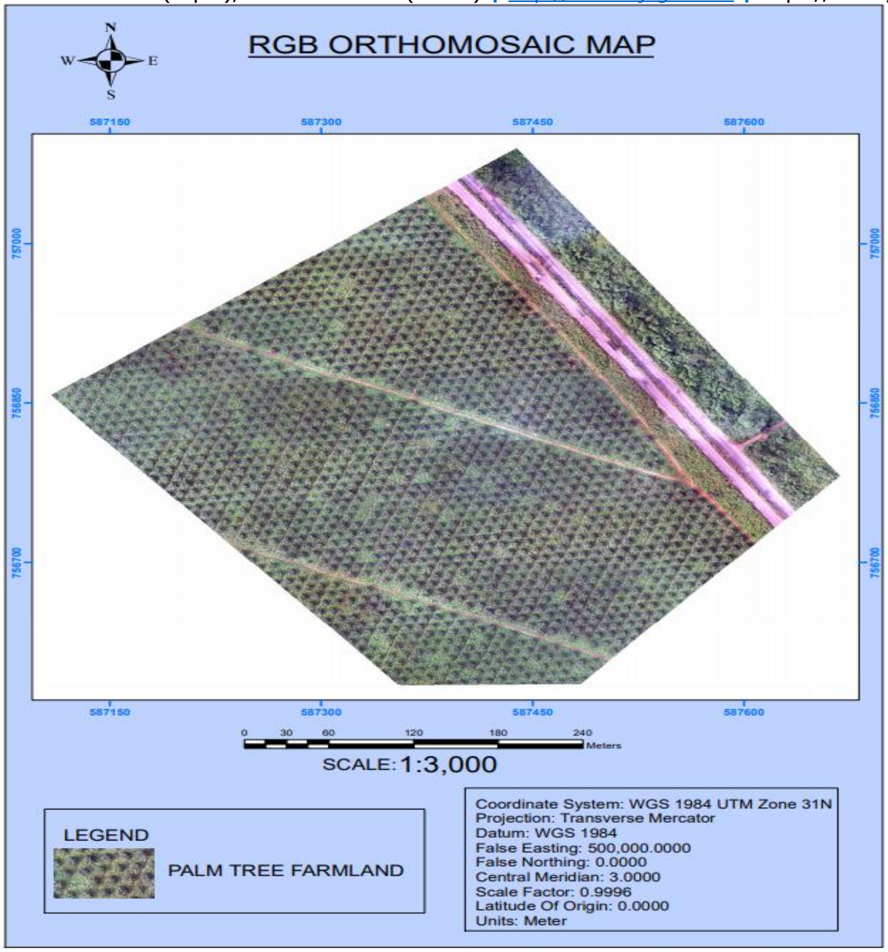

Figure 8: RGB Orthomosaic map

3.1 Vegetation Indices Map (MGRVI, RGBVI, NDVI)

Three vegetation indices, Modified Green Red Vegetation Index (MGRVI), Red Green Blue Vegetation Index (RGBVI), and Normalized Difference Vegetation Index (NDVI), offer varying insights into vegetative activity across the study area, each highlighting different aspects of canopy health:

The **MGRVI** map identifies three distinct vegetation cover classes, ranging from sparse to dense vegetation, with negative values corresponding to non-vegetated surfaces such as roads and bare soil. This index reflects vegetation density variations effectively and corroborates spatial agricultural heterogeneity. Notably, most farmland regions exhibited positive MGRVI values, confirming extensive vegetation presence (Figure 9).

