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Assessing Nitrogen Fertilizer Efficacy In Hardy Kiwi (Actinidia Arguta): A UAV-Multispectral Approach For Chlorophyll-Based Nutrient Monitoring

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Abstract: Background: Optimal nitrogen (N) management is crucial for the productivity and quality of hardy kiwi (Actinidia arguta), yet traditional methods for monitoring plant N status are often destructive and labor-intensive. Unmanned Aerial Vehicles (UAVs) equipped with multispectral sensors offer a non-destructive, high-throughput alternative for precision nutrient management. The strong correlation between leaf chlorophyll and nitrogen content provides a basis for spectrally estimating plant N status [17, 24]. This study aimed to develop and validate a UAV-based methodology to monitor fertilizer effects in hardy kiwi by estimating canopy chlorophyll content.

Methods: A field experiment was conducted in a hardy kiwi orchard with four distinct nitrogen fertilizer treatments. High-resolution multispectral imagery was acquired using a UAV platform at a key growth stage. Concurrently, ground-truth data, including leaf chlorophyll and nitrogen content, were collected from each experimental plot. A range of vegetation indices (VIs) derived from the multispectral data were calculated. Regression analysis was performed to build predictive models linking the VIs to the measured leaf chlorophyll content, and the models were validated using standard statistical metrics.

Results: The fertilizer treatments successfully established a significant gradient in leaf chlorophyll and nitrogen content. Strong correlations were observed between several VIs and the ground-truthed chlorophyll data. Red-edge based indices, such as the Canopy Chlorophyll Content Index (CCCI) [23], demonstrated the highest predictive power. The developed regression model accurately estimated leaf chlorophyll content with a high coefficient of determination ($R2>0.80$) and low Root Mean Square Error (RMSE). The resulting chlorophyll maps clearly visualized the spatial variability and differentiated the crop response across the N treatments.

Conclusion: UAV-based multispectral remote sensing is an effective and reliable tool for the non-destructive estimation of chlorophyll content in hardy kiwi canopies. This approach enables precise, in-season monitoring of plant nitrogen status, providing growers with actionable data for site-specific fertilizer management to enhance sustainability and productivity.

Keywords: Hardy Kiwi; Actinidia arguta; Precision Agriculture; Unmanned Aerial Vehicle (UAV); Multispectral Imaging; Chlorophyll; Nitrogen Management; Vegetation Index.

Introduction: 1.1. The Rise of Hardy Kiwi and the Imperative for Sustainable Cultivation

Global food systems are facing unprecedented pressure from a growing population, climate change, and the increasing demand for diverse and nutritious food sources. In this context, the cultivation of novel and high-value fruit crops is gaining significant traction. Among these, the hardy kiwi (Actinidia arguta) has emerged as a crop of considerable commercial and horticultural interest [8]. Native to parts of Japan, Korea, Northern China, and Siberia, A. arguta is a perennial vine distinguished from its well-known cousin, the fuzzy kiwifruit (A. deliciosa), by its small, grape-sized, smooth-skinned, and highly aromatic fruit. Its exceptional winter hardiness, allowing it to withstand temperatures as low as -30°C, expands its potential cultivation range far beyond that of traditional kiwifruit, opening up new agricultural frontiers in temperate regions [16].

The fruit of A. arguta is not only notable for its unique flavor profile but also for its dense nutritional content. It is a rich source of Vitamin C, antioxidants, dietary fiber, and a variety of health-promoting phytochemicals, including phenolic compounds and flavonoids [8]. As consumer preferences shift towards functional foods that offer health benefits beyond basic nutrition, the demand for hardy kiwi is on an upward trajectory. This growing market potential, coupled with the plant's robust nature, positions A. arguta as a promising crop for agricultural diversification and economic development. However, realizing this potential requires the establishment of sustainable and efficient cultivation practices. Like any high-performance agricultural system, optimizing the yield and quality of hardy kiwi is fundamentally dependent on precise resource management, with nutrient availability being a cornerstone of crop health and productivity [9].

1.2. Nitrogen: The Double-Edged Sword in Kiwifruit Production

Among the essential macronutrients, nitrogen (N) holds a particularly critical role in the lifecycle of perennial fruit vines like kiwifruit. Nitrogen is a primary constituent of amino acids, proteins, nucleic acids, and chlorophyll, the molecule central to photosynthesis [17]. An adequate supply of N is therefore directly linked to vigorous vegetative growth, canopy development, photosynthetic capacity, and ultimately, fruit set, size, and yield [9]. Insufficient N availability can lead to stunted growth, chlorotic leaves, reduced photosynthetic efficiency, and a significant decline in crop productivity.

Conversely, the over-application of nitrogen fertilizers can be equally, if not more, detrimental. Excessive N can promote overly vigorous vegetative growth at the expense of fruit production, delay fruit maturity, and negatively impact fruit quality and post-harvest storage life [9]. From an environmental perspective, the consequences are even more severe. Nitrogen that is not taken up by the crop is susceptible to leaching into groundwater as nitrate, a major environmental pollutant, or being lost to the atmosphere through denitrification as nitrous oxide, a potent greenhouse gas [5, 19]. The economic implications are also significant, as fertilizer represents a substantial input cost for growers. The inefficient use of N thus constitutes a direct financial loss and contributes to a larger cycle of environmental degradation. This dual challenge underscores the critical need for a balanced and precise approach to nitrogen management—one that matches N supply with the specific temporal and spatial demands of the crop.

