Tree Health Assessment Using UAV-Based Multispectral Imagery and NDVI Analysis

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Abstract

Unmanned Aerial Vehicles (UAVs) equipped with multispectral sensors enable the capture of imagery across various spectral bands, facilitating the use of vegetation indices such as the Normalized Difference Vegetation Index (NDVI) to assess plant health. This capability is increasingly important in forestry, agriculture, and environmental monitoring. This study investigates the effectiveness of UAV-based multispectral imagery for tree health assessment within the Universiti Teknologi MARA (UiTM) campus in Malaysia, using both conventional NDVI validation methods and ArcMap-based NDVI analysis. A DJI Phantom 4 drone with a Parrot Sequoia multispectral sensor was deployed, configured with auto capture mode, 1.5-second timelapse, 17.5-meter GPS interval, and 80% image overlap. Tree RGB images were processed in Pix4D, while NDVI images were analyzed using ArcMap's raster calculator. NDVI values obtained via conventional methods ranged from 0.720 to 0.842, indicating healthy vegetation based on comparisons with prior studies. In contrast, ArcMap-derived values ranged from 0.536 to 0.774. The root mean square error (RMSE) between both methods was 0.159, with a standard deviation of 0.201, indicating a consistent underestimation by ArcMap NDVI values. Notably, significant discrepancies were observed at points P1 and P5, while smaller differences occurred at P6. Overall, the findings support the reliability of UAV multispectral data and its integration into operational vegetation health monitoring. The results suggest that UAV and GIS-based workflows can provide cost-effective, scalable alternatives to traditional methods. For enhanced precision, future applications should consider high-resolution sensors with optimized parameters such as faster shutter speeds and appropriate sensor orientation.

Keywords: Multispectral Imagery, Normalized Difference Vegetation Index (NDVI), Tree Health Monitoring, Unmanned Aerial Vehicles (UAVs)

1. Introduction

Unmanned Aerial Vehicles (UAVs) are equipped with a variety of sensors, including GPS for navigation, gyroscopes, accelerometers, and cameras for capturing images and videos. For applications such as mapping and agriculture, more advanced UAVs can carry specialized sensors such as LiDAR (Light Detection and Ranging) and multispectral cameras [1]. UAVs come in various sizes and configurations, ranging from small quadcopters and fixed-wing drones to larger, more complex systems such as military drones and commercial aircraft. They are generally categorized into consumer drones, industrial drones, and military drones. UAVs are capable of generating high-resolution three-dimensional maps and collecting topographical data for land surveying and construction purposes. Additionally, UAVs are widely used for crop monitoring, precision agriculture, and the targeted application of fertilizers and pesticides. The advancement of UAV-based remote sensing systems has significantly enhanced the development of remote sensing and precision agriculture.

In recent years, UAV applications have gained popularity in geomatics. UAVs are utilized in photogrammetry, enabling rapid capture of high-resolution images from airborne cameras [2] and [3]. UAVs have become essential remote sensing tools due to their cost-effectiveness, efficiency, and ability to provide high spatial resolution imagery [4]. UAVs equipped with high-resolution multispectral cameras are increasingly used in urban planning, landscape management, and environmental monitoring, serving as valuable complements to traditional satellite remote sensing systems [5]. They have also emerged as promising tools for terrestrial surveys, particularly for forest health monitoring (FHM), offering advantages in assessing crown conditions and bridging the gap between ground-based surveys and conventional remote sensing platforms [6]. However, despite their contributions, knowledge gaps remain, especially regarding applications in natural forest environments [7].

Currently, various UAV-based multispectral mini-sensors capture surface reflectance or digital number (DN) values [8]. UAV remote sensing development offers exceptional opportunities for efficient and timely forest monitoring by employing spectral, textural, and structural measurements [9]. Multispectral data are valuable for assessing vegetation greenness and growth, including agricultural crops [10]. Multispectral cameras mounted on UAVs capture aerial spectral reflectance images of crops, allowing quantitative measurement of their physiological conditions directly linked to health status [11]. UAVs' primary advantages over other remote sensing platforms include very high spatial resolution data collection and ease of deployment, allowing users to define revisit intervals tailored to specific phenomena [12].