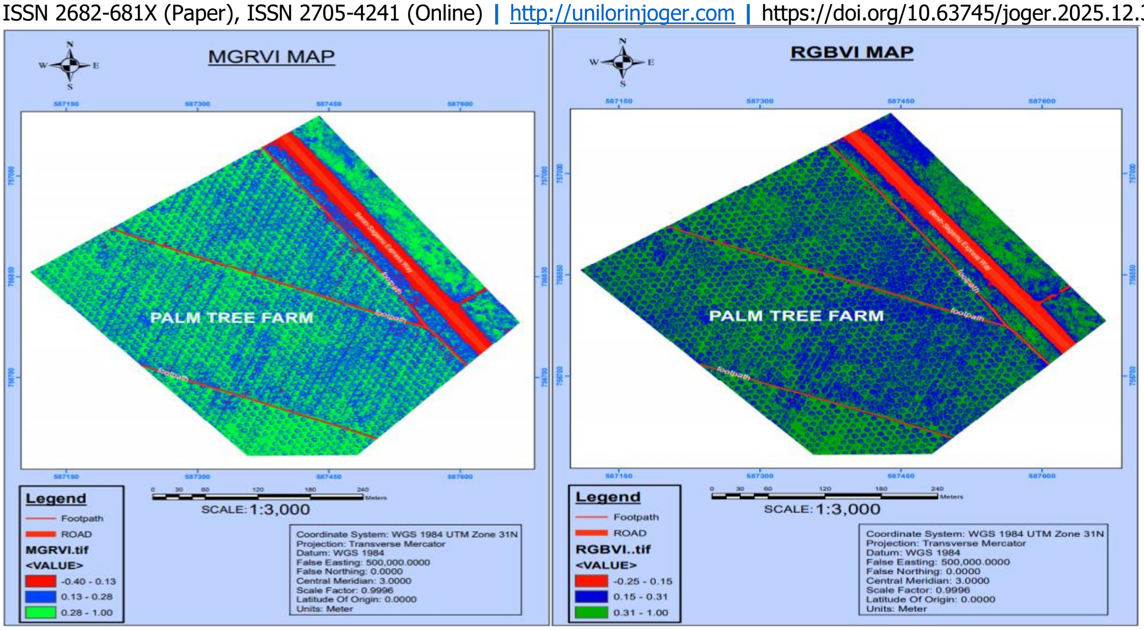

Figure 9: MGRVI map and **RGBVI** map

The **RGBVI** map, more sensitive to green canopy variations than MGRVI, displays a comprehensive spectrum from sparse to dense vegetative cover. Its scale distribution similarly segments the farmland into bare ground, sparse vegetation, and dense vegetation zones, aiding detailed health assessments of crop cover. The **NDVI** map uses a well-established scale from -1 to +1 to indicate vegetation vigor, with values near +1 signifying healthy, lush cover, and those near -1 indicating sparse or stressed vegetation. In this study, NDVI values predominantly ranged from -0.60 to 1, highlighting mostly healthy vegetation in the oil palm plantation (Figure 10). The ability of NDVI to capture photosynthetically active biomass and stress conditions makes it essential for precision crop monitoring.

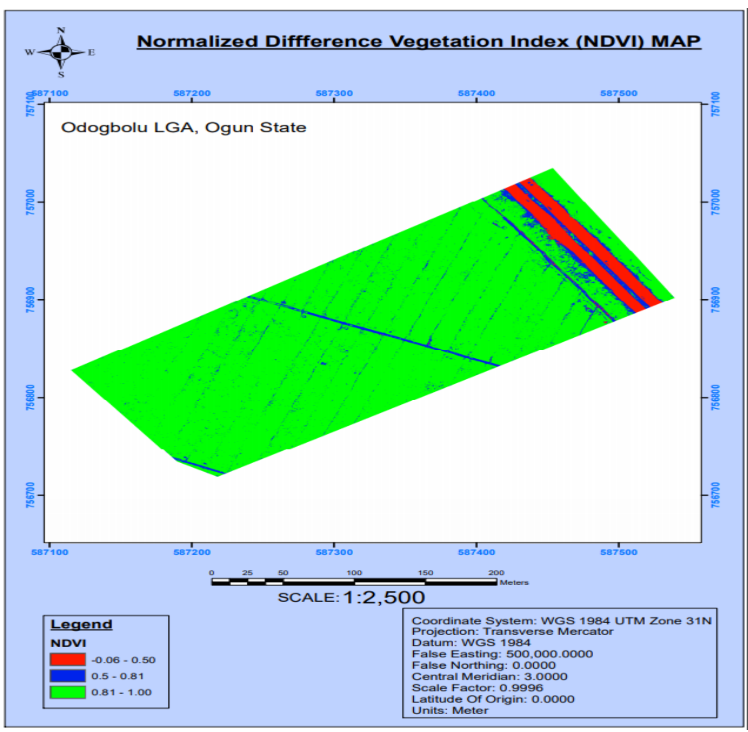

Figure 10: **NDVI** map

Together, these vegetation indices complement one another to provide a multidimensional understanding of crop health, variability, and spatial dynamics within the plantation landscape.