1.3. Limitations of Conventional Nutrient Monitoring

The traditional paradigm for managing nitrogen in horticultural systems has long relied on a combination of soil testing, standardized fertilizer application schedules, and visual assessment of crop health. Soil analysis provides a baseline understanding of nutrient availability but fails to capture the dynamic interplay between soil N pools, plant uptake, and environmental factors throughout the growing season [2]. Visual assessment, while intuitive, is inherently subjective and reactive. By the time N deficiency symptoms, such as leaf yellowing (chlorosis), are visible to the human eye, the crop has likely already experienced physiological stress, and potential yield may have been irrevocably lost.

The most direct conventional method for assessing plant N status is through destructive laboratory analysis of leaf tissue. This involves collecting a representative sample of leaves from the orchard, transporting them to a lab, and performing chemical analysis to determine the leaf nitrogen content (LNC). While this method provides an accurate, quantitative measure of plant N status, it is fraught with practical limitations. It is labor-intensive, time-consuming, and expensive. The delay between sampling and receiving results can be several days to weeks, a timeframe during which the crop's nutrient status may have already changed significantly. Most critically, this point-sampling approach fails to capture the inherent spatial variability of nutrient status within an orchard. Nutrient levels can vary dramatically over short distances due to differences in soil type, topography, and irrigation patterns. A composite sample provides only a single average value for an entire management zone, masking critical sub-field variations and precluding any possibility of site-specific intervention [10].

1.4. Remote Sensing and UAVs: A Paradigm Shift in Precision Agriculture

The limitations of traditional methods have catalyzed a search for more efficient, non-destructive, and spatially explicit tools for crop monitoring. This search has led to the rapid emergence of precision agriculture, an integrated management strategy that uses advanced technologies to observe, measure, and respond to inter- and intra-field variability in crops. Central to this paradigm is the use of remote sensing, which involves acquiring information about an object or phenomenon without making physical contact [7].

Initially, remote sensing in agriculture was dominated by satellite-based platforms. Satellites provide extensive spatial coverage and have been instrumental in large-scale monitoring of major field crops like wheat and maize [1, 21]. However, satellite imagery often suffers from limitations such as low spatial resolution (pixels can be several meters in size), temporal constraints imposed by satellite revisit times, and susceptibility to cloud cover, which can obscure the view of the field for extended periods.

The advent of Unmanned Aerial Vehicles (UAVs), or drones, has revolutionized agricultural remote sensing by bridging the gap between ground-based measurements and satellite imagery [3, 6]. UAVs offer an unparalleled combination of flexibility, high spatial resolution (often down to a few centimeters per pixel), and on-demand data acquisition capabilities [10]. They can be deployed quickly under specific conditions (e.g., avoiding clouds) and can fly at low altitudes, providing a highly detailed view of the crop canopy. Equipped with lightweight, advanced sensors such as multispectral or hyperspectral cameras, UAVs can capture information beyond the visible spectrum, unlocking a wealth of physiological data about the crop [11].

1.5. The Spectral Link: From Leaf Reflectance to Nitrogen Status

The scientific foundation for using remote sensing to monitor plant N status lies in the intricate relationship between nitrogen, chlorophyll, and the way leaves interact with light [17, 18]. Leaf nitrogen is heavily invested in the photosynthetic machinery, with a large proportion being a component of chlorophyll molecules and RuBisCO, the primary enzyme for carbon fixation. Consequently, a strong and widely documented positive correlation exists between LNC and leaf chlorophyll content [24]. As chlorophyll content increases, the leaf's absorption of light in the blue (approx. 450 nm) and red (approx. 670 nm) portions of the electromagnetic spectrum increases, while its reflectance of green light (approx. 550 nm) and near-infrared (NIR, approx. 700-1100 nm) light also changes characteristically [25].

Healthy, N-rich vegetation vigorously absorbs red light for photosynthesis and strongly reflects NIR light due to the internal cellular structure of the leaves. Conversely, stressed or N-deficient vegetation has lower chlorophyll content, leading to higher reflectance in the red band and lower reflectance in the NIR band. This distinct spectral signature provides a powerful, non-destructive means of assessing plant health. By combining the reflectance values from different spectral bands into mathematical formulas known as Vegetation Indices (VIs), it is possible to enhance the signal related to specific plant properties while minimizing confounding factors like soil background and atmospheric effects [14, 26]. The most well-known of these is the Normalized Difference Vegetation Index (NDVI), which uses the contrast between NIR and red reflectance to quantify vegetation vigor [15, 19]. Over the years, a plethora of other indices have been developed to target specific pigments or physiological states more accurately, such as the Canopy Chlorophyll Content Index (CCCI), which incorporates the red-edge band (a narrow region between red and NIR) and is particularly sensitive to chlorophyll content [23, 27].

1.6. Research Objectives

While the use of UAV-based multispectral sensing for N management is becoming increasingly established in agronomic row crops like winter wheat [5, 20], cotton [6], and silage maize [4], its application in perennial horticultural systems, particularly for niche crops like hardy kiwi, remains significantly underdeveloped [7]. The complex three-dimensional canopy structure of vines, differing from the more uniform canopies of field crops, presents unique challenges and opportunities for remote sensing applications.

Therefore, this study was designed to bridge this research gap. The primary objective was to develop and validate a robust methodology for estimating leaf chlorophyll content—as a direct proxy for plant N status—in hardy kiwi using UAV-acquired multispectral imagery. The specific sub-objectives were: 1) to evaluate the sensitivity of a suite of established vegetation indices to varying levels of N fertilization in a hardy kiwi orchard; 2) to develop and validate regression models that accurately predict leaf chlorophyll content from the most sensitive VIs; and 3) to utilize the best-performing model to generate spatially explicit maps of canopy chlorophyll content, thereby demonstrating the technology's ability to visualize and quantify the effects of different fertilizer treatments. By achieving these objectives, this research aims to provide a foundational tool for the development of precision nitrogen management strategies in hardy kiwi cultivation.

