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The reliability of Unmanned Aerial Vehicles (UAVs) equipped with multispectral cameras for estimating chlorophyll content, plant height, canopy area, and fruit total number of Lemons (*Citrus limon*)

Buyung Al Fanshuri[1,2], Cahyo Prayogo[3*], Soemarno[3], Sugeng Prijono[3], Novi Arfarita[4]

[1] Doctoral Program of Agriculture Science, Faculty of Agriculture, University of Brawijaya, Malang, Indonesia
[2] Indonesia Institute for Testing Citrus and Subtropical Standard Instrument, Indonesia
[3] Department of Soil Science, Faculty of Agriculture, University of Brawijaya, Malang, Indonesia
[4] Faculty of Agriculture, University Islam Malang, Malang, Indonesia

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***** *Corresponding Author*
Email address:
cahyoprayogo@yahoo.com

ABSTRACT

Monitoring lemon production requires appropriate and efficient technology. The use of UAVs can addressed these challenges. The purpose of this study was to determine the best vegetation indices (VIs) for estimating chlorophyll content, plant height (PH), canopy area (CA), and fruit total numberas (FTN). CCM 200 was used as a tool to measure the chlorophyll content index (CCI), the number of fruits was measured by hand-counter, and other variables were recorded in meters. The UAV used was a Phantom 4 with a multispectral camera capable of capturing five different bands. The VIs was obtained via analysis of digital numbers generated by the multispectral camera. Then, the VIs was correlated with the CCI, PH, CA and FTN. VIs tested included the following: the normalized difference vegetation index (NDVI), the normalized difference vegetation index-green (NDVIg), the normalized different index (NDI), green minus red (GMR), simple ratio (SR), the Visible Atmospherically Resistant Index (VARI), normalized difference red edge (NDRE), simple ratio red-edge (SR_{RE}), the simple ratio vegetation index (SR_{VI}), and the Canopy Chlorophyll Content Index (CCCI). The best model for predicting CCI was obtained using the NDVIg (R^2=0.8480; RMSE=6.1665 and RRMSE=0.0908). Meanwhile, SR turned out to be the best model for predicting PH (R^2=0.8266; RMSE=15.6432 and RRMSE=0.0883), CA (R^2=0.6886; RMSE= 0.8826 and RRMSE=0.1907), and FTN (R^2=0.6850; RMSE=24.5574 and RRMSE=0.3503). The implication of these results for future activities includes establishing early monitoring and evaluation systems for lemon yield and production. This model was developed and tested in this specific location and under these environmental conditions.

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1. INTRODUCTION

One of the most consumed fruits during the COVID-19 pandemic were lemons (*Citrus limon*) (Kutyauripo et al., 2021). Lemons contain a wide range of phytochemicals (vitamins and secondary metabolites), which are very beneficial for the body, including maintaining health and supporting the immune system (Ke et al., 2015). Lemons are not only consumed as fresh fruit but are also used as a main ingredient in beverages, medicines, and cosmetics. Thus, the consumption of this type of citrus is continuously growing (Lv et al., 2015).

The amount of citrus fruit production must be maintained at a sufficient level. Therefore, citrus production monitoring technology is needed. In many citrus producing countries, monitoring plant health through chlorophyll content is still manual (Zhang et al., 2017). Chlorophyll content of leaves and canopy of citrus plants closely related to the level of photosynthetic capacity and synthesis of plant carbohydrates to produce high quality production (Wang et al., 2018). Chlorophyll plays an important role in the photosynthesis process as a catalyst, this molecule is found in the chloroplasts of green plants (Myers, 2019). Leaf chlorophyll is traditionally measured by laboratory analysis following a destructive method developed by Wintermans and De Mots (1965). This method is expensive and laborious and requires experienced laboratory staff. It is also time consuming, especially on large tracts of land. Remote sensing technology can be used to determine plant growth and production without measuring directly (i.e., nondestructively) as an alternative to conventional methods (Sishodia et al., 2020). Agronomic factors also play a role in crop production, including plant height, canopy area, and number of fruits. Measurements of these factors in the field are still manual. The number of fruits is counted by hand counting and the crown area and plant height are measured with a roll meter.

A nondestructive method for measuring chlorophyll content long in development is ground remote sensing, including using the chlorophyll content meter CCM 200. Typical CCMs operate by differential absorption of light at two wavelengths. One is in the near-infrared range, passing through leaf pigments relatively unimpeded and serving as a reference beam, and the other is tuned to the peak absorbance of chlorophyll. The transmission of beam energy, expressed as the ratio of absorbance beam to reference beam, yields a unitless value called the chlorophyll content index (CCI). The CCM-200 is also an effective tool to estimate the chlorophyll concentration in date palm leaves quickly and non-destructively (Almansoori et al., 2021). Another measurement technique that is being developed is remote sensing with UAVs (unmanned aerial vehicles). This is a nondestructive technology that has been used to predict the value of leaf chlorophyll content without involving laboratory analysis. A multispectral camera can be mounted to the UAV apparatus (Yuan, 2019). Although the UAV methods collect data at lower altitudes than satellites, this technology is time-saving compared to direct measurement. UAV is able to non-destructively predict pigments in leaves and plant canopies accurately (Tahir et al., 2018; Yuan, 2019).