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3.3 Tree Health Mapping and Enumeration

Manual digitization of individual palm trees on the high-resolution RGB orthomosaic map facilitated accurate tree enumeration and geolocation. This manual approach accounted for the unique visual characteristics of palm trees, resulting in precise mapping of 651 trees throughout the study area (Figure 11). This count underpins subsequent assessments of health status and spatial distribution analyses.

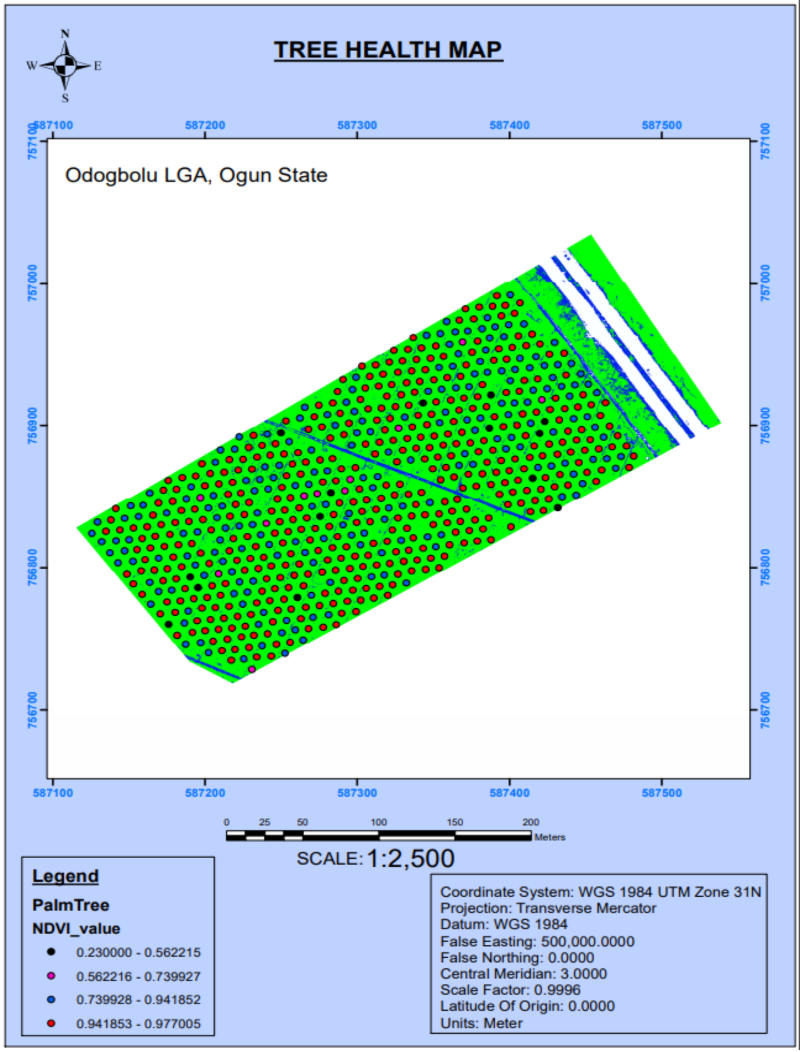

Figure 11: **Tree Health** map

Tree health assessment based on NDVI values was categorized using the Natural Break Jenks method, an objective, data-driven technique to classify data into meaningful groups. The classification revealed that an overwhelming majority, approximately 96.77%, of trees were healthy, with only 2.76% showing moderate health conditions and a minimal 0.46% exhibiting declining health (Table 2). This distribution indicates robust overall crop vigor within the study area (Figures 12).

The combined use of UAV multispectral imagery and GIS-based analytic methods demonstrates strong potential for high-precision crop health monitoring. Manual digitizing, although labor-intensive, enhanced the reliability of tree enumeration over automated methods in this context, owing to the distinct visual signature of palm trees.