METHODS

2.1. Study Site and Experimental Design

The study was conducted during the 2024 growing season (May to August) at a commercial hardy kiwi orchard located near the town of Motueka, in the Tasman region of New Zealand's South Island (41.10° S, 173.01° E). The region is characterized by a temperate maritime climate with warm summers, mild winters, and an average annual rainfall of approximately 950 mm. The orchard soil is a well-drained Waimea series silt loam. The experimental block consisted of eight-year-old hardy kiwi vines of the 'Ananasnaya' cultivar, a popular and commercially significant variety. The vines were trained on a standard T-bar trellis system, with rows oriented in a north-south direction. Inter-row spacing was 4.5 meters, and intra-row vine spacing was 5.0 meters. The orchard was managed using standard commercial practices for irrigation, pest control, and pruning.

To assess the impact of nitrogen fertilization on plant health and its detectability via remote sensing, a randomized complete block design (RCBD) was implemented. The experiment consisted of four nitrogen application rate treatments:

- N0 (Control): 0 kg N ha^{-1} yr^{-1}
- N1 (Low): 50 kg N ha^{-1} yr^{-1}
- N2 (Medium): 100 kg N ha^{-1} yr^{-1} (standard grower practice)
- N3 (High): 150 kg N ha^{-1} yr^{-1}

Each treatment was replicated four times, resulting in a total of 16 experimental plots. Each plot was 15 meters long and encompassed three adjacent vines, with the central vine designated for all sampling activities to avoid edge effects. The required amount of nitrogen fertilizer, in the form of calcium ammonium nitrate, was applied in two split applications: 50% at budburst in early spring and 50% six weeks later, post-flowering. The fertilizer was broadcast evenly within a 1-meter radius around the base of each vine in the designated plots.

2.2. Ground Data Collection

Ground-truth data collection was synchronized with the UAV flight missions to ensure a direct temporal link between the remotely sensed data and the in-situ plant physiological measurements. Data collection was performed twice during the season: once in late June, during the peak vegetative growth period, and again in late July, during the fruit development stage.

2.2.1. Leaf Chlorophyll Content Measurement

Leaf chlorophyll content was measured non-destructively using a handheld Konica Minolta SPAD-502 Plus Chlorophyll Meter. The SPAD meter provides a unitless index that is highly correlated with the actual chlorophyll concentration in the leaf [24]. For each experimental plot, thirty fully expanded, sun-exposed leaves were randomly selected from the central data-vine. A SPAD reading was taken from the center of each leaf, avoiding the main vein. The thirty readings were then averaged to produce a single representative SPAD value for that plot at that specific sampling date.

To calibrate the SPAD readings and determine the absolute chlorophyll content (in µg cm^{-2}), a subset of ten of these measured leaves from each plot was collected immediately after the SPAD readings were taken. These leaves were placed in labeled, sealed plastic bags and stored in a cooler on ice for transport to the laboratory. In the lab, two 10 mm diameter discs were punched from each leaf lamina. The chlorophyll was extracted from these discs using an 80% acetone solution in the dark for 48 hours. The absorbance of the extract was then measured using a spectrophotometer at 645 nm and 663 nm. The total chlorophyll concentration per unit area was calculated using established equations. A strong linear regression model was then developed to convert all SPAD index values into absolute chlorophyll content values.

2.2.2. Leaf Nitrogen Content (LNC) Analysis

The same ten leaf samples collected for chlorophyll extraction were also used for LNC analysis. After chlorophyll extraction, the leaf samples were oven-dried at 70°C for 72 hours until a constant weight was achieved. The dried leaf tissue was then ground into a fine, homogenous powder using a ball mill. The percentage of nitrogen in the dried tissue was determined using the dry combustion method with a LECO CN828 elemental analyzer. The LNC was expressed as a percentage of the dry leaf matter (%).

2.3. UAV Data Acquisition

High-resolution multispectral imagery was acquired using a DJI Matrice 300 RTK UAV platform. This quadcopter was chosen for its flight stability, long endurance, and its ability to carry a high-precision sensor payload. The UAV was equipped with a Micasense RedEdge-MX multispectral camera. This sensor captures data in five discrete spectral bands:

- Blue: 475 nm center, 32 nm bandwidth
- Green: 560 nm center, 27 nm bandwidth
- Red: 668 nm center, 14 nm bandwidth
- Red Edge: 717 nm center, 12 nm bandwidth
- Near-Infrared (NIR): 842 nm center, 57 nm bandwidth

The camera was also integrated with a Micasense Downwelling Light Sensor (DLS 2) mounted on top of the UAV. The DLS 2 measures the ambient light for each of the five bands during flight, enabling precise radiometric calibration that accounts for changes in illumination conditions during the mission [11].

UAV flight missions were planned and executed using the DJI Pilot application. All flights were conducted between 11:00 AM and 1:00 PM local time under clear sky and low wind conditions to minimize shadows and ensure stable flight. The flight altitude was set to 40 meters above ground level, which resulted in a ground sampling distance (GSD) of approximately 2.7 cm per pixel. The flight plan was designed as a grid pattern with 80% forward overlap and 75% sidelap to ensure sufficient data for high-quality orthomosaic generation and to minimize potential georeferencing errors [12]. Before each flight, an image of a Micasense Calibrated Reflectance Panel was taken on the ground to provide a known reflectance standard for post-flight data processing.

