

Article

Assessment of Premium Citrus Fruit Production Potential Based on Multi-Spectral Remote Sensing with Unmanned Aerial Vehicles

Guoxue Xie ^{1,2,3}, Wentao Nong ^{1,2,3} , Shaoe Yang ^{1,2,3}, Qiting Huang ^{1,2,3,*}, Zelin Qin ^{1,2,3}, Saisai Wu ^{1,2,3}, Canda Ma ^{1,2,3}, Yurong Ling ^{1,2,3}, Cunsui Liang ^{1,2,3} and Xinjie He ^{1,2,3}

- ¹ Agriculture Science and Technology Information Research Institute, Guangxi Academy of Agricultural Sciences, Nanning 530007, China; gxnky2020@gxaas.net (G.X.); nongwentao@gxaas.net (W.N.); yangshaoe@gxaas.net (S.Y.); alinqin@gxaas.net (Z.Q.); wusaisai@gxaas.net (S.W.); macanda@gxaas.net (C.M.); lingyurong@gxaas.net (Y.L.); l_c_shake95@gxaas.net (C.L.); hexinjie@gxaas.net (X.H.)
- ² Nanning Station of Guangxi (Farmland Type), Ecological Quality Comprehensive Monitoring Station of Ministry of Ecology and Environment, Nanning 530007, China
- ³ Guangxi Agricultural Remote Sensing Engineering Research Center, Nanning 530007, China
- * Correspondence: huangqiting830112@gxaas.net

Highlights

What are the main findings?

- Through systematic experiments and data analysis, the study reveals that the Normalized Pigment Chlorophyll Index (NPCl) index exhibits significant sensitivity to canopy fruit characteristics, leading to the development of a rapid canopy fruit boundary extraction method.
- A technical framework for selecting evaluation indicators for premium citrus production potential is proposed, including a methodology for classifying different threshold levels and defining specific value ranges for premium, standard, and commercial grades.

What are the implications of the main findings?

- Based on unmanned aerial vehicle (UAV) multispectral remote sensing images, this paper develops an integrated method combining agricultural practices and marker-controlled watershed segmentation to extract individual citrus tree canopy information, effectively addressing the challenges of low accuracy and difficulty in single-tree canopy identification in contiguous hilly orchards.
- Utilizing five evaluation indicators—Normalized Difference Vegetation Index (NDVI), Transformed Chlorophyll Absorption in Reflectance Index (TCARI), red-edge optimal soil-adjusted vegetation index (REOSAVI), canopy area, and canopy fruit area—a production potential model for premium citrus is established. This enables precise assessment at the individual tree level, providing a scientific basis and technical support for refined orchard management, graded harvesting, and quality enhancement.



Academic Editor: Liang Sun

Received: 2 December 2025

Revised: 5 January 2026

Accepted: 17 January 2026

Published: 20 January 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Abstract

Citrus, as a globally important economic crop, requires accurate assessment of premium fruit production potential for precise orchard management and enhanced economic benefits. This study develops a method for assessing the production potential of premium citrus using UAV-based multispectral imagery and ground data. Taking citrus orchards in Wuming District, Guangxi, China, as the experimental area, this study investigates techniques for assessing the production potential of premium fruit at the canopy scale of citrus trees

in southern hilly regions, aiming to rapidly predict the quality production potential of citrus before fruit ripening. The methodology involved the following: (1) Segmenting the study area using a Digital Surface Model (DSM) and extracting individual tree canopies by integrating NDVI with a marker-controlled watershed algorithm. Canopy fruit boundaries were identified using the NPCI index. (2) Selecting key assessment indicators—NDVI, TCAVI, REOSAVI, canopy area, and canopy fruit area—through correlation analysis with nutritional quality metrics. (3) Establishing threshold levels for these indicators and constructing a production potential assessment model. Experimental results demonstrated an individual tree identification accuracy (precision) of 98.75%, a recall of 98.47%, and an F-score of 98.61%. Canopy area extraction achieved a coefficient of determination (R^2) of 0.869 and a root mean square error (RMSE) of 0.489 m². The overall accuracy for production potential assessment reached 85.11%. This study provides a new approach for using UAV multispectral technology to non-destructively assess the production potential of premium citrus in the hilly regions of southern China, offering technical support for precise orchard management.

Keywords: citrus; UAV; multispectral remote sensing; production potential assessment; fruit tree extraction

1. Introduction

Citrus is among the world's most widely cultivated fruits [1]. Its annual production reaches about 158 million tons, accounting for 18% of global fruit output [2,3]. Citrus is grown in more than 140 countries and regions. China stands as one of the world's leading citrus producers [4]. According to the World Citrus Organization, China contributes about 28% of global citrus output. In China, Guangxi is the largest citrus-producing region. It has a cultivated area exceeding 631,000 hectares and produced 18.08 million tons in 2022 [5]. Recently, Guangxi's citrus industry has faced a problem: sharp price declines due to unplanned expansion. The lack of efficient and scientifically validated quality assessment technologies compounds the issue. Accurate pre-market evaluation is difficult, resulting in minimal price differences between premium and regular fruits. This situation discourages growers and threatens the sustainable growth of the sector. Fruit quality is a key factor in market competitiveness [6]. With oversupply in Guangxi, assessing citrus production potential is highly significant. Such research helps fruit farmers evaluate sales prices, plan harvests, and manage their orchards. It also provides buyers with accurate information on premium fruits, addressing the limited market and sourcing difficulties of premium citrus.

Citrus fruit quality includes appearance, nutritional, and flavor attributes [7]. In Guangxi, citrus production potential assessment is still mainly conducted using traditional manual methods. Growers judge fruit grade by observing tree growth and appearance indicators, such as color, shape, diameter, and smoothness, as well as flavor through tasting or simple field-testing. However, these methods are inefficient, costly, and subjective. This makes large-scale orchard evaluation difficult and fails to meet the digital needs of the sector. UAV remote sensing has gained researchers' attention due to its high resolution, frequent data collection, and low cost [8,9]. This technology has been widely studied for crop area monitoring [10], leaf area index (LAI) calculation [11], plant height and yield estimation [12,13], physiological and biochemical index inversion [14,15], health status monitoring [16], and biomass estimation [17]. Lu et al. [18] fused multimodal UAV data to estimate citrus LAI. They built a regression model, VPNet, using RGB images and point cloud data. The model achieved a mean square error (MSE), mean absolute error (MAE), and R-squared (R^2) of 0.129, 0.028, and 0.647, respectively. Chang et al. [19] compared

canopy shape and vegetation indices (NDVI, Normalized Difference Red-Edge Index (NDRE), Modified Soil-Adjusted Vegetation Index (MSAVI), and Chlorophyll Index (CI)) in Huanglongbing (HLB)-infected and healthy citrus trees using UAV multispectral images. Red-Edge was more effective for HLB detection. UAV-based flush ratio and canopy volume also helped distinguish HLB fruit trees. Zhang et al. [20] combined UAV multispectral data and random forest models to monitor wheat growth. NDRE and Triangular Vegetation Index (TVI) were most effective, and the random forest model achieved higher plant height prediction accuracy, especially during flowering and maturity, with errors less than 1.01 cm. Lucas et al. [21] used UAV multispectral imagery and the random forest algorithm to predict citrus canopy nitrogen content. The random forest algorithm outperformed other models, achieving an R^2 of 0.90, MAE of $0.341 \text{ g} \cdot \text{kg}^{-1}$, and MSE of $0.307 \text{ g} \cdot \text{kg}^{-1}$. Zhou et al. [22] used agricultural practice information (API) and multi-temporal UAV features, including vegetation indices (VIs) and texture features, to predict rice yield ($R^2 = 0.795$, $RMSE = 0.298$, $RRMSE = 0.072$). Pryabrata et al. [23] combined hyperspectral imaging (HSI) and few-shot learning (FSL) for grain quality detection, achieving accuracy comparable to that of larger-sample approaches. Zhang et al. [24] fused multispectral and RGB UAV imagery features to estimate grassland biomass, achieving R^2 values of 0.89 and 0.83. Kim et al. [25] estimated Wenzhou citrus yield (*Citrus unshiu* Markovich and *Citrus reticulata* Blanco) using UAV hyperspectral data and support vector machine. Predicted yields were 1316.20, 12,151.74, and 3903.56 kg at test sites, with actual yield differences ranging from 5.00% to 13.30%. Kwon et al. [26] studied optimal UAV imaging altitude for estimating citrus yield. Reliable fruit size estimates require an image resolution of 5 pixels/cm or higher, with a flight altitude of 30 m or less preferred. The sensitivity of fruit detection in the image can be improved by applying histogram equalization.