The UAV method is faster and more effective than nondestructive analysis that employs satellite imagery, which is now widely used in agriculture. Satellite methods have the advantage of being able to cover large areas of land and save time (Zaigham Abbas Naqvi et al., 2021). Generally, remote sensing measurements use NDVI which has a close correlation with plant growth and yield (Huang & Han, 2014). This method posits that the vegetation spectral index's estimate of photosynthetic capability is directly related to crop yield (Peroni Venancio et al., 2020). This assumption is based on research that imply that spectral measurements like as the NDVI can capture many of the factors that affect crop growth, development, and ultimately yield (Benincasa et al., 2018). Target objects containing green living plants or not are assessed using a graphic indicator called NDVI (Gitelson, 2011). Other vegetation indices have been developed to compare with NDVI approaches, such as the Normalized Difference Vegetation Index-green (NDVIg) (Peroni Venancio et al., 2020), the Normalized Different Index (NDI) (Widjaja Putra & Soni, 2018), Green Minus Red (GMR) (Wang et al., 2013), Simple Ratio (SR) (Wang et al., 2013), the Visible Atmospherically Resistant Index (VARI) (Widjaja Putra & Soni, 2018), Nnormalized Difference Red Edge (NDRE) (Widjaja Putra & Soni, 2018), Simple Ratio red edge (SR_{RE}) (Gitelson et al., 1996), the Simple Ratio vegetation index (SR_{VI}) (Widjaja Putra & Soni, 2018), and the Canopy Chlorophyll Content Index (CCCI) (Widjaja Putra & Soni, 2018). A previous study reported that UAV imagery can be used to distinguish between healthy and diseased citrus plants (Fanshuri & Yunimar, 2021). Zaigham Abbas Naqvi et al. (2021) used the DVI (Difference Vegetation Index), the RDVI (Renormalized Difference Vegetation Index), the MTVI2 (Modified Triangular Vegetation Index 2), the SARVI (Soil and Atmospherically Resistant Vegetation Index) and the Iron Oxide index to determine regression models between Vegetation Indices (VIs) and citrus leaf chlorophyll content. However, the implementation of UAV techniques using various VIs to predict citrus chlorophyll content, plant height, canopy area, and fruit total number is not well investigated. This study aims to develop a vegetation index that can be used to predict chlorophyll content, plant height, canopy area, and number of fruits in lemon citrus plants.

2. MATERIAL AND METHODS

2.1. Location and soil conditions

This research was conducted at the Tlekung Experimental Garden, Indonesian Citrus and Subtropical Fruit Research Institute (ICSFRI), in Batu City, East Java, Indonesia (-7.90344, 112.53483), which has an altitude of 950 m above sea level. Five-year-old citrus trees were used under rain-fed irrigation (Figure 1). The lemon variety used in this experiment was *Cai kahuripan*, which is the most popular lemon variety in Indonesia. Soil at the research site was classified as sandy loam (32% sand, 28% silt, and 40% clay). Soil analysis showed that total N content was 0.14%, C-organic was 1.46%, P available was 82.4 ppm, K available was 0.67 cmol.kg^{-1}, Ca was 0.76 cmol.kg^{-1}, Mg was 0.3 cmol.kg^{-1}, and CEC was 14.97 cmol.kg^{-1}.

2.2. Experiment design

The lemon *(Citrus limon)* trees utilized in this experiment were cultivated in a sloping area, and different positions along the slope (top, middle, and bottom positions) were selected. The middle position had the steepest incline. Fifteen plants from each slope position were collected, resulting in a total of 45 plants for sampling. The sample plants were measured for plant height, canopy area, and total fruit number, so there were 45 points of data for each. The chlorophyll content of each plant from different slope positions was collected from five different leaf positions (north, west, south, east, and middle of the canopy), for a total of 225 leaf samples. The leaves selected were the second or third from the tip of the twig.

2.3. UAV high-resolution multispectral imaging and image processing

In general, farmers in Indonesia have citrus orchards that are narrow and scattered. A tool for remote sensing that is more suitable under these conditions than satellite imagery is the UAV.