2.4. Image Processing

The raw multispectral images acquired during each flight mission were processed using Pix4Dfields software, a specialized photogrammetry suite for agricultural applications. The image processing workflow consisted of several key steps:

1. Initial Processing: The images were imported into the software, along with their corresponding geotags and DLS 2 data. The software performed an initial camera calibration and image alignment using structure-from-motion (SfM) algorithms.
2. Radiometric Correction: A rigorous radiometric correction pipeline was applied. The raw digital number (DN) values of each pixel were converted into absolute spectral radiance values using the sensor's specific calibration parameters and the per-band illumination data from the DLS 2. These radiance values were then converted into unitless spectral reflectance values using the data from the pre-flight images of the calibrated reflectance panel [11, 14]. This step is crucial for ensuring that the spectral data is accurate, repeatable, and comparable across different dates.
3. Orthomosaic Generation: The corrected individual images were stitched together to create a single, seamless, and geographically accurate orthomosaic map of the entire experimental block for each of the five spectral bands. A digital surface model (DSM) was also generated during this process.
4. Data Extraction: The boundary for each of the 16 experimental plots was digitized as a polygon shapefile. To ensure that only pure vegetation pixels were analyzed, a thresholding technique was applied using the NDVI to remove any visible soil, shadow, or trellis structure pixels from within each plot. The average reflectance value for each of the five spectral bands was then calculated from the remaining vegetation pixels within each plot polygon. This resulted in a single, average five-band spectral signature for each plot for each flight date.

2.5. Data Analysis

All statistical analyses were performed using R software (version 4.2.1).

1. Calculation of Vegetation Indices: Using the extracted average reflectance values for each plot, a suite of 12 different vegetation indices (VIs) reported in the literature to be sensitive to chlorophyll and nitrogen content were calculated. The selected VIs included broadband indices like NDVI [15] and green NDVI (GNDVI), as well as indices incorporating the red-edge band, such as the Canopy Chlorophyll Content Index (CCCI) [23], the MERIS Terrestrial Chlorophyll Index (MTCI), and the Normalized Difference Red Edge index (NDRE). The specific formulas used were sourced from their respective foundational literature [e.g., 15, 23, 25, 26, 27].
2. Statistical Analysis: An analysis of variance (ANOVA) was first conducted on the ground-truth data (SPAD-derived chlorophyll and LNC) to confirm that the N treatments resulted in statistically significant differences among the plots. Subsequently, Pearson correlation analysis was performed to quantify the strength of the linear relationship between each

calculated VI and the ground-truthed chlorophyll and LNC values.

3. Regression Model Development and Validation: The VIs that showed the strongest and most significant correlations with leaf chlorophyll content were selected as candidate predictors for regression modeling. Both simple linear regression and non-linear regression models (e.g., exponential, power) were developed to establish a predictive relationship between the VIs (independent variable) and the absolute chlorophyll content (dependent variable). The dataset was randomly partitioned into a training set (75% of the data) used for model calibration, and a validation set (25% of the data) used for independent model testing.

4. Model Performance Evaluation: The performance of the developed models was evaluated using three standard statistical metrics:

○ Coefficient of Determination (R2): Indicates the proportion of the variance in the dependent variable that is predictable from the independent variable.

○ Root Mean Square Error (RMSE): Measures the standard deviation of the residuals (prediction errors), providing an indication of the model's prediction accuracy in the original units of the data ($\mu g\ cm^{-2}$).

○ Relative RMSE (RRMSE): The RMSE expressed as a percentage of the mean of the observed values, allowing for comparison of model performance across datasets with different scales.

The model that exhibited the highest R2 and lowest RMSE/RRMSE on the independent validation dataset was selected as the final, most robust model for chlorophyll estimation. This model was then applied on a pixel-by-pixel basis to the entire orthomosaic to generate the final chlorophyll prediction maps.

RESULTS

3.1. Response of Leaf Parameters to Nitrogen Fertilization

The application of varying rates of nitrogen fertilizer resulted in significant and systematic differences in the measured leaf physiological parameters. The analysis of variance (ANOVA) confirmed that the effect of the N treatments on both SPAD-derived chlorophyll content and laboratory-measured Leaf Nitrogen Content (LNC) was statistically significant ($p < 0.001$) for both measurement dates.