Previous research has demonstrated that remotely sensed spectral data can predict tree health and vitality. With advancements in UAV technology, acquiring high-resolution imagery at both tree and stand levels is now feasible [13]. Defining tree health requires a comprehensive approach considering multiple scales, from individual branches to entire forest ecosystems, accounting for both biotic and abiotic factors [14]. Presently, tree monitoring relies heavily on repeated manual observations of individual growth stages, which are labor-intensive, time-consuming, and demand extensive management of field data [15]. Over recent decades, remote sensing researchers have focused on integrating multiscale information for ecologically significant observations [16]. The Normalized Difference Vegetation Index (NDVI) and other vegetation indices support accurate monitoring and decision-making in agriculture, environmental conservation, and forestry, enhancing resource management and sustainability [17].

NDVI is a critical tool in precision agriculture for assessing plant health. From a metrological perspective, evaluating vegetation index quality is essential, as these indices derive from processed multispectral images measuring vegetation, soil, and environmental parameters [18]. Remotely sensed data provide vital information on crop and soil conditions, enabling more effective management practices in agriculture [19]. Integrating these disciplines allows collection, processing, and analysis of temporal, spatial, and individual data sets, which combine to implement effective solutions for resource use, productivity, quality, profitability, and sustainability in agricultural production [20]. Vegetation information is also critical for decision-making in urban regeneration, planning, environmental management, and landscaping [21].

Tree health is fundamental to environmental sustainability, biodiversity, and ecosystem services. Traditional tree health assessment methods such as visual inspection and manual sampling are labor-intensive, time-consuming, subjective, and lack comprehensive coverage over large areas. Given the increasing impacts of climate change, pollution, and urbanization, there is a pressing need for efficient, accurate, and scalable tree health monitoring approaches. Multispectral imaging offers a promising solution by capturing data across multiple wavelengths beyond the visible spectrum, revealing key physiological information about trees. However, challenges remain in developing and validating reliable methodologies and algorithms to analyze multispectral images and extract meaningful indicators of tree health, such as chlorophyll content, moisture levels, and stress markers.

This study addresses the development of a robust framework for assessing tree health using multispectral images. It aims to identify effective spectral bands and indices like NDVI that correlate with specific health indicators and to establish a reliable process for analyzing and interpreting multispectral data. Overcoming these challenges will improve the precision, efficiency, and scalability of tree health assessments, offering valuable tools for forestry management, urban planning, and environmental conservation. Pixel-based classification results show that classifiers perform better with multispectral data than with RGB data [22]. The aim of this study is to advance the assessment of UAV multispectral technology's potential for monitoring tree health. The objectives are to assess tree health using UAV multispectral imagery and to validate tree health conditions through conventional NDVI methods.

2. Materials and Methods

In this study, there were four stages to achieve the objective of the study. The stages involved were preliminary studies, data acquisition, data visualization, and data analysis. Figure 1 shows the flow of the study.

2.1 Preliminary Studies

In this stage, the study will use a multirotor drone and a multispectral sensor for equipment selection. The multirotor drone used in this study is the DJI Phantom 4, and the multispectral sensor is the Parrot Sequoia (Figure 2).