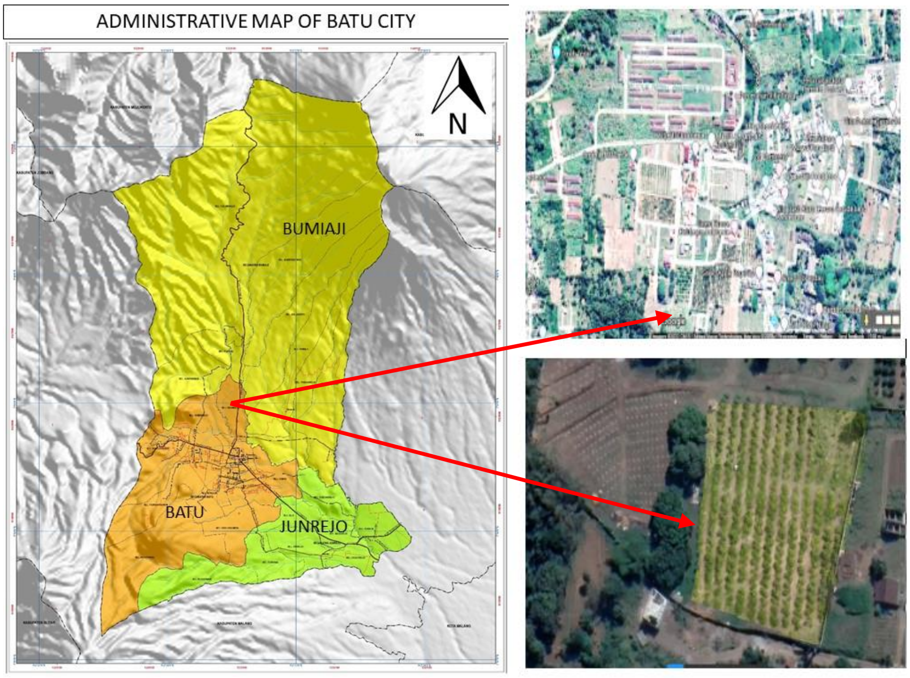

Figure 1. Location of study

The lower flying altitude of the UAV results in higher photo resolution, time saved, and low atmospheric interception (Yuan, 2019). For this reason, UAVs were used in this research. The current investigation, in particular, made use of high-resolution multispectral imagery captured by the DJI Phantom 4 (P4) instrument. The P4 Multispectral is a high-precision drone capable of multispectral imaging functions. The imaging system contains six cameras with 1/2.9-inch CMOS sensors, including an RGB camera and a multispectral camera array containing five cameras for multispectral imaging, covering the following bands: blue (B): 450 nm ± 16 nm; green (G): 560 nm ± 16 nm; red (R): 650 nm ± 16 nm; red edge (RE): 730 nm ± 16 nm; and near-infrared (NIR): 840 nm ± 26 nm. The DJI Phantom 4 Pro aircraft weighs 1487g, contains a 6000mAh LiPo2S battery, and has a maximum flight speed of 6m.s^{-1} (automatic flight) or 5m.s^{-1} (manual control). The UAV was flown at a height of 30 m at 09.00 local time (UTC+07:00). Radiometric corrections increased the radiometric quality of the data by correcting image reflectance while taking scene illumination and sensor effect into account. Multispectral image radiometric corrections and calibrations were carried out in three steps: (1) orthomosaicking, (2) digital surface map (DSM), and (3) index computation (McCluney, 2014). This process was carried out using DJI TERRA software and by extracting digital numbers using ArcGIS software.

2.4. On-site chlorophyll, plant height, canopy area, and fruit total number data acquisition

In June 2022, fieldwork was conducted to obtain in-situ chlorophyll data from citrus tree leaves. The chlorophyll content of 45 citrus plants was measured using a chlorophyll meter (CCM 200). CCM 200 is a nondestructive tool for measuring chlorophyll content in leaves without harming them. Five leaves from each tree were collected and measured with a CCM 200 plus chlorophyll meter (Opti-Sciences Inc., Tyngsboro, MA, USA), and the mean value for each plant sample (CCI) was obtained. All measurements were carried out in the morning (09.00-10.00) to avoid variations caused by chloroplast movement throughout the day (Pereyra et al., 2014). The plant agronomic variables measured in this study were plant height, canopy area, and fruit total number. Plant height was measured from the ground surface to the tip of the tallest plant using a tape measure. Canopy area was calculated using the circle formula (3.14 x r_1 x r_2), where r_1 is the north-south canopy width and r_2 is the east-west canopy width. The number of fruits, from the smallest to the largest, was counted for each plant using a hand counter. Plant height, canopy area, and total number of fruit are important agronomic parameters in determining citrus production in Indonesia. Lemons in Indonesia (a tropical climate) are different from those in the subtropics. The color of the fruit produced is not yellow as in subtropical areas. This is because the temperature is higher than in subtropical regions. Local markets prioritize the content of the juice produced, not the color of the fruit, so the harvest is carried out when the fruit is green. The rainy and dry seasons in the tropics also result in less leaf loss than in the subtropics.

2.5. Vegetation indices

Ten vegetation indices were selected based on calculations from the five bands of the UAV multispectral cameras. The digital number of each band was obtained by extracting the red (R), green (G), blue (B), near infrared (NIR), and red edge (RE) values. The extracted values were used to calculate the 10 selected vegetation indices, which are the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Vegetation Index-green (NDVIg), the Normalized Different Index (NDI), Green Minus Red (GMR), Simple Ratio (SR), the Visible Atmospherically Resistant Index (VARI), Normalized Difference Red Edge (NDRE), Simple Ratio red edge (SR_{RE}), the Simple Ratio vegetation index (SR_{VI}), and the Canopy Chlorophyll Content Index (CCCI). The purpose of calculating the vegetation index is to test the proximity of the vegetation index to the greenish character of the leaves. The greenness of the leaves was nondestructively measured using a Chlorophyll Content Meter (CCM) as described above. The formula for obtaining the vegetation index is presented in Table 1.