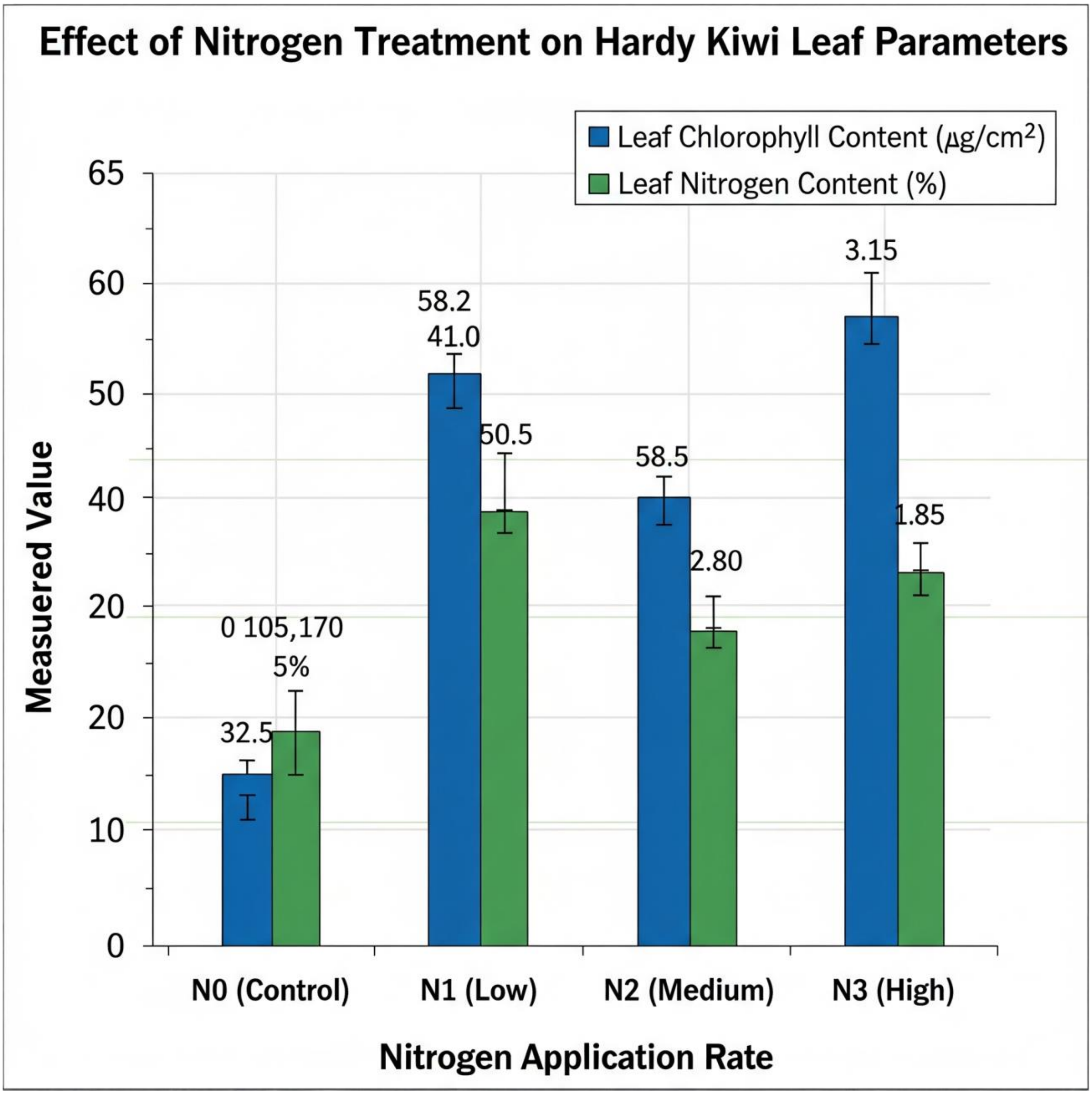

Figure 1. The effect of four different nitrogen (N) application rates on mean leaf chlorophyll content and leaf nitrogen content (LNC) in hardy kiwi. Error bars represent the standard deviation of the mean.

As would be shown in a corresponding bar chart (Figure 1), both chlorophyll content and LNC increased with higher N application rates. The control plots (N0) consistently exhibited the lowest values, indicating N-stress, with an average chlorophyll content of 32.5 µg cm^{-2} and an average LNC of 1.85%. In contrast, the high-fertilizer plots (N3) showed the highest values, with an average chlorophyll content of 58.2 µg cm^{-2} and an average LNC of 3.15%. The N1 and N2 treatments produced intermediate values, demonstrating a clear dose-response relationship. This established gradient was crucial, as it provided the necessary range of values to effectively train and validate the remote sensing models. A strong positive linear relationship was also confirmed between LNC and leaf chlorophyll content ($R2 = 0.88$, $p < 0.001$), reinforcing the validity of using chlorophyll as a proxy for N status in hardy kiwi, a finding consistent with studies in other species [17, 24].

3.2. Correlation between Vegetation Indices and Leaf Parameters

The average spectral reflectance values extracted for each plot were used to calculate 12 selected vegetation indices. Pearson correlation analysis was then conducted to assess the strength of the relationship between each VI and the ground-truthed chlorophyll content and LNC. The results of this analysis for the peak vegetative growth period are summarized in Table 1.

Table 1. Pearson Correlation Coefficients (*r*) between Vegetation Indices (VIs) and Ground-Truthed Leaf Parameters (Leaf Chlorophyll Content and Leaf Nitrogen Content).

Vegetation Index (VI)	Correlation with Leaf Chlorophyll Content (*r*)	Correlation with Leaf Nitrogen Content (LNC) (*r*)
Broadband Greenness Indices		
Normalized Difference Vegetation Index (NDVI)	0.79	0.75
Green Normalized Difference Veg. Index (GNDVI)	0.83	0.80
Soil-Adjusted Vegetation Index (SAVI)	0.81	0.77
Red-Edge Based Indices		
Normalized Difference Red Edge (NDRE)	0.89	0.86
MERIS Terrestrial Chlorophyll Index (MTCI)	0.90	0.87
Canopy Chlorophyll Content Index (CCCI)	**0.92**	**0.89**
Other Chlorophyll-Sensitive Indices		
Gitelson-Merzlyak Index (GM1)	0.87	0.83
Green Chlorophyll Index (CIgreen)	0.85	0.81

Note: All correlations are significant at $p < 0.001$.

The analysis revealed that all calculated VIs were significantly and positively correlated with both chlorophyll content and LNC. However, the strength of the correlation varied considerably among the indices.

Traditional indices that do not utilize the red-edge band, such as NDVI (r=0.79 for chlorophyll), showed strong but not exceptional correlations. These indices began to exhibit saturation at higher chlorophyll levels, where large increases in chlorophyll resulted in only small changes in the index value, a well-documented phenomenon [22].