Table 2: Natural Break Jenks:

Healthy	**630/651 × 100 = 96. 77%**
Moderate	18/651 × 100 = **2.76%**
Declining health	3/651 × 100 = **0.46%**

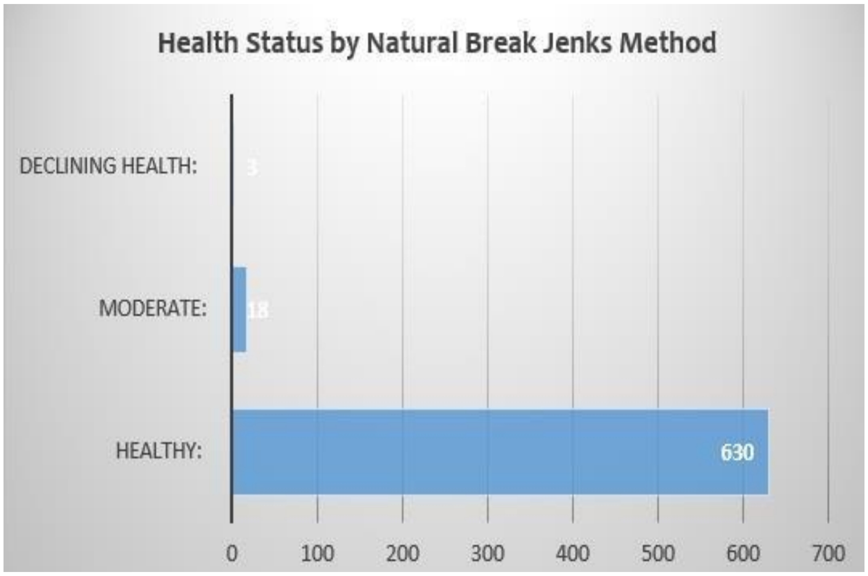

Figure 12: 2D bar chart showing health status count (Source: Table 2)

3.4 Discussion

The findings affirm that UAV-based imagery, coupled with advanced vegetation indices, effectively captures variations in crop health and spatial structure in oil palm plantations. The RGB orthomosaic offers a geospatial framework for field-scale analysis, while vegetation indices CVI, RGBVI, and NDVI each provide differentiated yet complementary insights into canopy density and health.

The high proportion of healthy trees reflects favorable growing conditions and effective farm management. However, the presence of trees with moderate and declining health highlights areas where targeted intervention could optimize yield. The Natural Break Jenks classification method proved invaluable in segmenting these health categories, providing actionable data to inform precision agriculture management strategies. This is corroborated by the study of Manu *et al*., (2024) where it was reported that Unmanned Aerial system assisted in monitoring maize health in a small scale farm in Ghana.

Manual tree digitization enhanced data accuracy, but is less scalable for larger plantations. Future integration of machine learning and automated feature extraction could augment the efficiency of such assessments. The study underscores UAV remote sensing as an indispensable tool that, when combined with robust GIS analyses, supports timely, data-informed decisions in precision agriculture to improve sustainability and productivity.

4. CONCLUSION AND RECOMMENDATION

4.1 Conclusion

This study successfully demonstrated the significant potential of UAV-based remote sensing technology for the assessment of crop health in an oil palm plantation. By leveraging high-resolution multispectral imagery combined with advanced data processing tools such as Pix4D Mapper and ArcGIS, the research provided detailed spatial insights into vegetation health, canopy structure, and tree distribution. The derivation of key vegetation indices, including NDVI, RGBVI, and MGRVI, facilitated accurate monitoring of crop vigor and health status.

The manual digitization of tree geolocations and enumeration proved effective in this setting, enabling precise identification and assessment of 651 oil palm trees. Health classification using the Natural Break Jenks method revealed that the overwhelming majority of trees are in healthy condition, validating the robustness of the UAV-based approach for dynamic crop health monitoring.
The findings hold important implications for precision agriculture, offering actionable information to optimize resource allocation, improve yield predictions, and enhance sustainable crop management. The study further highlights the value of integrating UAV multispectral imaging with GIS analysis as a scalable tool for informed decision-making in agricultural landscapes. Limitations of this study include the manual digitizing and single epoch data used.

Future work is encouraged to incorporate machine learning techniques for automation, as well as primary data collection for improved accuracy and reliability. Enhanced collaboration with agricultural experts can further enrich analytical interpretations and practical implementations. Overall, UAV-based crop health assessment presents a promising path towards advancing smart farming and improving agricultural productivity in oil palm and other crop systems.

4.2 Recommendations

For future research, it is advisable to utilize machine learning algorithms to automate image analysis and enhance accuracy, particularly for larger study areas. Strengthening collaboration with agricultural experts, agronomists, and researchers will improve data interpretation and practical relevance. Adding primary data collection alongside UAV imagery will yield more precise and context-specific insights, thereby reducing biases associated with secondary sources. These strategies will advance UAV-based smart farming, enabling better crop health monitoring, disease detection, and yield prediction, ultimately enhancing agricultural productivity and sustainability.

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