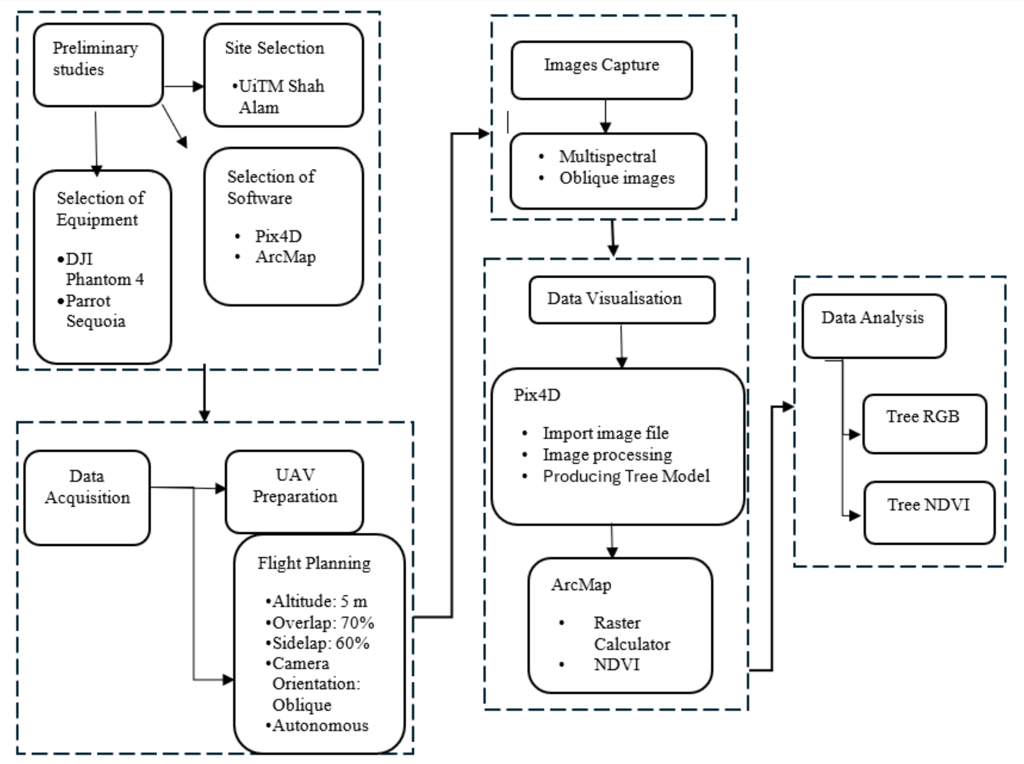

Figure 1: Three health assessment using UAV methodology

Figure 2: Dji Phantom 4 with Parrot Sequoia

The DJI Phantom 4 is a highly regarded drone known for its advanced features and reliable performance. It weighs 1,380 grams, including the battery and propellers, and has a diagonal size of 350 mm (excluding propellers). The drone can reach a maximum speed of 20 m/s in S mode and A mode, and 14 m/s in P mode. Its maximum ascent speed is 6 m/s in S mode and 5 m/s in P mode, while the maximum descent speed is 4 m/s in S mode and 3 m/s in P mode. The Phantom 4 has an approximate flight time of 28 minutes and a maximum flight distance of 5 km. It operates within a temperature range of 0°C to 40°C.

The gimbal provides a controllable pitch range from 90 degrees downward to 30 degrees upward. The camera includes a 1/2.3-inch CMOS sensor with 12.4 effective megapixels and a lens with a 94-degree field of view, a 20 mm focal length (35 mm equivalent), an f/2.8 aperture, and infinity focus. The ISO range is 100 to 3200 for video and 100 to 1600 for photos. Shutter speeds range from 8 seconds to 1/8000 of a second. The camera can capture images at a maximum resolution of 4000 × 3000 pixels. Photography modes include single shot, burst shooting (3, 5, or 7 frames), auto exposure bracketing (AEB) with 3 or 5 bracketed frames at 0.7 EV bias, and time-lapse. Video recording options include 4K at 24, 25, or 30 frames per second, 2.7K at 24, 25, or 30 fps, Full HD at up to 120 fps, and HD at up to 60 fps. The maximum video bitrate is 60 Mbps. Supported file formats include JPEG and DNG (RAW) for photos, and MP4 and MOV (MPEG-4 AVC/H.264) for videos. The Parrot Sequoia features a high-resolution RGB camera with a 4608 × 3456 pixel sensor, with each pixel measuring 1.34 micrometres and a 4.88 mm focal length. It also includes four monochrome cameras sensitive to specific spectral bands: green (530 to 570 nm), red (640 to 680 nm), red edge (730 to 740 nm), and near-infrared (770 to 810 nm). These monochrome cameras have a resolution of 1280 × 960 pixels, with each pixel measuring 3.75 micrometres and a focal length of 3.98 mm.