In summary, research demonstrates that UAV remote sensing offers significant technical advantages in precision agriculture. Especially, UAV multispectral remote sensing is rich in information and cost-effective, supporting broad technology adoption. Breakthroughs have already been made in using UAV multispectral technology for canopy extraction, nitrogen inversion, HLB monitoring, and citrus yield studies. However, studies on the production potential of premium citrus fruits are still rare. This study proposes an evaluation method for premium citrus production potential before trees mature and reach market (from 1–2 months before maturity through to harvest). This method is based on citrus trees and combines indicators such as nutritional quality, canopy size, fruiting area, and tree health to assess the likelihood of producing premium-quality, standard-quality, and commercial-quality fruits. Premium fruit production potential assessment is fundamentally different from yield and quality monitoring. The latter relies on fruit images collected with drones or cameras and evaluates outcomes based on parameters such as color, smoothness, diameter, and quantity.

This study developed a new technology that integrates multiple indicators to assess the potential for premium-quality citrus production. It uses UAV multispectral remote sensing and ground measurements to evaluate the canopy-scale potential for premium fruit production in orah mandarin citrus orchards in Wuming District, China (the hilly areas of southern China). The research aims to predict citrus production potential before maturity, enhance competitiveness in Guangxi citrus, and promote industry sustainability. The study focuses on four objectives: (1) acquire experimental data through ground and UAV methods, (2) extract information on individual tree canopies and fruits from UAV data, (3) identify effective indicators and set thresholds for rating levels, and (4) build a model based on five indicators to evaluate each tree's production potential.

2. Materials and Methods

2.1. Overview of the Research Area

The research center is located in the citrus orchard of Chang'an Village, Ningwu Town, Wuming District, Guangxi Province, China (23°2'N, 108°14'E). It is situated in a subtropical monsoon climate zone, with an average annual temperature of 21.7 °C and an annual rainfall of 1700 mm. The research area is located on a slope with significant terrain undulations, and the planted variety is orah mandarin. The fruit trees are 5 years old and densely planted in each row. The canopy of fruit trees is arranged in a strip-like pattern, and weeds are overgrown around them. The high-resolution UAV images of the research area were collected using a DJI Elf 4 multispectral UAV in March 2023 (Figure 1). After data processing, high-resolution drone images with a resolution of 3 pixels/cm were generated.

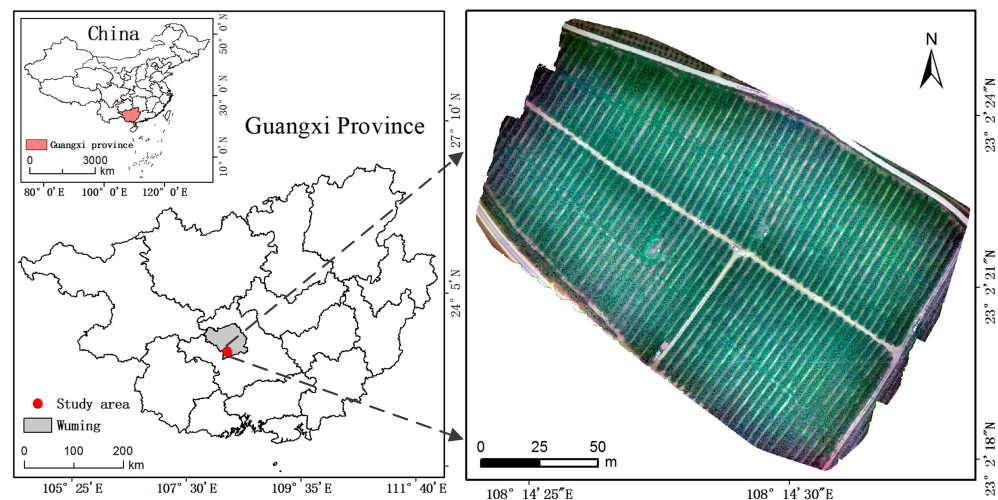


Figure 1. The geographical location of the research area.

2.2. Methods

The technical approach of this research has four parts, as shown in Figure 2. The first part is the collection and processing of data from citrus orchards. Through ground measurements and UAV photogrammetry, parameters such as citrus orchard agronomic measures, fruit physiological indicators, UAV multispectral imagery, VIs, etc., are obtained. The second part is the selection of sample fruit trees and the extraction of sample boundaries. Based on ground-measured indicators and inspection results, sample fruit trees are classified into premium, standard, and commercial production potential categories. Fruit trees are evenly selected within the study area, and their crown boundaries are manually extracted as samples to verify the accuracy of crown extraction. Similarly, fruit trees are selected, and the boundaries of fruits within the crowns are drawn to verify the accuracy of fruit extraction from the crowns. The third part is the extraction of canopy and fruit information. Using a UAV multispectral orthophoto as the data source, the DSM and NDVI are jointly used to partition and extract information on the fruit tree canopy. Based on planting agronomy and the marker-control watershed algorithm (PAMWA), single-tree canopy identification is achieved. The NPCI is used to extract canopy fruit boundary information, verify the accuracy of the canopy and canopy fruit boundaries, and then calculate the area of the single-tree canopy and canopy fruit. The fourth part is the evaluation of production potential, selecting effective evaluation indicators based on the correlation between fruit physiological indicators and VIs, building a production potential assessment model to evaluate each fruit tree's production potential, verifying and evaluating accuracy, and analyzing and evaluating results.

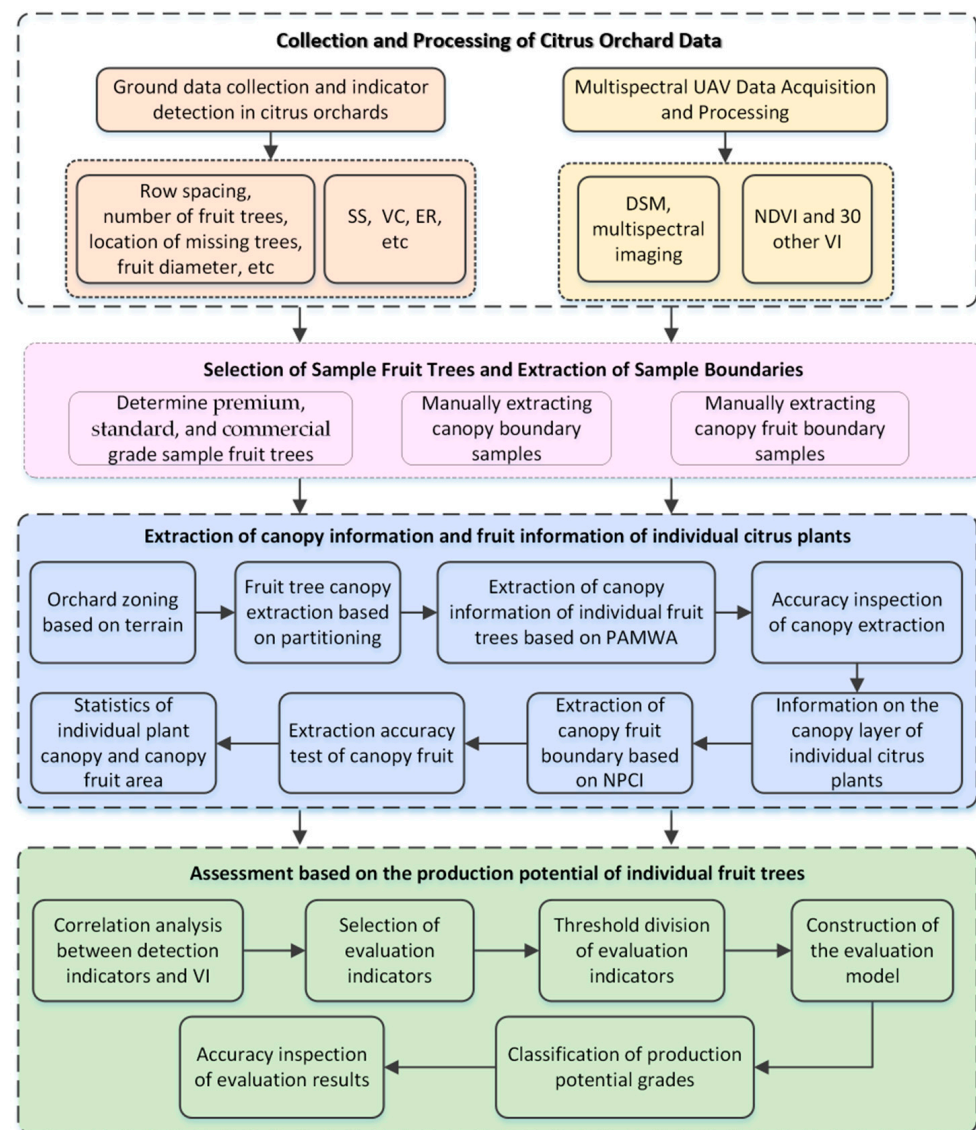


Figure 2. The workflow of the steps of the proposed method.