2.6. Data analysis

The data was analyzed using Microsoft Excel. Descriptive analysis aims to describe the data generally. A correlation was conducted to discover the relationships between the research variables. Variables that had both positive and negative correlations were analyzed using regression analysis. In regression analysis, the outcome variables (Y) are CCI, plant height, canopy area, and fruit total number, while the input variables (X) are NDVI, NDVIg, NDI, GMR, SR, VARI, NDRE, SR_{RE}, SR_{VI}, and CCCI.

Table 1. Selected broadband vegetation indices for UAV multipectral cameras

No	Vegetation indices	Formula	Reference
1	Normalized Difference Vegetation Index (NDVI)	$\frac{NIR - R}{NIR + R}$	(Berger et al., 2019)
2	Normalized Difference Vegetation Index-green (NDVIg)	$\frac{G - R}{G + R}$	(Peroni Venancio et al., 2020)
3	Normalized Different Index (NDI)	$\frac{G - R}{G + R + 0.01}$	(Widjaja Putra & Soni, 2018)
4	Green Minus Red (GMR)	G - R	(Wang et al., 2013)
5	Simple Ratio (SR)	$\frac{G}{R}$	(Wang et al., 2013)
6	Visible Atmospherically Resistant Index (VARI)	$\frac{G - R}{G + R - B}$	(Widjaja Putra & Soni, 2018)
7	Normalized Difference Red Edge (NDRE)	$\frac{NIR - RedEdge}{NIR + Rededge}$	(Widjaja Putra & Soni, 2018)
8	Simple Ratio red edge (SR_{RE})	$\frac{NIR}{RedEdge}$	(Gitelson et al., 1996)
9	Simple Ratio vegetation index (SR_{VI})	$\frac{NIR}{R}$	(Widjaja Putra & Soni, 2018)
10	Canopy Chlorophyll Content Index (CCCI)	$\frac{NDRE}{NDVI}$	(Widjaja Putra & Soni, 2018)

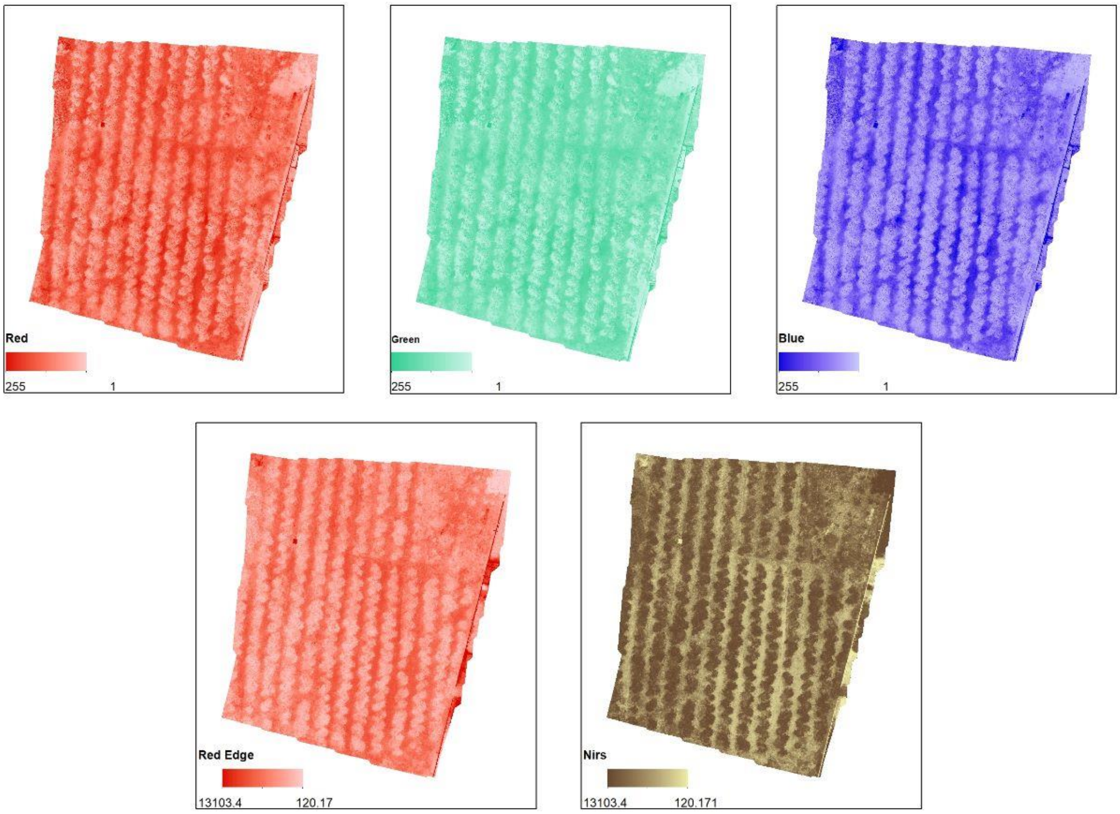

Figure 2. Results of UAV image processing on citrus orchards

Table 2. Descriptive analysis data for five bands

Variable	Mean	Maximum	Minimum	Standard Deviation
R	85.74	152.60	44.80	30.53
G	100.05	159.60	61.60	27.18
B	42.89	99.00	8.00	26.55
NIR	6322.33	11892.92	3698.85	1442.96
Red edge	4459.72	9860.49	2337.18	1572.64