The area selected for this study is UiTM Shah Alam, located in the Petaling District of Selangor, Malaysia, as shown in Figure 3. In this study, the focus area is the trees that are part of the roadside landscape. The software used in this study includes Pix4D and ArcMap.

2.2 Data Acquisition

The second phase of the study was data acquisition. The multispectral images of the trees will be captured using a DJI Phantom 4 drone and a Parrot Sequoia camera. The Parrot Sequoia multispectral camera is equipped with four specific sensors tailored for agricultural applications, capturing data in the green, red, red edge, and near-infrared (NIR) wavelengths with their respective wavelengths and bandwidths. The flight altitude should be close to the trees for optimal image resolution, with 70% overlap and 60% side lap, and the drone must capture the entire tree from a suitable camera angle to prevent data loss. The multispectral sensor settings include auto capture mode, a 1.5 second timelapse interval, a 5 meter GPS interval, and 80% overlap. The camera sensor has a 1.2 MP resolution and 10 bit depth. The images captured will have two outputs: multispectral images from the Parrot Sequoia camera and oblique images from the DJI Phantom 4 camera.

2.3 Data Visualisation

The third phase of the study was data visualization. In this phase, the oblique images were imported into Pix4D software. The software processes triangulation, bundle adjustment, sparse reconstruction, and dense reconstruction. For the multispectral images, the images were imported into ArcMap software. The process started with importing the multispectral images, which included near-infrared (NIR) and red images. The workflow continued with the use of the Raster Calculator, a spatial analyst tool. The Raster Calculator in ArcMap was used to create the NDVI images. The processing then continued by classifying the NDVI values through the symbology properties. The color ramp was changed from red to green to display the NDVI values according to the NDVI classes shown in Table 1.

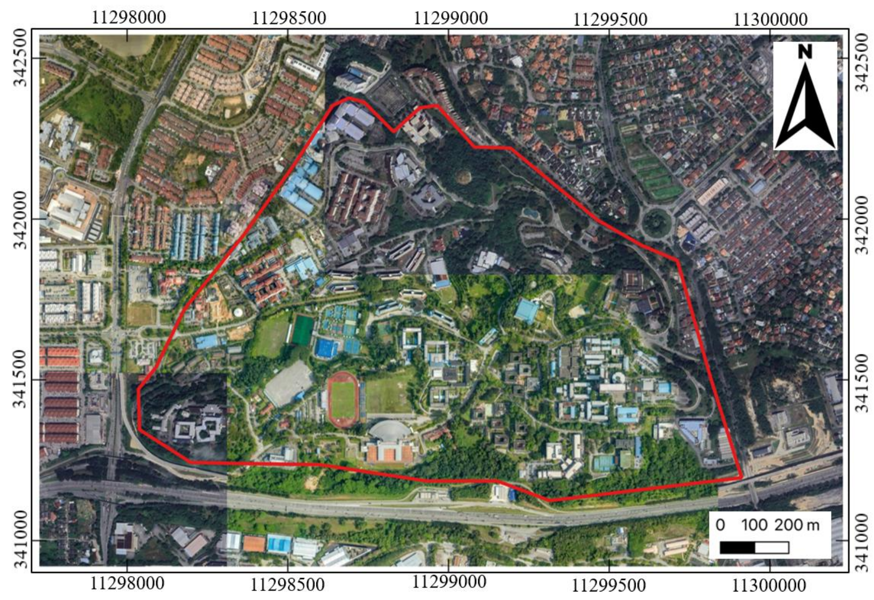

Figure 3: UiTM Shah Alam, Petaling District of Selangor, Malaysia

Table 1: The Classes of NDVI [23]

NDVI	Class
-1.00 to 0.00	Inanimate object
0.10 to 0.30	Diseased plant
0.31 to 0.60	Moderate healthy plant
0.61 to 1.00	Healthy plant

2.4 Data Analysis

The last phase of the study was data analysis. In this stage, the two types of imagery, which were RGB and NDVI images, were compared. Validation of NDVI (Normalized Difference Vegetation Index) using conventional methods involved a comprehensive approach that incorporated field measurements and advanced technologies. In this study, a spectroradiometer was used to validate the NDVI values obtained from ArcMap software.