2.2.1. Citrus Orchard Ground Data Collection and Indicator Detection

On 7 March 2023, data were collected in the citrus orchard on inter-row spacing, trees per row, and missing trees. The average spacing between adjacent tree trunks was 4.5 m, and the spacing within rows ranged from 1.4 to 1.6 m, averaging 1.5 m. After this, the positioning data was gathered, and multiple sample trees with varying production potential were selected for further study. Their external quality indicators—including fruit diameter, count, color, peel blemish rate, and growth vigor of the fruit tree—were recorded. Subsequently, fruits from these sample trees were collected and tested for nutritional quality, including soluble sugars (SS), vitamin C (VC), total soluble solids (TSS), titratable acidity (TA), and edible rate (ER).

2.2.2. Selection of Sample Fruit Trees and Drawing of Sample Boundaries

Sample fruit trees with production potential were selected based on appearance quality indicators and inspection results, yielding 13 premium-, 19 standard-, and 15 commercial-quality trees. Premium trees have large canopies, vigorous growth, abundant fruit, smooth, round, and uniformly colored fruit, consistent size (most with a diameter over 65 mm), minimal russeting (less than 15%), high soluble sugar and ER, and low TA. Standard trees have medium-to-large canopies, good growth vigor, moderate-to-medium fruit quantity,

slightly uneven color and size, most fruit over 60 mm, russetting on up to 30% of the peel, and medium levels of soluble sugar, ER, and TA. Commercial-quality trees have smaller canopies, moderate growth vigor, deformed fruit, greenish skin, russetting on over 30% of the peel, low soluble sugar, and high TA.

Seventeen sample fruit trees were evenly selected within the orchard, and the canopy boundaries were manually drawn as samples for verifying the accuracy of canopy information extraction. Eighteen sample fruit trees were evenly selected, and within their canopies, the fruit boundaries were manually drawn as samples to verify the accuracy of canopy fruit information extraction. The locations of the 17 canopy sample trees and the 18 canopy fruit sample trees do not overlap.

2.2.3. Multispectral UAV Data Acquisition and Processing

Ground data collection for the citrus orchard and UAV data collection were conducted simultaneously. Data collection was carried out using a DJI (Shenzhen, China) Phantom 4 multispectral imaging system UAV, which integrates six multispectral cameras responsible for visible and multispectral imaging. All cameras have a resolution of 2 million pixels and a global shutter, enabling high-precision multispectral data collection. After the UAV completed the surveying task, the collected data was processed using the Pix4D (Lausanne, Switzerland) Mapper software (version 4.3.9). The agricultural multispectral data processing template was used to calibrate data from each spectral band camera, using the calibration board placed in the study area as a reference (50% reflectance). Through the software's radiometric correction function, the DN value of each image was converted into reflectance, outputting TIFF-format DSM and single-band reflectance orthophotos (Figure 3), corresponding to blue (B: 450 ± 16 nm), green (G: 560 ± 16 nm), red (R: 650 ± 16 nm), red-edge (RE: 730 ± 16 nm), and near-infrared (NIR: 840 ± 16 nm) bands. The band combination function (Composite bands) of ArcGIS (ESRI, Redlands, California, USA) software (Arcmap 10.8.2) was used to recombine the images, forming multispectral orthophotos with a resolution of 0.03 m.

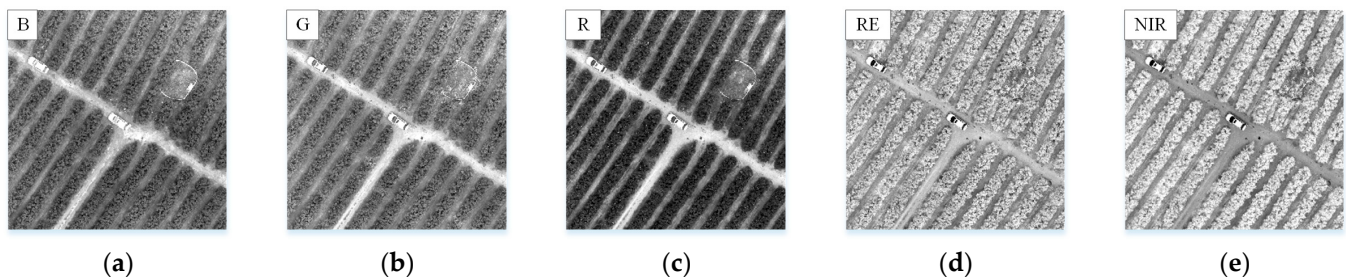


Figure 3. Single-band reflectance orthophoto rendering: (a) blue band (B); (b) green band (G); (c) red band (R); (d) red-edge band (RE); (e) near-infrared band (NIR).

2.2.4. Vegetation Index Calculation

Based on the spectral bands of UAV imagery, 30 VIs were calculated using the Pix4D Mapper software (calculation formulas are shown in Table 1), producing TIFF image files. The referenced VIs were closely related to physiological and biochemical indicators of fruit tree leaves, such as chlorophyll content, water content, and levels of nitrogen, phosphorus, and potassium. VIs were primarily used to extract information about the fruit tree canopy and canopy fruits, as well as to correlate with nutritional quality indicators.

Table 1. Vegetation index calculation formula.

Vegetation Index	Full Name	Formula *	References
NDVI	Normalized Difference Vegetation Index	$(\text{NIR} - \text{R})/(\text{NIR} + \text{R})$	[27]
GNDVI	Green Normalized Difference Vegetation Index	$(\text{NIR} - \text{G})/(\text{NIR} + \text{G})$	[28]
RDVI	Renormalized Difference Vegetation Index	$(\text{NIR} - \text{R})/\text{SQRT}(\text{NIR} + \text{R})$	[29]
R/RENDVI	Normalized Difference Red/Red-Edge Index	$(\text{NIR} - \text{R})/(\text{NIR} + \text{RE})$	[29]
TCAVI	Transformed Chlorophyll Absorption in Reflectance Index	$3 \times [(\text{RE} - \text{R}) - 0.2 \times (\text{RE} - \text{G}) \times (\text{RE}/\text{R})]$	[29]
TDVI	Transformed Difference Vegetation Index	$1.5 \times [(\text{NIR} - \text{R})/\text{SQRT}(\text{NIR}^2 + \text{R} + 0.5)]$	[29]
NLI	Non-linear Index	$(\text{NIR}^2 - \text{R})/(\text{NIR}^2 + \text{R})$	[30]
NDCI	Normalized Difference Chlorophyll Index	$(\text{RE} - \text{R})/(\text{RE} + \text{R})$	[31]
RVI	Ratio Vegetation Index	NIR/R	[32]
NRI	Nitrogen Reflectance Index	$(\text{G} - \text{R})/(\text{G} + \text{R})$	[33]
GDVI	Green Difference Vegetation Index	$\text{NIR} - \text{G}$	[34]
SAVI	Soil-Adjusted Vegetation Index	$1.5 \times [(\text{NIR} - \text{R})/(\text{NIR} + \text{R} + 0.5)]$	[35]
OSAVI	Optimized Soil-Adjusted Vegetation Index	$(\text{NIR} - \text{R})/(\text{NIR} + \text{R} + 0.16)$	[36]
GOSAVI	Green Optimal Soil-Adjusted Vegetation Index	$(1 + 0.16) \times (\text{NIR} - \text{G})/(\text{NIR} + \text{G} + 0.16)$	[37]
GSAVI	Green Soil-Adjusted Vegetation Index	$1.5 \times (\text{NIR} - \text{G})/(\text{NIR} + \text{G} + 0.5)$	[38]
REOSAVI	Red-Edge Optimal Soil-Adjusted Vegetation Index	$(1 + 0.16)(\text{NIR} - \text{RE})/(\text{NIR} + \text{RE} + 0.16)$	[39]
GRVI	Green Ratio Vegetation Index	NIR/G	[40]
LCI	Land Cover Index	$(\text{NIR} - \text{RE})/(\text{NIR} + \text{RE})$	[41]
NPCI	Normalized Pigment Chlorophyll Index	$(\text{R} - \text{B})/(\text{R} + \text{B})$	[42]
PSRI	Plant Senescence Reflectance Index	$(\text{R} - \text{B})/\text{NIR}$	[43]
REDVI	Red-Edge Difference Vegetation Index	$\text{NIR} - \text{RE}$	[44]
RERVI	Red-Edge Ratio Vegetation Index	NIR/RE	[45]
SIPI	Structure Insensitive Pigment Index	$(\text{NIR} - \text{B})/(\text{NIR} + \text{B})$	[46]
TVI	Triangular Vegetation Index	$60 \times (\text{NIR} - \text{G}) - 100 \times (\text{R} - \text{G})$	[47]
NDWI	Normalized Difference Water Index	$(\text{G} - \text{NIR})/(\text{G} + \text{NIR})$	[48]
mSR705	Modified Red-Edge Simple Ratio Index	$(\text{RE} - \text{B})/(\text{RE} + \text{B})$	[49]
NGRDI	Normalized Green–Red Differential Index	$(\text{G} - \text{R})/(\text{G} + \text{R})$	[50]
RGBVI	Red Green Blue Vegetation Index	$(\text{G}^2 - \text{B} \times \text{R})/(\text{G}^2 + \text{B} \times \text{R})$	[51]
NGBDI	Normalized Green–Blue Difference Index	$(\text{G} - \text{B})/(\text{G} + \text{B})$	[52]
GLI	Green Leaf Index	$(2\text{G} - \text{R} - \text{B})/(2\text{G} + \text{R} + \text{B})$	[53]