3. RESULTS

3.1. Image mapping

Image processing produced an integrated map of the citrus groves. The resulting map is presented in Figure 2. The map is presented based on each band (R, G, B, RE, and NIR). The maximum and minimum numbers on the map show the digital number values of all objects contained in the image. Meanwhile, a description of the digital numbers of the selected leaf samples is presented in Table 2. In principle, the camera captures the wavelength reflections of sunlight. At the visible wavelength (RGB), the highest average value was obtained in band G (100.05), and the lowest was recorded in band B (42.89), which is shown in Table 2. The deviation value of R (red) (30.53) is higher than that of G (green) and B (blue). The range of values was 55.21–116.27 for R, 72.87–127.23 for G, 16.34–69.44 for B, 4879.37–7765.29 for NIR, and 2887.08–6032.36 for RE.

3.2. Ground confirmed clorophyll content, plant height, canopy area, fruit total number, and vegetation indices

Ground confirmed clorophyll content, plant height, canopy area, and fruit total number values were acquired from field collection data. The value of the vegetation indices was obtained by entering the digital number values into the appropriate formula according to Table 1. Plant samples were taken at the same point. Table 3 shows the descriptive analysis of CCI, plant height, canopy area, fruit total number, and vegetation indices. From Table 3, it can be concluded that the range of CCI was 44.2658–87.6104, while PH values were 136.1219–229.5599 cm, CA values were 3.0759–7.0963 m^2, FTN values were 47.6767–162.1453, NDVI values were 0.7410–0.8584, NDVIg values were 0.0398–0.1402, NDI values were 0.0398–0.1402, GMR values were 9.3816–19.2043, SR values were 1.0796–1.3294, VARI values were 0.0576–0.1609, NDRE values were 0.0127–0.3505, SR_{RE} values were 1.0206–2.0709, SR_{VI} values were 50.5909–111.8648, and CCCI values ranged from 0.0166–0.4584.

3.3. Correlation among vegetation indices and ground confirmed chlorophyll content, plant height, canopy area, fruit total number

The value of r indicates the level of correlation between variables. Table 4 shows that the vegetation indices have strong and very strong relationships to CCI and plant height, respectively, while the canopy area and fruit total number have moderate to very strong relationships. NDRE, SR_{RE}, and CCCI were negatively correlated with crop variables, while the other vegetation indices were positively correlated. As shown

Table 3. Descriptive analysis data for ground-truthed chloropyll content (CCI), plant height (PH), canopy area (CA), fruit total number (FTN), and selected vegetation indices

Variable	Mean	Maximum	Minimum	Standard Deviation
CCI	65.9381	100.3000	38.1000	21.6723
PH(cm)	183.0000	280.0000	105.0000	46.3485
CA(m^2)	5.0861	9.3258	1.9134	2.0102
FTN	104.9111	255.0000	12.0000	57.2343
NDVI	0.7997	0.8925	0.6758	0.0587
NDVIg	0.0900	0.1824	0.0183	0.0502
NDI	0.0900	0.1824	0.0183	0.0502
GMR	14.2929	24.0000	4.6000	4.9113
SR	1.2045	1.4462	1.0373	0.1249
VARI	0.1093	0.2087	0.0255	0.0516
NDRE	0.1816	0.4875	-0.2517	0.1689
SR–RE	1.5458	2.9028	0.5978	0.5252
SR–VI	81.2278	204.3457	37.0941	30.6369
CCCI	0.2375	0.6401	-0.2976	0.2209

in Table 4, the highest r value was obtained between NDVIg and all parameters (CCI=0.9205, plant height = 0.8946, canopy area = 0.8211, fruit total number = 0.8137). SR_{RE} had the lowest correlation with CCI (-0.6994), plant height (-0.6313), and canopy area (-0.5776), while the lowest correlation to fruit total number was recorded by NDRE (-0.5642).