A spectroradiometer is a valuable tool used to measure NDVI, which helps assess plant health and vigor. This device works by measuring the amount of light that plants reflect at different wavelengths, focusing on the red and near-infrared (NIR) parts of the light spectrum. Healthy plants absorb a significant amount of red light for photosynthesis but reflect much of the NIR light. The spectroradiometer captures these reflections, and by using the formula (NIR minus RED) divided by (NIR plus RED), it calculates the NDVI value (Equation 1). This value ranges from minus one to one, where higher values indicate healthier and denser vegetation. The spectroradiometer used in this study was the GER 1500, as shown in Figure 4.

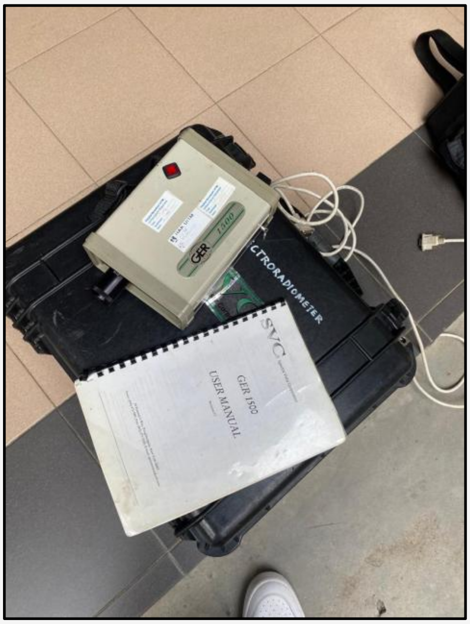

Figure 4: GER 1500 Spectroradiometer

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

Equation 1

Where:

$NDVI$ = Normalized Difference Vegetation Index

NIR = Spectral reflectance acquired from near-infrared region

R = Spectral reflectance acquired from red region

3. Results and Discussion

The results from the data processing will be discussed. The results are divided into three sections. First, the results of the Tree RGB produced by Pix4D Mapper software. Next, the results of the Tree NDVI produced by ArcMap. The results from these two methods will be compared using the NDVI values for analysis.

3.1 Result of Tree RGB

In this study, the Tree RGB results were produced using Pix4D software. The process was set to 3D Maps. There are two steps involved in producing the results. The processing started with initial processing, followed by Point Cloud and DSM generation. Figure 5 shows the result of the Tree RGB.

3.2 Result of Tree NDVI

The Tree NDVI results were produced using ArcMap. The process of generating Tree NDVI involved using the Raster Calculator to calculate the values. In the Raster Calculator, the NIR and Red images were used to calculate the NDVI values according to the formula in Equation 1. Then, the process continued by setting the symbology to classified in order to categorize the classes. Four classes were classified based on Table 1. Figure 6 shows the results of this process, which are images with NDVI colors that classify the health of the trees.

3.3 Comparison of NDVI Value

The study continues with a comparison of the Normalized Difference Vegetation Index (NDVI). The comparison was made between the Tree RGB produced by Pix4D Mapper and the Tree NDVI produced by ArcMap. A spectroradiometer was used to represent the NDVI values of the Tree RGB. Twenty points were selected for comparison of the NDVI values, as shown in Figures 7 and 8. The values obtained from the two different methods were compared by calculating the differences between the NDVI values. The points are labelled from P1 to P20, and the differences between the two methods are shown in Table 2 and Figure 9.