* B, G, H, RE, and NIR represent the reflectance of blue, green, red, red-edge, and near-infrared spectra, respectively.

2.2.5. Citrus Individual Tree Canopy Extraction

1. Partition-based Tree Canopy Extraction

The study area has gentle slopes and standard row spacing for fruit trees. The trees grow vigorously, and the boundary lines of individual tree canopies are not distinct, with the canopies distributed in continuous strips. Weeds grow abundantly around the fruit trees. Citrus orchards can be divided into vegetated and non-vegetated land categories (e.g., roads, rocks, bare soil), and NDVI can be used to differentiate vegetated from non-vegetated areas. Weeds around the trees can easily interfere with canopy information. Given the height difference between the tree canopies and the weeds, the study area is divided into four zones based on the DSM (Figure 4), and canopy information is extracted using a combined DSM and NDVI zonation. Using multispectral orthophotography images of the citrus orchard as the data source, and based on the boundaries of these zones, objects are formed using a multi-scale segmentation algorithm (scale 500), constructing a multi-zone canopy information extraction model (Table 2). The segmentation scale size is an empirical

value and usually requires repeated trials. You can start experimenting with a segmentation scale of 300. When adjacent features are not over-segmented, and different features can be roughly separated to form independent objects, it indicates that the segmentation scale is appropriate. The DSM thresholds in Table 2 are not fixed; boundaries can be drawn based on elevation values, roughly dividing the study area by terrain. NDVI values also vary across regions, so it is recommended to start at an NDVI value of 0 and observe during the threshold adjustment process whether most fruit trees can be extracted. This allows for the extraction of tree canopy information in each zone, and with a small amount of manual correction, canopy results are generated (Figure 5). During the experiment, the ratio of manual corrections to the total area was calculated, yielding 3.2%, indicating that the method is well scalable.

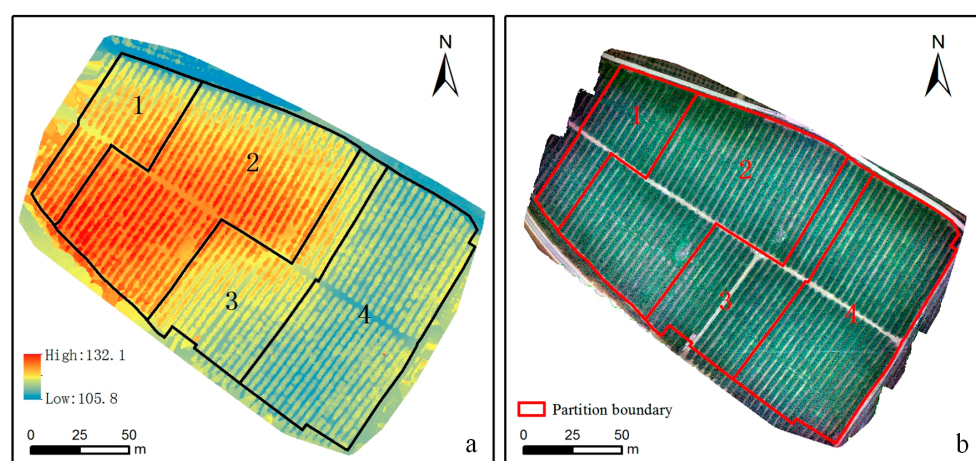


Figure 4. DSM-based partitioning example: (a) the overlay of zoning boundaries with DSM; (b) the overlay of zoning boundaries with UAV imagery. Zones 1–4 represent different regions classified according to the DSM.

Table 2. Multi-region canopy information extraction model.

Partition Number	Extraction Model
Partition 1	$\text{NDVI} \geq -0.1$ and $\text{DSM} \geq 110.5$
Partition 2	$\text{NDVI} \geq 0.05$
Partition 3	$\text{NDVI} \geq 0$ and $\text{DSM} \geq 111$
Partition 4	$\text{NDVI} \geq 0$ and $\text{DSM} \geq 109$
Partition 5	$\text{NDVI} \geq -0.1$ and $\text{DSM} \geq 110.5$

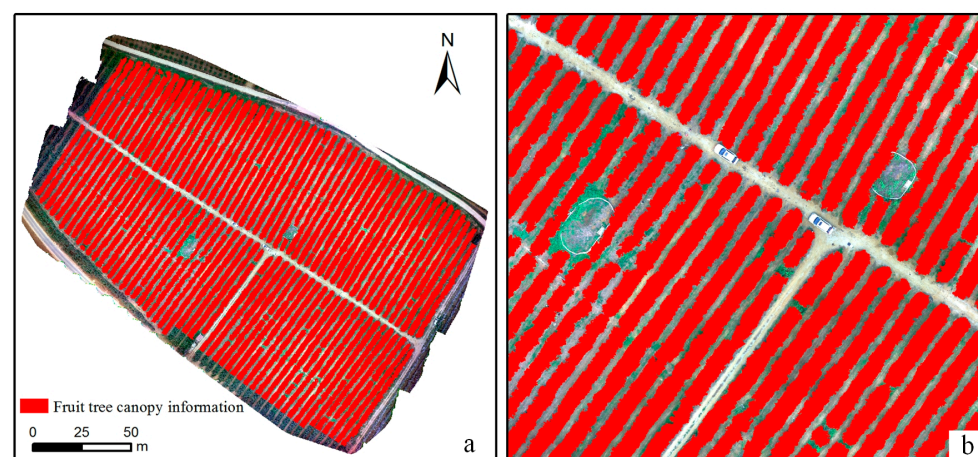


Figure 5. Example of fruit tree canopy information extraction: (a) the overall effect of fruit tree canopy information extraction; (b) the detailed effect of fruit tree canopy information extraction.

2. Individual Fruit Tree Canopy Information Recognition

The canopy information of fruit trees is used as the object to identify individual tree canopies. Figure 6 shows this process. First, the trunk position of the first tree is measured in each row in the field. This position becomes the first trunk point. Then, all other trunk points are automatically generated at 1.5 m intervals. The center point between two trunk points is taken and then expanded 0.25 m to the left and right and 3 m vertically from that center to create a rectangular region of interest (ROI). The ROI is used to crop the DSM and produce a DSM dataset. Each DSM boundary line is formed with the marker-controlled watershed algorithm. These boundary lines are used to segment canopy information and obtain individual tree canopy data. Then, each tree's projected area is calculated. The core of the marker-controlled watershed algorithm is identifying valley points in the DSM. A set of minimum pixels is formed by starting from the image's minimum pixels and marking neighboring vertical pixels one by one. This set is converted into data points through image conversion, and these points are connected to form boundary lines. Figure 7 shows the identification results for individual citrus tree canopies.