3.4. Chlorophyll content, plant height, canopy area, and fruit total number modeling using vegetation indices

The results of regression modeling between vegetation indices and crop parameters are shown in Table 5. Generally, three types of regression curves were found: exponential, polynomial, and linear. For chlorophyll content modeling, NDVI and GMR showed exponential relationships, SRRE and SRVI generated polynomial regressions, and the other indices showed linear relationships. Plant height showed a linear relationship with GMR and polynomial relationships with all other calculated indices. For canopy area modeling, VARI, NDRE, and ICCC showed linear relationships, while other indices had polynomial models. Fruit total number modeling resulted in polynomial regression models for NDVI, SR, and SRVI, while other indices showed linear relationships. SR has the highest R^2 value and lowest RMSE for plant height modeling (R^2=0.8266 and RMSE=15.6432) with the equation PH = -695.69SR^2 + 2051.7SR–1268.4.

Table 4. Correlation coefficient and significance between vegetation indices and ground-truthed chlorophyll content (CCI), plant height, canopy area, and fruit total number

Vegetation indices	CCI		Plant height		Canopy area		Fruit total number	
	r	sig	r	sig	r	sig	r	sig
NDVI	0.8889	**	0.8140	**	0.7683	**	0.7460	**
NDVIg	0.9205	**	0.8946	**	0.8211	**	0.8137	**
NDI	0.9204	**	0.8946	**	0.8211	**	0.8137	**
GMR	0.7770	**	0.8047	**	0.7331	**	0.7096	**
SR	0.9122	**	0.8862	**	0.8149	**	0.8060	**
VARI	0.9028	**	0.8783	**	0.8178	**	0.8021	**
NDRE	-0.722	**	-0.6373	**	-0.6062	**	-0.5642	**
SR–RE	-0.6994	**	-0.6313	**	-0.5776	**	-0.5774	**
SR–VI	0.7137	**	0.7483	**	0.6402	**	0.6011	**
CCCI	-0.7604	**	-0.6794	**	-0.6387	**	-0.6024	**

Remarks: r = Correlation coefficient, ** = Highly significant (p<0.01)

Table 5. Model, coefficient determinant (R^2), root mean square error (RMSE), and relative root mean square error (RRMSE) between ground-truthed chlorophyll content (CCI) and vegetation indices

Vegetation indices	Equation	R^2	RMSE	RRMSE
NDVI	CCI = 0.9530 exp (5.2310 NDVI)	0.8465	7.1828	0.1248
NDVIg	CCI = 397.1135 NDVIg + 30.2065	0.8480	6.1665	0.0908
NDI	CCI = 397.3294 NDI + 30.1826	0.8480	6.1666	0.0908
GMR	CCI = 28.9328 exp (0.0539 GMR)	0.6287	10.5360	0.1690
SR	CCI = 158.2573 SR–124.6865	0.8325	6.4910	0.0951
VARI	CCI = 378.8461 VARI + 24.5458	0.8161	6.8871	0.1027
NDRE	CCI = -92.6414 NDRE + 82.7603	0.5407	39.6706	0.7943
SR–RE	CCI = 12.4679 SR RE^2–70.9672 SR RE + 142.4970	0.5339	11.7762	0.1920
SR–VI	CCI = -0.0051 SR VI^2 + 1.5924 SR VI–25.2848	0.6633	10.0057	0.1632
CCCI	CCI = -74.6055 CCI + 83.6589	0.5994	11.3860	0.1758

SR also has the highest R^2 and the lowest RMSE for canopy area modeling (R^2=0.6886 and RMSE=0.8826) with the equation CA = -23.291SR^2 + 70.794SR–46.04, and for fruit total number modeling (R2=0.6850 and RMSE=24.5574) with the equation FTN = -794.71SR^2 + 2337.5SR–1545.5. This can be seen in Tables 6, 7, and 8. Meanwhile, NDVIg has the highest R^2 (0.8480) and the lowest RMSE (6.1665) for chlorophyll content modeling with the linear regression equation CCI = 397.1135 NDVIg + 30.2065. The most accurate model is that which has the highest R^2 value with the lowest RMSE. Therefore, the least accurate models were found for NDRE in all modeling (Tables 5, 6, 7, and 8).

4. DISCUSSION

Nondestructive measurement is needed to save time and money. This research produced a formula for estimating chlorophyll content, plant height, canopy area, and number of fruits. The use of a multispectral camera in a UAV can produce a vegetation index to estimate chlorophyll content and plant agronomy. Differences in chlorophyll contentand plant agronomy are caused by the position of the land. The best agronomic variables were at the lowest land position, followed by the top and middle. This is because of the slope of the land; the most sloping land has the lowest growth. Remote sensing data in this study was obtained from a multispectral camera installed on a UAV. The results of image processing were used to calculate vegetation indices, which were then related to CCI, plant height, canopy area, and fruit total number. CCI measurement uses an absorption approach (Parry et al., 2014; Vesali et al., 2015), while the UAV camera utilizes a reflectance measure (Samseemoung et al., 2012).