Figure 5: Result of Tree RGB

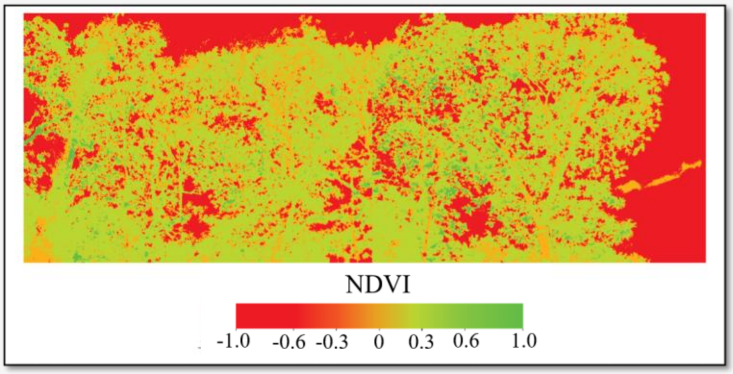

Figure 6: Result of Tree NDVI

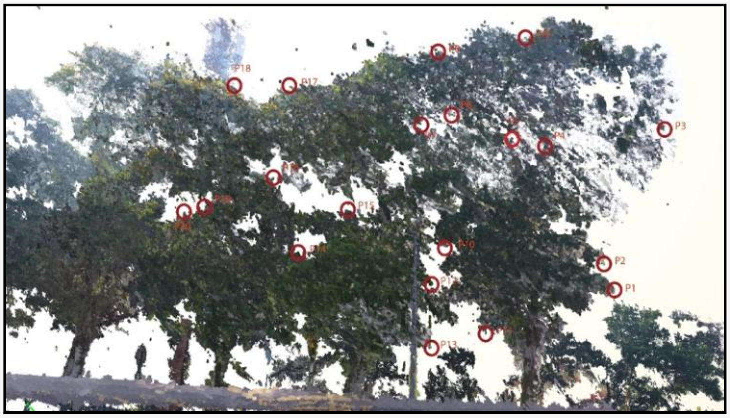

Figure 7: Pointed Tree RGB

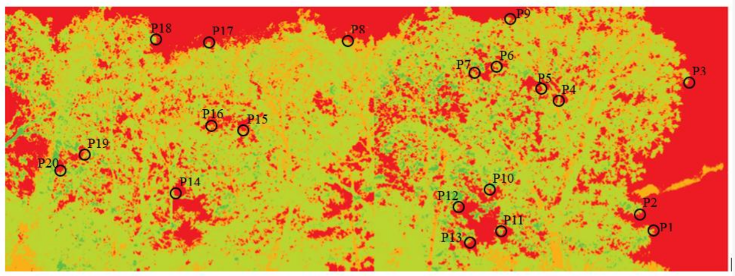

Figure 8: Pointed Tree RGB

Table 2: The Classes of NDVI

Point	NDVI value (Conventional)	NDVI value (ArcMap)	Difference
P1	0.828	0.587	-0.241
P2	0.740	0.598	-0.142
P3	0.714	0.581	-0.133
P4	0.725	0.635	-0.090
P5	0.797	0.536	-0.261
P6	0.820	0.774	-0.046
P7	0.772	0.601	-0.171
P8	0.757	0.632	-0.125
P9	0.830	0.608	-0.222
P10	0.782	0.705	-0.077
P11	0.720	0.656	-0.065
P12	0.838	0.708	-0.241
P13	0.796	0.637	-0.159
P14	0.782	0.627	-0.155
P15	0.838	0.656	-0.182
P16	0.825	0.588	-0.237
P17	0.838	0.627	-0.211
P18	0.842	0.711	-0.131
P19	0.786	0.706	-0.080
P20	0.772	0.695	-0.077
		RMSE	0.159