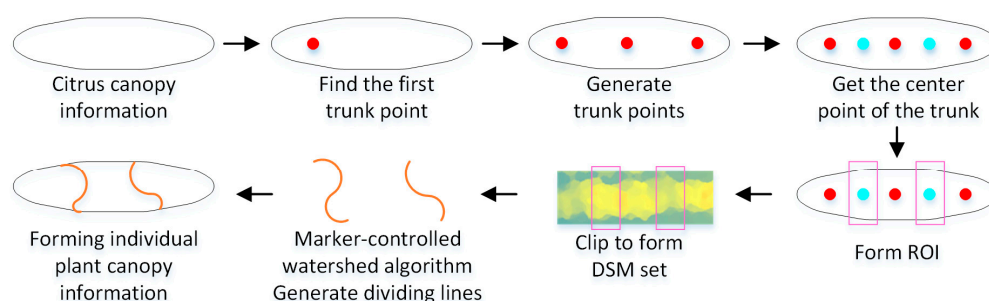


Figure 6. Flow chart of single-plant canopy information recognition. The red dots represent the trunk points, the blue dots represent the center points between two trunks, and the red boxes represent the generated rectangular ROIs.

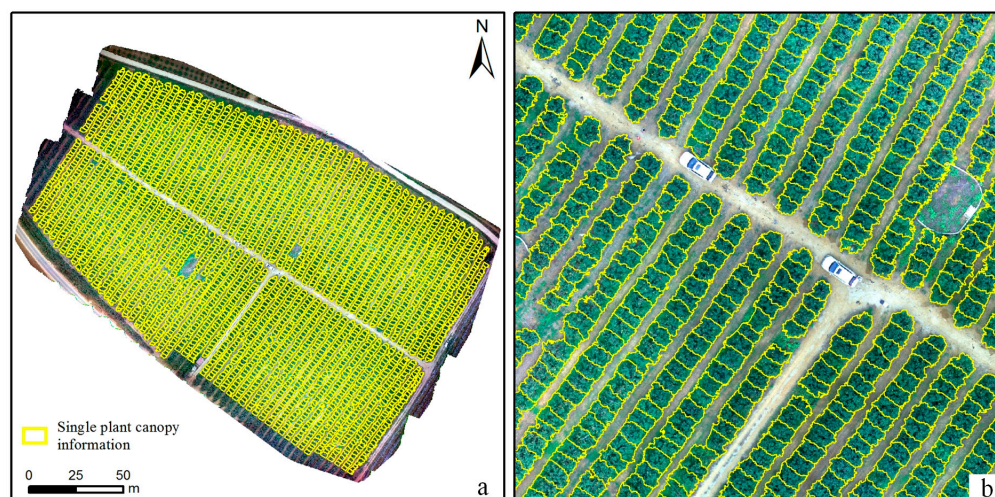


Figure 7. Example of fruit tree individual canopy information recognition: (a) the overall effect of fruit tree individual canopy information recognition; (b) the detailed effect of fruit tree individual canopy information recognition.

2.2.6. Canopy Fruit Boundary Extraction

Canopy fruit area can reflect the quantity of fruit on a tree and is an important indicator for assessing the quality and production potential of fruit trees. NPCI is sensitive to detecting canopy fruits, with fruit NPCI values being much higher than those of other objects; the larger the fruit area, the higher the NPCI value. To reduce misclassification, the

NPCI value should be appropriately increased. A small number of fruits may be missed, but the probability of errors can be reduced. The first step is to use the fruit tree canopy information to crop the NPCI image and reclassify it into a binary format. NPCI values greater than 0 are considered fruit information and assigned a value of 1, while others are assigned a value of 2. The second step is to convert the binary raster image to vector format, with attributes set with 1 representing the preliminary boundaries of citrus fruits. The third step is to refine the preliminary fruit boundaries by deleting small patches, merging fragmented areas, and then intersecting the results with individual tree canopy information to form the final fruit boundary information. The fourth step is to check the accuracy of the extracted canopy fruit boundaries, and if the accuracy does not meet the requirements, the algorithm and results are further refined. The effect of canopy fruit boundary extraction is shown in Figure 8.

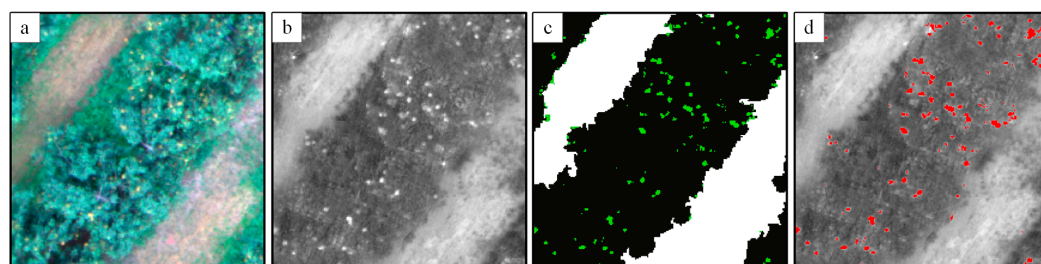


Figure 8. Example of canopy fruit boundary extraction: (a) orthophoto; (b) NPCI image (the white bright spots in the canopy represent fruit information); (c) binarized NPCI raster map (green represents fruit information); (d) overlay of extracted fruit boundary information with NPCI image (red represents fruit boundary information).

2.2.7. Selection of Evaluation Metrics

Using individual fruit tree canopies as units, we obtained the maximum, minimum, and average values of 30 VIs. Next, to select inversion indicators for nutritional quality, we linearly correlated the average values of these indices with soluble sugar, VC, soluble solids, titratable acid, and edibility. We then used the Pearson correlation coefficient (r), calculated as shown in Formula (1), to measure the degree of correlation.

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}}, \quad (1)$$

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i, \bar{y} = \frac{1}{n} \sum_{i=1}^n y_i. \quad (2)$$

The range of r is $[-1, 1]$, where $r > 0$ indicates a positive correlation and $r < 0$ indicates a negative correlation. Generally, $|r| < 0.4$ indicates a weak correlation, $0.4 \leq |r| < 0.6$ indicates a moderate correlation, $0.6 \leq |r| < 0.8$ indicates a strong correlation, and $|r| \geq 0.8$ indicates a very strong correlation. VIs with strong or higher correlations were selected as indicators for fruit production potential.

In Formula (1), r represents the correlation between the nutritional quality index and the vegetation index, x represents the nutritional quality index value of a sample fruit tree, $\bar{x}$ represents the average nutritional quality index value of all sample fruit trees, y represents the vegetation index value of a sample fruit tree, taking the mean vegetation index of each tree's canopy, $\bar{y}$ represents the average vegetation index value of all sample fruit trees, and n is the number of sample fruit trees, which is 30.

Figure 9 presents the correlation analysis between nutritional quality indices and VIs. The 30 VIs are weakly correlated with SS; REDVI is moderately negatively correlated with

VC ($r = -0.491$); at a 0.05 significance level, mSR705 is moderately positively correlated with soluble solids ($r = 0.566$); at a 0.01 significance level, TCAVI is strongly positively correlated with titratable acid ($r = 0.707$), and REOSAVI is extremely strongly negatively correlated with edibility rate ($r = -0.889$). Thus, TCAVI and REOSAVI are selected as representative indices for titratable acid and edibility rate, respectively.