Ten vegetation indices have varying correlations with CCI, plant height, canopy area, and fruit total number value. Moderate correlations were found in SRRE for the canopy area and total fruit number, and in NDRE for the total fruit number. Other vegetation indices had strong or very strong correlations to the plant variables. Meanwhile, for CCI and plant height modeling, all vegetation models had strong and very strong correlations, respectively. The results of the regression analysis also show that there are variations in the coefficient of determination of the modeling sought. The coefficient of determination in CCI modeling ranges from 0.5 to 0.8, for plant height it ranges from 0.4–0.8, and for canopy area and total fruit number it ranges from 0.3 to 0.6. This shows that the highest model accuracy is in CCI modeling, followed by plant height, canopy area, and fruit total number. SR obtained the highest R^2 and the lowest RMSE and RRMSE in plant height, canopy area, and fruit total number modeling. Meanwhile, NDVIg has the highest R^2 and the lowest RMSE in CCI modeling. However, R^2, RMSE, and RRMSE value gaps between NDVI, NDVIg, NDI, SR, and VARI are only slightly different, with CCI under 0.02 (R^2), 1.1 (RMSE), and 0.02 (RRMSE); PH under 0.15 (R^2), 6.5 (RMSE), and 0.04 (RRMSE); CA under 0.04 (R^2), 0.08 (RMSE), and 0.02 (RRMSE); and FTN under 0.11 (R^2), 3.83 (RMSE), and 0.02 (RRMSE). This is in accordance with previous research that chlorophyll content has strong correlations with the NDVI from UAVs (R > 0.8) in maize (Marcial-Pablo et al., 2021) and rice (Ban et al., 2022). This shows that UAVs with multispectral cameras can be used to measure chlorophyll content (Benincasa et al., 2018) and other agronomic factors effectively. This means that measurement will be more time-efficient and cover more land area than ground remote sensing (Zaigham Abbas Naqvi et al., 2021) or agronomic measurements in the field. The lower R values on measurements of plant height, canopy area, and fruit total number are due to the interference from the reflections of the surrounding objects. This study's findings revealed that the regression coefficient between the vegetation index and leaf chlorophyll content ranged from 0.5339 to 0.8480. This result is better than satellite remote sensing based on existing research. Satellites are able to cover a wider capture area than UAVs. However, atmospheric disturbances caused by clouds and reflections of other objects result in lower regression coefficients (Benincasa et al., 2018). The resolution produced by a UAV image is also more detailed, where one pixel in the image represents 2.5 cm in the field. This is different from satellite imagery, where one pixel represents 0.6-1 m in the field at high resolutions.

Table 6. Model, coefficient determinant (R^2), root mean square error (RMSE), and relative root mean square error (RRMSE) between plant height (PH) and vegetation indices

Vegetation indices	Equation	R^2	RMSE	RRMSE
NDVI	PH = 2009.7NDVI^2–2531.9NDVI + 915.72	0.6786	22.0535	0.1275
NDVIg	PH = -2990.6NDVIg^2 + 1426.2NDVIg + 86.242	0.8206	15.9654	0.0904
NDI	PH = -2990.9NDI^2 + 1426.3NDI + 86.241	0.8206	15.9656	0.0904
GMR	PH = 7.5943GMR + 74.454	0.6476	21.8218	0.1212
SR	PH = -695.69SR^2 + 2051.7SR–1268.4	0.8266	15.6432	0.0883
VARI	PH = -1856.8VARI^2 + 1219.5VARI + 76.765	0.7819	17.5650	0.0972
NDRE	PH = -139.89NDRE^2–137.8NDRE + 216.54	0.4212	28.2436	0.1632
SR–RE	PH = 21.241SR RE^2–127.47SR RE + 323.56	0.4264	28.2682	0.1665
SR–VI	PH = -0.0053SR VI^2 + 2.2595SR VI + 38.9	0.5962	24.1920	0.1440
CCCI	PH = -69.721CCCI^2–114.47CCCI + 217.45	0.4716	26.7949	0.1505

Table 7. Model, coefficient determinant (R^2), root mean square error (RMSE), and relative root mean square error (RRMSE) between canopy area (CA) and vegetation indices

Vegetation indices	Equation	R^2	RMSE	RRMSE
NDVI	CA = 156.25NDVI^2–220.36NDVI + 80.854	0.6549	0.9086	0.2014
NDVIg	CA = -88.546NDVIg^2 + 50.648NDVI + 1.4633	0.6836	0.8859	0.1912
NDI	CA = -88.549NDI^2 + 50.651NDI + 1.4633	0.6836	0.8860	0.1912
GMR	CA = 0.005GMR^2 + 0.1553GMR + 1.722	0.5418	1.0444	0.2331
SR	CA = -23.291SR^2 + 70.794SR - 46.04	0.6886	0.8828	0.1907
VARI	CA = 31.834 VARI + 1.6079	0.6689	0.8964	0.1927
NDRE	CA = -7.2142NDRE + 6.396	0.3674	1.2296	0.2744
SR–RE	CA = 1.1489SR RE^2–6.0926SR RE + 11.449	0.3771	1.2042	0.2999
SR–VI	CA = -0.0003SR VI2 + 0.1047SR VI - 1.2185	0.4692	1.1478	0.2656
ICCC	CA = -5.8126ICCC + 6.4667	0.4080	1.2153	0.2702