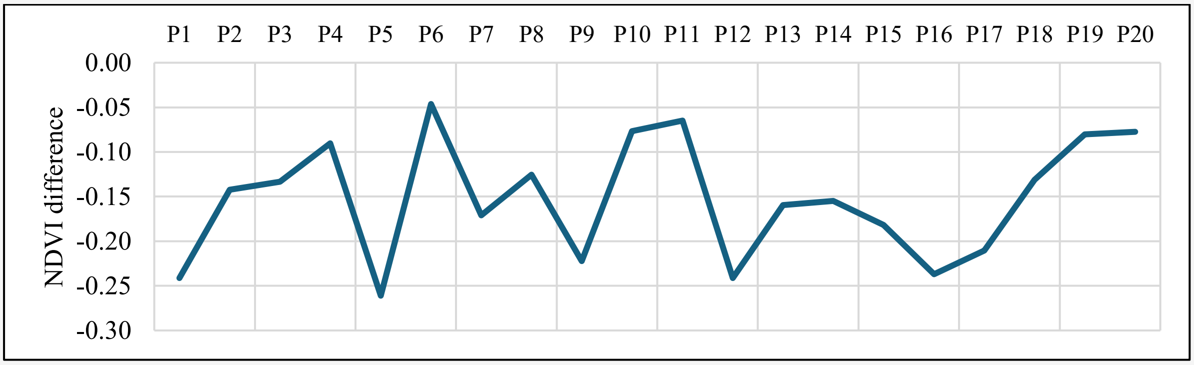

Figure 9: Differences between Conventional NDVI and Arcmap NDVI

The magnitude of these differences varies significantly across different points. For example, point P10 shows a conventional NDVI value of 0.782 and an ArcMap value of 0.705, resulting in a difference of -0.077. Meanwhile, point P18 has a conventional NDVI value of 0.842 and an ArcMap value of 0.711, giving a difference of -0.131. Notably, all differences are negative, indicating that NDVI values calculated using ArcMap are consistently lower than those obtained through conventional methods. This trend is evident at all points. For instance, at point P1, the conventional NDVI value is 0.828, while the ArcMap NDVI value is 0.587, resulting in a significant difference of -0.241. Similarly, at point P5, the conventional NDVI value is 0.797 and the ArcMap value is 0.536, showing an even larger difference of -0.261. Conversely, at point P6, the difference is relatively small, with a conventional NDVI value of 0.820 and an ArcMap value of 0.774, resulting in a difference of -0.046. The NDVI values obtained from the conventional method ranged from 0.720 to 0.842, while the ArcMap-derived NDVI values ranged from 0.536 to 0.774. Based on prior studies, NDVI values between 0.40 and 0.70 generally represent moderate vegetation health, whereas values above 0.70 are typical of dense and healthy vegetation [23][24] and [25]. Therefore, the conventional NDVI values in this study indicate healthy vegetation.

The ArcMap-based NDVI values were consistently lower than the conventional measurements, with a root mean square error (RMSE) of 0.159 and a standard deviation of 0.201. This deviation corresponds to an approximate 19–22%

difference, which can be considered moderate to high. Given that the conventional NDVI values were derived using a spectroradiometer an instrument known for its high accuracy the observed RMSE reflects potential limitations in the ArcMap-derived NDVI values produced from UAV multispectral images. However, the deviation may still be acceptable in operational forestry and environmental applications where high-frequency, wide-area monitoring is prioritized over pinpoint spectral accuracy. This trade-off between accuracy and efficiency highlights the practical relevance of UAV-based NDVI mapping, particularly when supported by proper calibration and optimized sensor settings.

4. Conclusions

This study examines the relationship between Tree RGB and NDVI to assess NDVI accuracy. The Tree NDVI results demonstrate the potential of UAV multispectral imaging for monitoring tree health by producing NDVI images from multispectral data. Comparing Tree RGB and Tree NDVI allows evaluation of tree condition. The NDVI values indicate that the trees are in good condition, as values closer to 1 represent healthy trees. The RMSE value of 0.159 reflects the average error magnitude between NDVI values from conventional methods and ArcMap. The standard deviation of 0.201 indicates the variability in differences between the two NDVI data sets.

The study recommends using high-resolution sensors with fast shutter speeds and proper orientation to capture high-quality images. It is important to ensure sensors are well-maintained to avoid blurry images and to consider weather conditions to provide sufficient light. Instruments like spectroradiometers should be regularly calibrated and handled consistently, including maintaining a fixed height and stable sample conditions, to minimize errors in NDVI measurements. Adequate lighting due to favourable weather is essential for accurate NDVI data. This research contributes to landscape and forest management by providing effective tree health monitoring and supports state authorities in ensuring the safety of roadside trees.

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