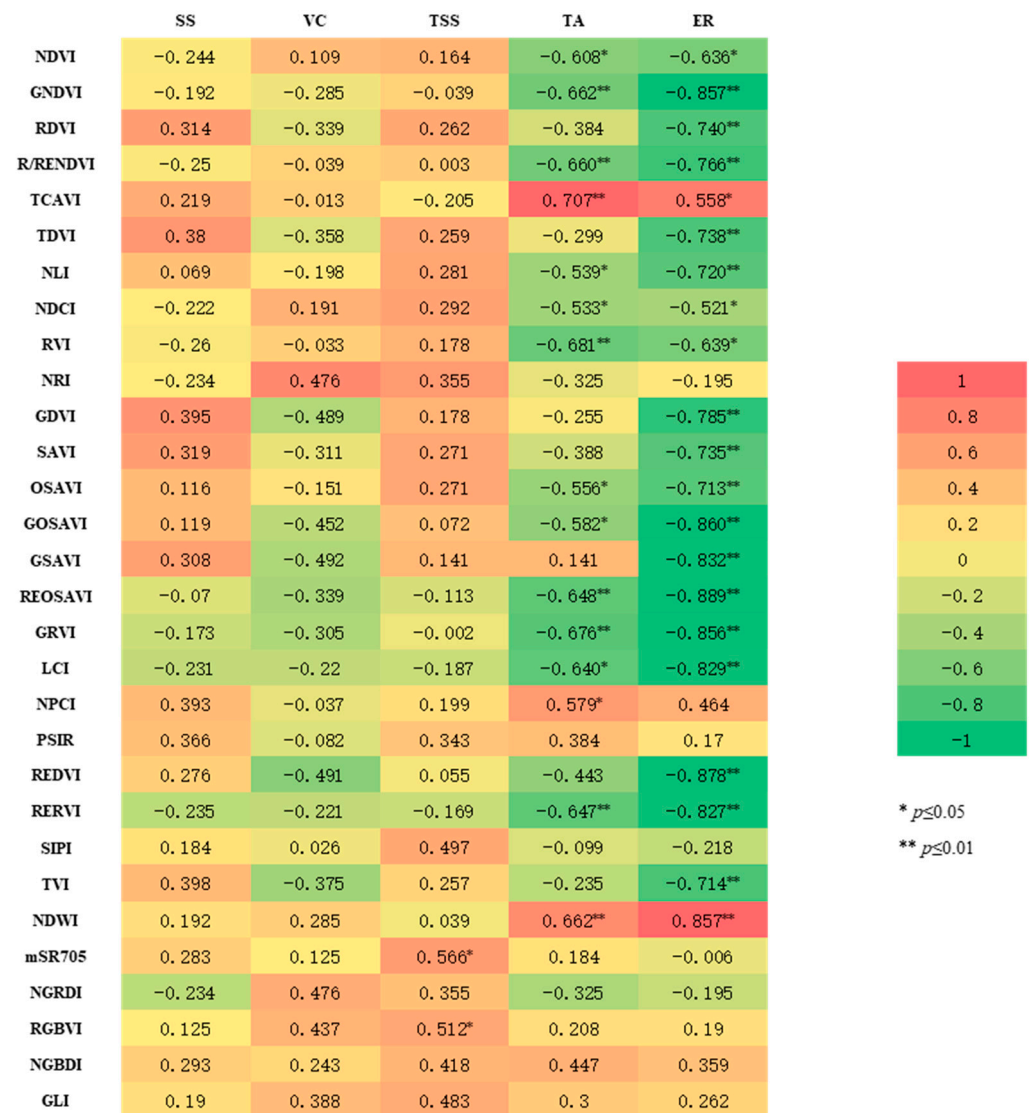


Figure 9. Heatmap of the correlation between nutritional quality indicators and vegetation index. * p indicates that the correlation is significant at the 0.05 level, and ** p indicates that the correlation is significant at the 0.01 level.

2.2.8. Assessment of Citrus Fruit Production Potential

Considering that NDVI is one of the commonly used indicators reflecting plant health, NDVI (health status), TCAVI, REOSAVI, canopy area, and canopy fruit area—a total of five indicators—were used to conduct an assessment of fruit production potential at the tree level. The maximum, minimum, and average values of the five evaluation indicators for the sample tree were calculated. For each grade, 10 sample trees were selected. During the experiment, it was found that even when selecting premium, standard, and commercial fruit tree samples strictly according to appearance quality indicators and test results, there were still overlaps in the values of the five evaluation indicators. For example, the canopy fruit area on premium trees was not necessarily larger than that of standard or commercial trees. To address overlapping evaluation indicator values across samples of different

grades, a method of dividing indicators by grade rank was adopted. Based on the statistical results, the range values for each evaluation grade were defined, and the thresholds for the evaluation indicators were set in the order of premium, standard, and commercial. The threshold determination process is as follows: (1) Priority is given to the premium grade. Given that the maximum, average, and minimum values of the evaluation indicators exhibit low dispersion, starting from the average, smaller interval increments and decrements are used for quantity statistics. In this study, a span of ± 0.05 around the average value is used (in practical operation, this value can be adjusted based on data dispersion; the greater the dispersion, the more appropriately the span should be increased). The number of trees within the range from the average to the maximum and minimum values was counted. When the cumulative number of trees exceeds 50% of the premium-grade sample trees, this range is set as the premium-grade threshold. (2) For the standard grade, the number of standard-grade sample trees that fall within the premium threshold, k , is counted. The actual number of standard-grade sample trees, h , is obtained by subtracting k from 10. Based on the premium threshold, the range is adjusted, and the corresponding number of trees is calculated. When the number exceeds 50% of h , this range is set as the standard-grade threshold. (3) The ranges outside the premium- and standard-grade thresholds are set as the commercial-grade threshold. To address inconsistent dimensions across evaluation metrics, the membership degrees for the five metrics at premium, standard, and commercial levels are set to 0.5, 0.3, and 0.1, respectively. The membership value can be determined using the Analytic Hierarchy Process (AHP) method. The higher the level, the greater the membership value. There is no fixed way to assign values; researchers can also adjust them to 0.6, 0.4, 0.2, or other values. The threshold values and membership degree divisions of the evaluation metrics are shown in Table 3.

Table 3. Evaluation index thresholds and membership division table.

Metrics	Level			
	Premium	Standard	Commercial	
NDVI	[0.78, 0.80]	(0.76, 0.78) or (0.80, 0.81)	≥ 0.81 or ≤ 0.76	
TCAVI	[−0.01, 0.05]	(−0.02, −0.01) or (0.05, 0.12)	≥ 0.12 or ≤ -0.02	
REOSAVI	[0.28, 0.30]	(0.30, 0.32)	≥ 0.32 or < 0.28	
Canopy area (m ²)	[6.50, 8.50]	(5.30, 6.50) or > 8.50	≤ 5.30	
Canopy fruit area (m ²)	≥ 0.1	(0.04, 0.10)	≤ 0.04	
The membership degrees	0.5	0.3	0.1	

In multi-criteria comprehensive evaluation or decision analysis, commonly used weight determination strategies include the entropy method, the AHP, and methods based on principal component analysis (PCA). The entropy-weight method is highly objective but requires a large sample size to accurately reflect the information entropy of indicators. With small samples, weight distortion can easily occur due to data fluctuations. AHP is suitable for complex multi-objective decision-making, but its judgment matrix relies heavily on subjective expert judgment, and inconsistent expert opinions can introduce bias. The PCA weighting method focuses on dimensionality reduction and information condensation, making it suitable for high-dimensional scenarios with many highly correlated indicators. In this study, there are 5 evaluation indicators and 47 sample fruit trees; the evaluation objectives are not complex, and the sample size is small, making entropy-weighted and PCA methods unsuitable. Although several citrus experts were consulted during the experiment, there were disagreements on the ranking of indicator importance. To avoid the uncertainty of AHP's subjective weighting and, simultaneously, based on the biological

logic that premium fruit production potential should reflect a coordinated optimization across multiple dimensions such as nutritional quality, health status, canopy structure, and fruit load, while also considering methodological operability, equal weighting was ultimately adopted for the comprehensive evaluation. Although this strategy does not finely depict differences in indicator importance, it can reflect the overall potential for producing premium fruit in a lightweight manner, fitting the practical needs of small sample sizes and low-dimensional evaluation indicators.

Adopting the principle that the weights of evaluation indicators are equally important, a premium fruit production potential model is constructed based on t evaluation indicators to calculate the composite index. The specific calculation method is shown in formula (3):

$$y = \sum_{i=1}^n \frac{1}{t} P_i \quad (3)$$

In the above formula, y is the comprehensive index; t is the number of evaluation indicators, which is 5; p_i is the membership degree of the i -th evaluation factor; i is the evaluation indicator number; and n is the number of evaluation indicators. The higher the y value, the greater the likelihood that the corresponding citrus tree belongs to premium produce, and vice versa.