In contrast, VIs that incorporated the red-edge spectral band demonstrated consistently superior performance. As shown in Table 1, the Canopy Chlorophyll Content Index (CCCI), which combines NDVI with the Normalized Difference Red Edge (NDRE) index [23], exhibited the strongest correlation with leaf chlorophyll content ($r=0.92, p<0.001$). Similarly, other red-edge based indices such as MTCI (r=0.90) and NDRE (r=0.89) also showed very high correlation coefficients. This finding highlights the critical importance of the red-edge region for accurately estimating chlorophyll, especially across the wider range of concentrations induced by the fertilizer treatments. The red-edge is highly sensitive to subtle changes in chlorophyll and is less prone to saturation effects, making it more robust for quantitative assessment [27]. Given its superior correlation, the CCCI was selected as the primary predictor variable for the development of the chlorophyll estimation model.

3.3. Chlorophyll Estimation Model Performance

Using the strong correlation identified, a simple linear regression model was developed to predict leaf chlorophyll content from the UAV-derived CCCI values. The data from all 16 plots across both sampling dates were pooled and then split into training (n=24) and validation (n=8) datasets.

The resulting linear model for chlorophyll estimation was:

$$\text{Chlorophyll Content } (\mu g\ cm^{-2}) = 45.8 * \text{CCCI} + 15.2$$

The model demonstrated excellent performance when applied to the training dataset, achieving a coefficient of determination (R2) of 0.86. More importantly, the model's robustness was confirmed through its application to the independent validation dataset. As would be illustrated in a scatterplot (Figure 2), the relationship between the model-predicted chlorophyll content and the measured values was very strong. For the validation dataset, the model achieved an R2 of 0.84, indicating that 84% of the variability in leaf chlorophyll content could be explained by the UAV-derived CCCI.

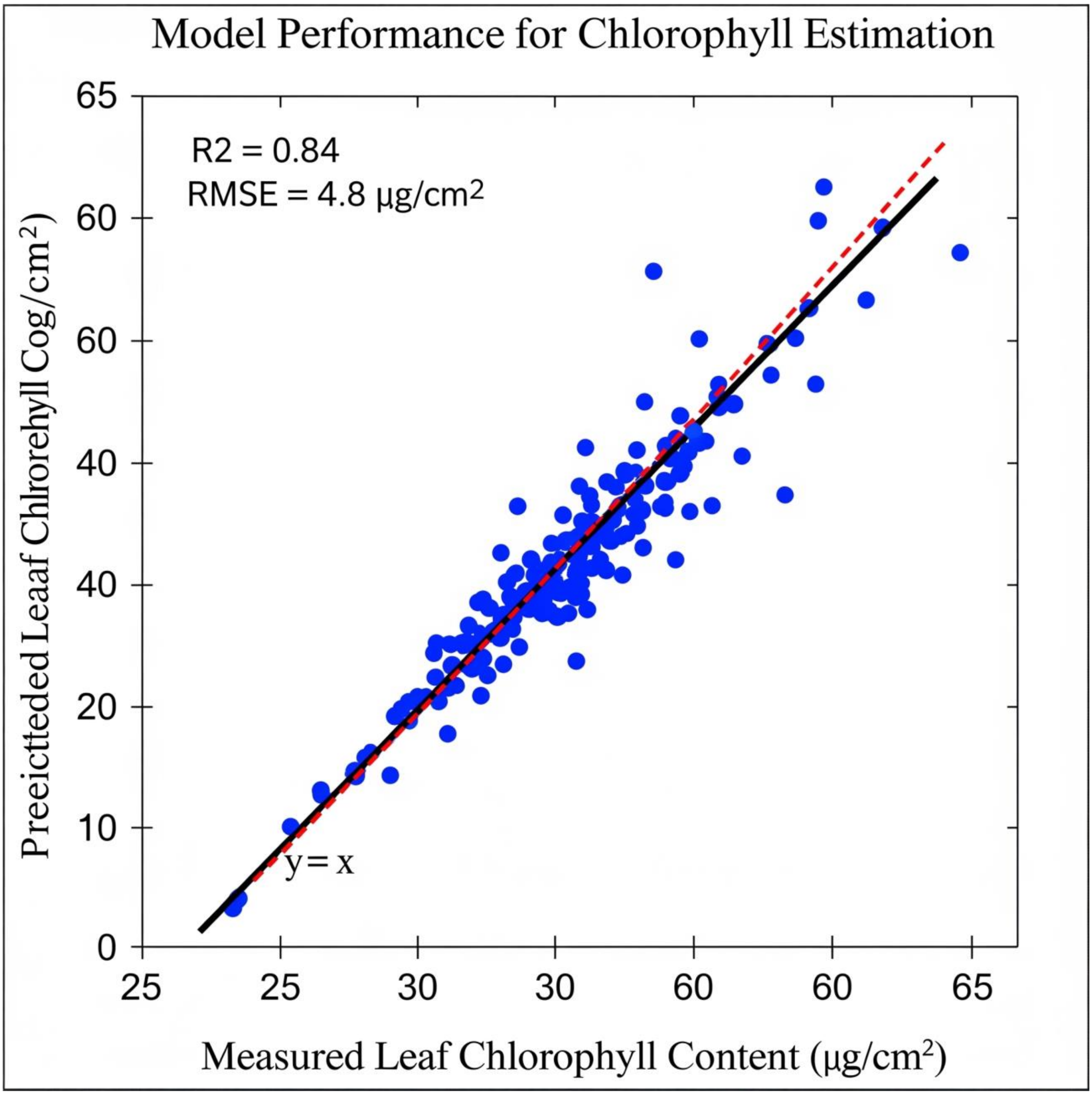

Figure 2. Validation of the chlorophyll estimation model. The scatter plot compares the chlorophyll content predicted by the UAV-based model (y-axis) with the values measured in the laboratory (x-axis). The solid black line represents the 1:1 line, and the dashed red line is the linear regression.