Table 8. Model, coefficient determinant (R^2), root mean square error (RMSE), and relative root mean square error (RRMSE) between fruit total number (FTN) and vegetation indices

Vegetation indices	Equation	R2	RMSE	RRMSE
NDVI	FTN = 2790.8NDVI^2–3678.3NDVI + 1252.3	0.5820	28.3853	0.3655
NDVIg	FTN = 927.49NDVIg + 21.441	0.6621	24.7273	0.3429
NDI	FTN = 927.58NDI + 21.439	0.6621	24.7273	0.3429
GMR	FTN = 8.269GMR - 13.277	0.5035	29.8595	0.4377
SR	FTN = -794.71SR^2 + 2337.5SR - 1545.5	0.6850	24.5574	0.3503
VARI	FTN = 888.92VARI + 7.7887	0.6433	25.5826	0.3527
NDRE	FTN = -191.17NDRE + 139.62	0.3183	37.8861	0.5677
SR–RE	FTN = -62.929SR RE + 202.18	0.3334	37.6443	0.5932
SR–VI	FTN = -0.0102SR VI^2 + 3.3159SR VI - 87.557	0.4511	32.0799	0.4985
ICCC	FTN = -156.07ICCC + 141.98	0.3629	36.8112	0.5458

The results also show that the highest accuracy is achieved by modeling that uses three-band (RGB) data and the NDVIg in CCI modeling and SR in other modeling. The order of modeling findings based on band data is an RGB-based formula followed by NIR and red edge. This is due to the reflection of the observed object as the observed field variable is included in the visible wavelength (400−700 nm). This statement is supported by previous research on rice that variables related to canopy cover are influenced by green and red bands (Ban et al., 2022). However, red edge data-based modeling can be used to predict chlorophyll content (R^2 = 0.5–0.6). This is also supported by previous research on coffee plants, where the vegetation index using the red edge band produced a significant relationship to chlorophyll content in coffee leaves (Widjaja Putra & Soni, 2018). In general, VI is an index of vegetation coverage, but vegetation is highly reflective in the near infrared and strongly absorbing in the red range (low reflectivity). This harmful canopy background as well as other ground effects and noise have been masked by the appearance of blue channels (Senecal, 2019). Therefore, VIs from red edge are only used as an alternative (Delegido et al., 2013).

The best equations obtained for chlorophyll content, plant height, canopy area, and fruit total number are CCI = 397.1135 NDVIg + 30.2065, PH = -695.69SR2 + 2051.7SR–1268.4, CA = -23.291SR2 + 70.794SR–46.04, and FTN = -794.71SR2 + 2337.5SR–1545.5. This research also succeeded in developing vegetation indices that were used in previous studies. According to previous studies, a UAV multispectral camera can be utilized to evaluate chlorophyll levels in citrus plants using the vegetation indices DVI (Vegetation Difference Index), RDVI (Renormalized Difference Vegetation Index), MTVI2 (Modified Triangle Vegetation Index 2), SARVI (Soil and Atmosphere Resistant Vegetation Index) and Iron Oxide index. These estimations had R^2 values of 0.5–0.8 (Zaigham Abbas Naqvi et al., 2021). Other research used the VIs Normalized Difference Vegetation Index (NDVI), the Transformed Normalized Difference Vegetation Index (TNDVI), the Modified Chlorophyll Absorbed Ratio Index (MCARI2), the Soil Adjusted Vegetation Index (SAVI), and the Modified Soil Adjusted Vegetation Index (MSAVI2) and had R^2 values of 0.7-0.8 (Tahir et al., 2018). SR has been proven to be able to detect biomass, N content, and LAI in rice plants. The R value is higher than NGI, NRI, and H (Wang et al., 2013). The NDVI is a vegetation index that is generally used in remote sensing. This index only uses the red and NIR bands in its calculations. It has been proven not only to estimate chlorophyll but also yield in wheat plants (Benincasa et al., 2018). When compared to the NDVI, the SR index (R^2 = 0.843) predicted soybean grain yield better (Gcayi et al., 2019).

5. CONCLUSION

This study proves that the vegetation index resulting from the analysis of UAV imagery results can be used to estimate the chlorophyll content, plant height, canopy area, and total fruit number of lemon (*Citrus limon*) gardens. The relationship of the vegetation index to CCI and plant height is strong and very strong, respectively, while the crown area and number of fruits have a moderate to very strong relationship. These results indicate that the use of UAVs can be used to replace manual measurementson the ground. Accurate and fast forecasting of production components is needed in the future to assist the decision making of farmers and the government.

However, this research was conducted on green lemons with site-specific environmental conditions (i.e., dry land, a mountainous area with average rainfall of 1889 mm/year, and soil developed from Kawi volcanic material, which is classified as an inceptisol). The results obtained may differ depending on climatic conditions, geographic locations, and soil characteristics. Therefore, future studies will need to be carried out under different environmental conditions and with different varieties of lemons.

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Declaration of Competing Interest

The authors declare that no competing financial or personal interests that may appear and influence the work reported in this paper.

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