In the study, the assessment criteria for potential to produce premium fruits are as follows: $y \geq x_1$ indicates premium quality, $x_2 < y < x_1$ indicates standard quality, and $y \leq x_2$ indicates commercial quality, where x_1 and x_2 are threshold values corresponding to the comprehensive index y . The comprehensive index of sample fruit trees is sorted in descending order, with x_1 being the comprehensive index value corresponding to the top 40% of sample fruit trees and x_2 being the comprehensive index value corresponding to the top 75% of sample fruit trees. In this experiment, $y \geq 0.36$ is classified as premium, $0.24 < y < 0.36$ is classified as standard, and $y \leq 0.24$ is classified as commercial.

2.2.9. Accuracy Inspection

To assess the accuracy of canopy extraction and canopy fruit extraction for individual citrus trees and their potential for premium fruit production, precision (P), recall (R), and F-score (F) are introduced as evaluation metrics. The formulas are as follows:

$$P = \frac{TP}{TP + FP} \times 100\%, \quad (4)$$

$$R = \frac{TP}{TP + FN} \times 100\%, \quad (5)$$

$$F = 2 \times \frac{P \times R}{P + R} \times 100\%, \quad (6)$$

In the above formula, TP represents the number of correct extractions (or evaluations); FP represents the number of incorrect extractions (or evaluations); FN represents the number of missed extractions (or unevaluated items); P represents the proportion of correct extractions (or evaluations) to the total number of extractions (or the corresponding grade); R represents the proportion of correct extractions (or evaluations) to the total actual number (or the corresponding grade); and F is a comprehensive measure of precision and recall. A higher F value indicates better extraction (or evaluation) results. If all objects in the orchard are correctly extracted (or evaluated), F is 100%; conversely, if all objects in the orchard are incorrectly extracted (or evaluated), F is 0.

3. Results

3.1. Analysis of Canopy Extraction Results

Application of the citrus individual tree canopy extraction technique resulted in the identification of 3411 citrus trees. Cross-referencing with field records of plant locations enabled row-by-row verification of canopy information, which revealed 36 patches incorrectly identified as citrus canopies (see Figure 10). After removing non-citrus canopy information, 3375 individual tree canopies were accurately identified.

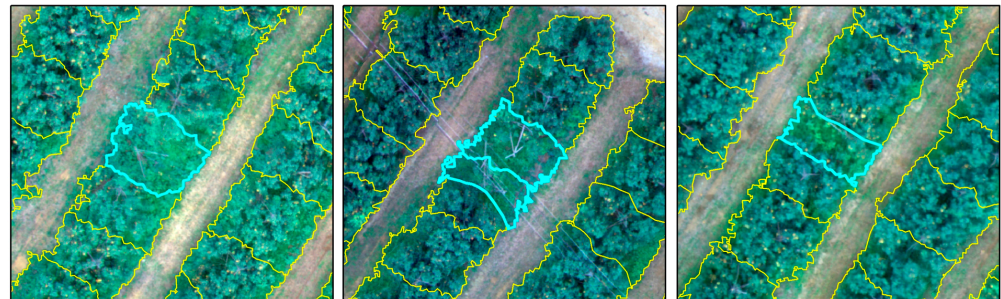


Figure 10. Example of misclassified tree canopies. The misclassified canopies marked in blue. And correctly classified canopies are marked in yellow.

To further verify the accuracy of fruit tree count identification, a sampling survey was conducted along roads in the study area. The left and right regions were divided, and the number of citrus trees in each row was counted. Tables 4 and 5 present a comparison between the actual number of citrus trees planted and the number identified. The actual number of sampled citrus trees was 1043, while remote sensing identified 1040, with 13 trees incorrectly identified and 16 trees missed. The precision (P) was 98.75%, the recall (R) was 98.47%, and the F-score was 98.61%, indicating that the extraction of individual tree canopies was effective. Incorrect canopy identification primarily resulted from vigorous weed growth and outward-extending branches from adjacent trees after tree felling, which caused image features in the felled area to be confused with citrus canopy features. During multi-scale automatic segmentation, this area could not be separated into distinct objects from the citrus canopies. Reducing the current segmentation scale would create an excessive number of objects, which is not conducive to canopy recognition. Missing tree canopies were mainly due to inconsistent planting spacing, dense plantings, and vigorous branch growth, which led to interconnected crowns. Leaves accumulating at the edges increased the edge elevation, causing displacement of the boundary lines.

To verify the accuracy of the canopy area, 17 fruit tree canopies were manually drawn as samples, and their projected canopy areas were measured. A correlation analysis was performed between the measured projected areas and the extracted values (Figure 10). The coefficient of determination (R^2) and root mean square error (RMSE) were used as evaluation indicators to assess the accuracy of the extracted canopy areas, with the following formulas:

$$R^2 = \frac{\sum_{i=1}^n (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^n (y_i - \bar{y})^2}, \quad (7)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}}, \quad (8)$$

in Formulas (7) and (8), y represents the measured value, $\hat{y}$ denotes the extracted value, $\bar{y}$ is the mean of the measured values, and n is the number of plants. An R^2 value closer to 1 indicates a higher correlation between extracted and measured values, while a smaller

RMSE value signifies greater extraction accuracy. Figure 11 shows that R^2 was 0.869 and RMSE was 0.489 m², indicating good accuracy in canopy area extraction.

Table 4. Comparison table of actual and identified number of citrus plants (right area). The accuracy rate P (%) is 98.75%, the recall rate R (%) is 98.47%, and the F-score (%) is 98.61%.

Region	Number of Lines	Actual Number of Plants	Number of Identified Plants	Number of Misclassified Strains	Number of Missed Divisions
Right	Line 2	36	36	0	0
	Line 3	36	37	1	0
	Line 5	38	37	0	1
	Line 7	37	37	0	0
	Line 11	37	37	0	0
	Line 14	33	35	2	0
	Line 17	37	37	0	0
	Line 23	36	37	1	0
	Line 24	37	36	0	1
	Line 30	34	33	0	1
	Line 31	33	34	1	0
	Line 36	31	31	0	0
	Line 38	31	30	1	2
	Line 39	30	29	0	1
	Line 43	28	28	0	0
	Line 47	25	24	0	1
Sum		539	538	6	7

Table 5. Comparison table of actual and identified number of citrus plants (left area). The accuracy rate P (%) is 98.75%, the recall rate R (%) is 98.47%, and the F-score (%) is 98.61%.

Region	Number of Lines	Actual Number of Plants	Number of Identified Plants	Number of Misclassified Strains	Number of Missed Divisions
Left	Line 3	36	36	1	1
	Line 4	34	34	0	0
	Line 5	35	36	1	0
	Line 11	36	34	0	2
	Line 23	33	34	1	0
	Line 24	29	30	1	0
	Line 28	38	37	0	1
	Line 30	36	36	1	1
	Line 36	32	32	0	0
	Line 37	33	32	0	1
	Line 42	30	29	0	1
	Line 43	28	28	0	0
	Line 49	27	29	2	0
	Line 50	26	26	0	0
	Line 51	26	25	0	1
	Line 52	25	24	0	1
Sum		504	502	7	9

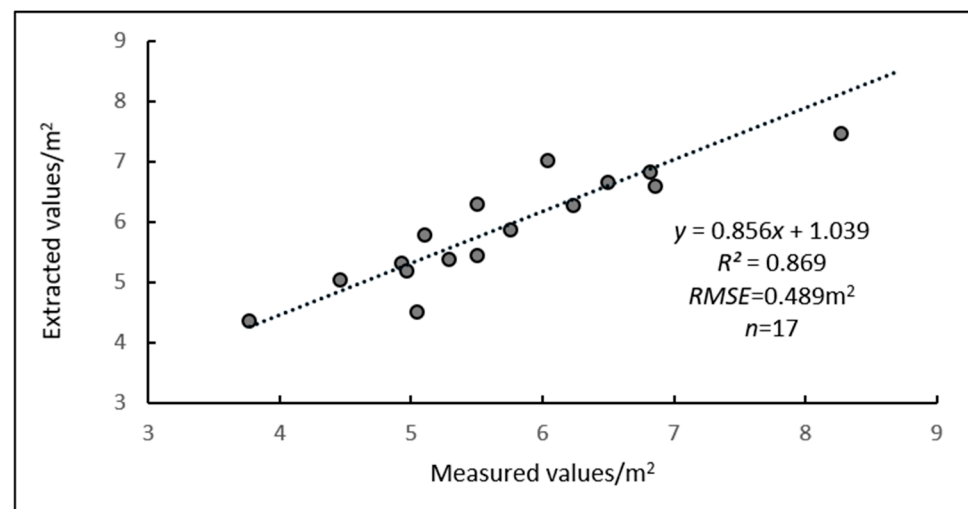


Figure 11. Canopy extraction area accuracy verification.