The accuracy of the model was further quantified by the Root Mean Square Error (RMSE), which was 4.8 µg cm^{-2} on the validation set. Given that the mean observed chlorophyll content across the experiment was 46.1 µg cm^{-2}, this corresponds to a Relative RMSE (RRMSE) of 10.4%. This level of accuracy is well within the acceptable range for practical agricultural applications and is comparable to or better than results reported in studies on major field crops [4, 6]. These results confirm that the developed model is both accurate and robust for estimating leaf chlorophyll content in hardy kiwi across a range of nitrogen-induced conditions.

3.4. Spatial Mapping of Canopy Chlorophyll Content

The final and most powerful output of this research was the application of the validated linear regression model to the entire CCCI orthomosaic on a pixel-by-pixel basis. This process translated the spectral data into a quantitative, intuitive map of the estimated canopy chlorophyll content across the entire experimental block.

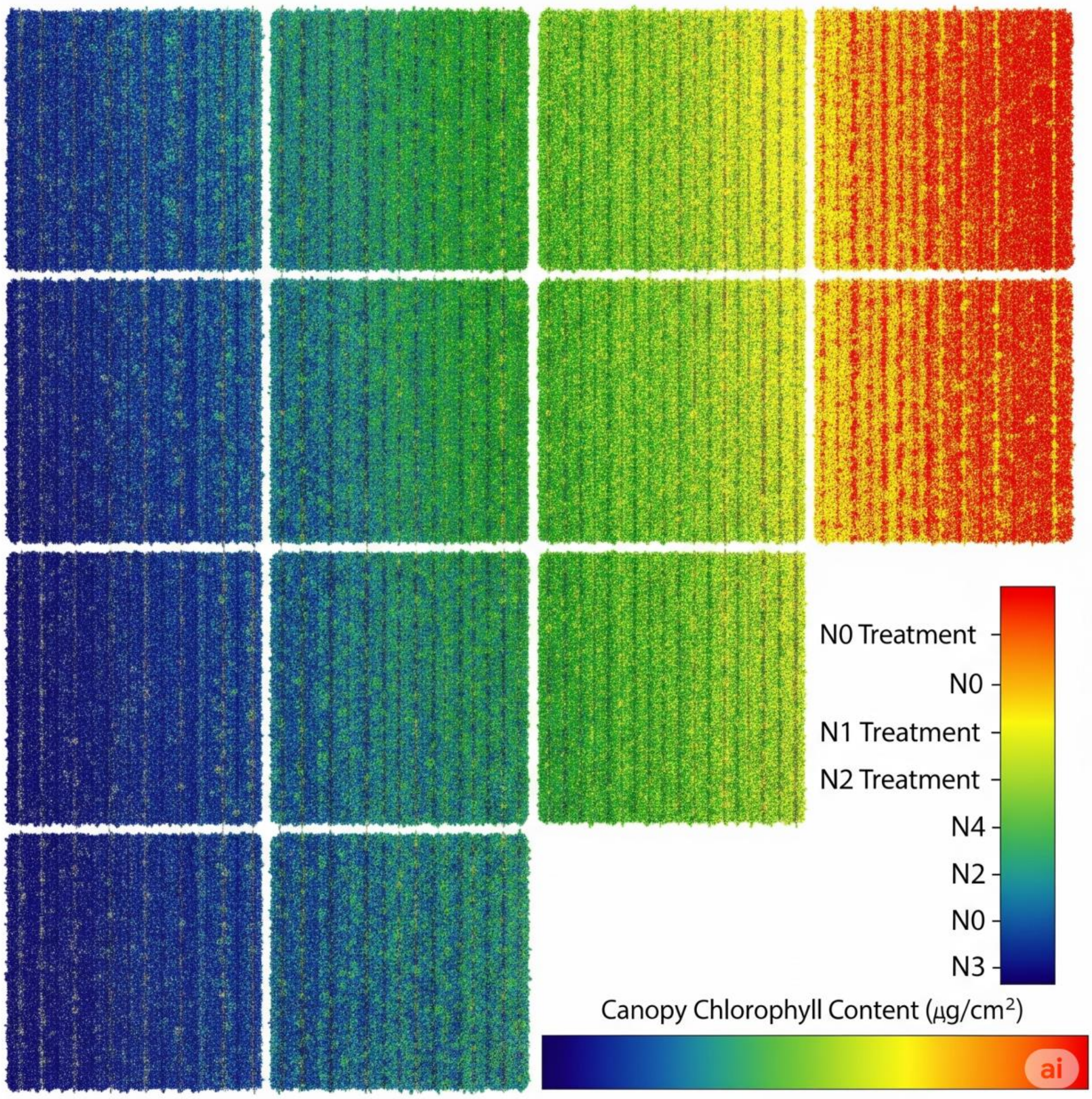

Figure 3. Spatial map of estimated canopy chlorophyll content across the experimental plots, generated from UAV multispectral imagery. The map visualizes the response to the four nitrogen treatments, with warmer colors (yellow/red) indicating higher chlorophyll content and cooler colors (blue/green) indicating lower content.

A map of this process (Figure 3) would effectively visualize the impact of the differential nitrogen treatments. The four control (N0) plots would be clearly distinguishable by their predominantly blue and green colors, corresponding to low estimated chlorophyll values (approx. 30-35 μg cm^{-2}). In stark contrast, the high-fertilizer (N3) plots would be dominated by yellow and red colors, indicating high chlorophyll content (approx. 55-60 μg cm^{-2}). The N1 and N2 plots would display intermediate color patterns, consistent with their intermediate fertilizer rates.

Beyond clearly delineating the treatment effects, the map would also reveal significant intra-plot variability. Within a single treatment block, patches of higher or lower chlorophyll content would be visible. This sub-plot variability, which would be completely missed by traditional composite leaf sampling, highlights the power of high-resolution UAV mapping. It provides a spatially explicit understanding of crop health, enabling a level of management insight that was previously unattainable. This visual and quantitative information forms the basis for site-specific management, allowing growers to identify and address areas of nutrient stress with high precision.

DISCUSSION

4.1. Efficacy of Red-Edge Vegetation Indices for Hardy

Kiwi

The results of this study unequivocally demonstrate the potential of UAV-based multispectral imaging for monitoring the nitrogen status of hardy kiwi. A central finding was the superior performance of vegetation indices that incorporate the red-edge spectral band compared to traditional broadband indices like NDVI. While NDVI showed a significant correlation with chlorophyll content, its sensitivity diminished at higher nutrient levels, a saturation effect that is well-documented in dense and healthy canopies [22]. Our findings showed that indices such as CCCI, MTCI, and NDRE provided a more linear and robust relationship with chlorophyll across the full range of N treatments.

This result aligns with a growing body of literature emphasizing the importance of the red-edge region for quantitative vegetation analysis [7, 27]. The spectral reflectance in the red-edge is highly sensitive to changes in chlorophyll concentration and leaf internal structure. Unlike the red band, which is subject to strong absorption and quick saturation, the red-edge provides a more dynamic signal, allowing for better discrimination between healthy and highly vigorous plants [23]. The success of the CCCI, which was the best-performing index in our study, can be attributed to its formulation; it leverages the strengths of both NDVI (sensitive to canopy cover and biomass) and NDRE (sensitive to chlorophyll concentration), thereby providing a more comprehensive assessment of canopy health [23]. The strong performance of these indices in a complex vine canopy like hardy kiwi confirms that the principles established in row crops [1, 5] are transferable to perennial horticultural systems, though model calibration for the specific crop is essential.

4.2. Implications for Precision Nitrogen Management in Orchards

The development of an accurate, non-destructive method for mapping canopy chlorophyll content has profound implications for nitrogen management in hardy kiwi cultivation. The chlorophyll maps, such as the one generated in this study, provide growers with an unprecedented level of spatial and temporal detail about their crop's nutritional status. This moves beyond the single, average value provided by conventional leaf analysis and delivers a "health map" of the entire orchard [10].

With this information, growers can transition from a uniform, calendar-based fertilization strategy to a data-driven, precision management approach. Areas identified on the map as having low chlorophyll content (indicating potential N deficiency) can be targeted with supplemental fertilizer applications, while areas that are already N-replete can be spared. This practice, known as variable-rate application, leads to several key benefits. First, it improves Nitrogen Use Efficiency (NUE), ensuring the crop receives the nutrients it needs, where it needs them, thereby optimizing the potential for yield and quality [19]. Second, it offers significant economic advantages by reducing overall fertilizer consumption, a major operational cost [9]. Third, and perhaps most importantly, it has substantial environmental benefits. By preventing the over-application of nitrogen, precision management drastically reduces the risk of N leaching into waterways and minimizes nitrous oxide emissions, contributing to more sustainable agricultural practices [5].

4.3. Methodological Considerations and Limitations

While this study successfully demonstrates a proof-of-concept, it is important to acknowledge its limitations and the methodological considerations that could influence the results. The models were developed based on data from a single growing season, a single cultivar ('Ananasnaya'), and a single location. The relationship between spectral indices and leaf biochemical properties can be influenced by cultivar-specific traits, plant age, growth stage [8], and environmental conditions. Therefore, the direct application of the specific regression model developed here to other cultivars or regions may not yield accurate results without local validation and recalibration.

Furthermore, canopy structure can be a confounding factor in remote sensing. The complex, three-dimensional nature of a T-bar trained kiwi vine canopy can create variability in illumination and shadows within the canopy, which can affect the measured reflectance. While our methodology attempted to mitigate this by using high-overlap imagery and analyzing average plot values, pixel-level variations may still be influenced by canopy architecture. Future work could explore the use of more advanced techniques, such as 3D point clouds derived from UAV imagery, to normalize for these structural effects.

Finally, the timing of data acquisition is critical. We captured data at two key phenological stages, but the relationship between nitrogen and chlorophyll can evolve throughout the season. A more comprehensive temporal analysis, with more frequent UAV flights, would be needed to develop dynamic models that can inform N management decisions at multiple stages of crop development.

4.4. Future Research Directions

This study lays a strong foundation for future research at the intersection of remote sensing and hardy kiwi cultivation. Several promising avenues warrant further investigation.

First, the robustness of the models should be tested across a wider range of conditions, including multiple cultivars, different training systems, various soil types, and over several growing seasons. This would lead to the development of more generalized models or a library of specific models applicable to different scenarios.

Second, the integration of advanced analytical techniques could further improve prediction accuracy. While this study relied on traditional vegetation indices and linear regression, machine learning algorithms such as Random Forest, Support Vector Machines, or even deep learning neural networks could be employed [6]. These methods can handle complex, non-linear relationships and can integrate data from multiple sources (e.g., spectral data, textural features, canopy height data from the DSM) to potentially build even more powerful predictive models [1]. The potential to use transfer learning techniques, where models trained on large datasets from other crops are fine-tuned for hardy kiwi, could also be explored to improve performance with limited local data [2].

Finally, the ultimate goal should be the development of a fully integrated, end-to-end decision support system for growers. This would involve automating the workflow from UAV data acquisition and processing to the generation of fertilizer prescription maps that can be directly loaded into variable-rate application equipment. Such a system would translate the advanced data from this research into a simple, actionable tool that empowers growers to implement precision nitrogen management seamlessly in their daily operations.

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