3.2. Analysis of Canopy Fruit Extraction Results

Similarly, to verify the accuracy of the canopy fruit area, the canopy fruit boundaries of 18 fruit trees were manually drawn as samples, and the canopy fruit projection area was calculated as the measured value. This was then correlated with the projection area of the 18 automatically extracted canopy fruit boundaries (extracted value) (Figure 12). The experiment found an R^2 of 0.914 and an $RMSE$ of $0.019 m^2$, indicating that most canopy fruits could be identified, with only a small number missed or misidentified. To further assess accuracy, precision (P), recall (R), and F-score were also used for evaluation. Table 6 shows a precision of 94.74%, a recall of 86.24%, and an F-score of 90.29%, indicating good performance in canopy fruit extraction. The phenomenon of missed detection was more prominent than misidentification, which aligns with the situation in which the NPCI value was set slightly high during technical processing. Considering that during evaluation, correctly identifying most of the fruit area is sufficient, the NPCI value was adjusted upward to reduce misidentification caused by interference from branches, leaves, and supporting bamboo poles.

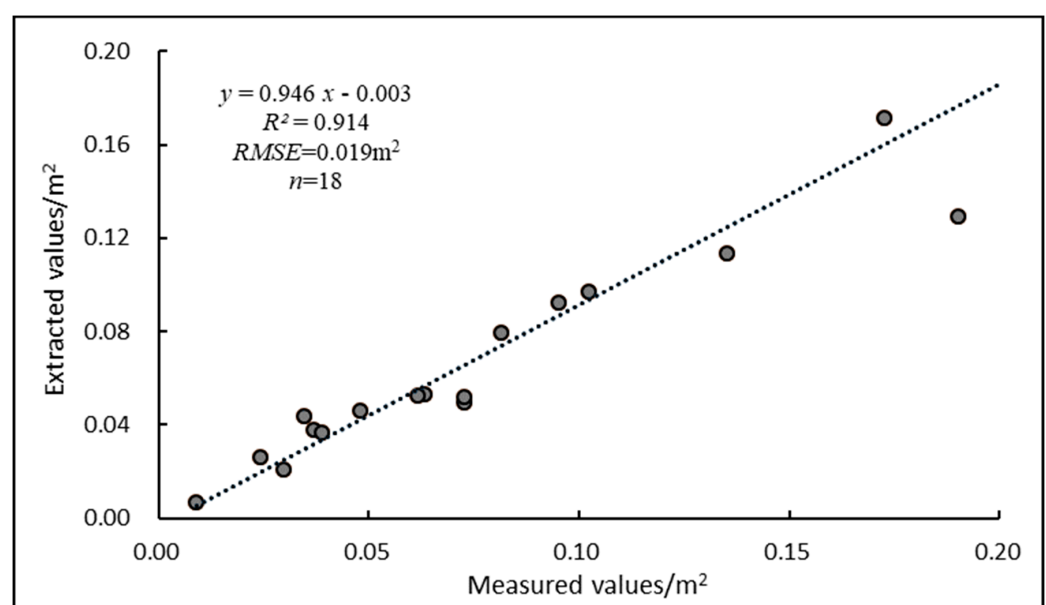


Figure 12. Canopy fruit extraction area accuracy inspection chart.

Table 6. Citrus canopy fruit extraction accuracy inspection form (unit: m²). The accuracy rate *P* (%) is 94.74%; the recall rate *R* (%) is 86.24%; the F-score (%) is 90.29%.

No.	Measured Value	Extracted Value	<i>TP</i>	<i>FP</i>	<i>FN</i>
1	0.095	0.092	0.091	0.001	0.004
2	0.009	0.007	0.006	0.001	0.003
3	0.030	0.021	0.020	0.001	0.010
4	0.135	0.114	0.112	0.002	0.023
5	0.073	0.050	0.049	0.001	0.024
6	0.024	0.026	0.023	0.003	0.001
7	0.172	0.171	0.170	0.001	0.002
8	0.081	0.079	0.078	0.001	0.003
9	0.048	0.046	0.044	0.002	0.004
10	0.037	0.038	0.032	0.006	0.005
11	0.215	0.242	0.209	0.033	0.006
12	0.073	0.052	0.050	0.002	0.023
13	0.102	0.097	0.094	0.003	0.008
14	0.035	0.043	0.034	0.009	0.001
15	0.039	0.037	0.036	0.001	0.003
16	0.063	0.053	0.052	0.001	0.011
17	0.190	0.129	0.128	0.001	0.062
18	0.062	0.053	0.051	0.002	0.011

3.3. Evaluation Accuracy Analysis

To evaluate the accuracy of the citrus fruit production potential assessment, an accuracy test was performed using 47 sample trees (30 were used to determine quality-grade thresholds, and 17 were not). The accuracy test results are presented in Table 6. In this table, the diagonal entries represent the number of sample trees of a given grade that were correctly assessed (*TP*). The columns represent the number of trees misclassified into a particular grade (*FP*), and the rows indicate the number of trees in a given grade that were omitted (*FN*). Table 7 shows that there were 13, 19, and 15 sample trees in the premium, standard, and commercial production potential grades, respectively. A total of 40 trees were correctly classified, resulting in an overall assessment accuracy of 85.11%. The premium grade exhibited the highest assessment accuracy, followed by the commercial grade. For the premium grade, precision (*P*) was 85.71%, recall (*R*) was 92.31%, and the F-score was 88.89%. For the standard grade, precision was 83.33%, recall was 78.95%, and the F-score was 81.08%. For the commercial grade, the precision, recall, and F-score were all 86.67%. Among the premium sample trees, one was misclassified as standard. Among the standard-grade trees, two were misclassified as premium and two as commercial. Among the commercial-grade trees, two were misclassified as standard. Misclassification between standard-grade trees and either premium-grade or commercial-grade trees was most frequent. This misclassification primarily resulted from irregular fluctuations in the five assessment indicators. For example, even if the tree's health status and canopy area are good, extremely high or low values in other indicators can influence the assessment result and cause confusion. This type of misclassification cannot be entirely eliminated, but it may be reduced by increasing the number of assessment indicators or tree samples and by optimizing the threshold values for assessment indicators and comprehensive indices.

Table 7. Citrus fruit production potential assessment accuracy test.

	Premium	Standard	Commercial	Number of Samples	FN	R (%)
Premium	12	1	0	13	1	92.31
Standard	2	15	2	19	4	78.95
Commercial	0	2	13	15	2	86.67
Number of trees	14	18	15	47		
FP (%)	2	3	2			
P (%)	85.71	83.33	86.67			
F-score (%)	88.89	81.08	86.67			

3.4. Assessment Results of Citrus Fruit Production Potential

Figure 13 presents the distribution of citrus fruit production potential within the study area. Remote sensing technology identified 3375 citrus trees. Of these, 1187 trees exhibited premium production potential, 1517 demonstrated standard potential, and 671 showed commercial potential, representing 35.17%, 44.95%, and 19.88% of the orchard, respectively. Trees with production potential above commercial accounted for 80.12% of the orchard, suggesting a good capacity to produce premium fruit and indicating that orchard management practices are relatively scientific and standardized. Premium potential trees are primarily located in the middle of each row in the left area and in the southeast of the right area. Trees with standard potential are evenly distributed across both areas, while those with commercial potential are concentrated in the southwest and central parts of the right area and the southwest part of the left area. Overall, the first to second trees along the road mostly have standard (Line 46) or commercial (Line 48) production potential. Usually, trees along the road receive ample sunlight, support strong photosynthesis, and benefit from good air circulation, which is more conducive to nutrient accumulation and improved fruit quality. However, these trees do not show advantages, mainly due to improper management. Pedestrians or agricultural machinery entering and exiting the orchard can cause mechanical damage to roadside trees, such as damaged roots and scratched branches, affecting healthy growth. Additionally, soil compaction from agricultural machinery and vehicles reduces aeration and water permeability, restricting root development and limiting water and nutrient uptake, which negatively affects tree growth and fruit development. It is recommended that orchard managers implement targeted management strategies based on these assessment results to enhance citrus fruit yield and quality.

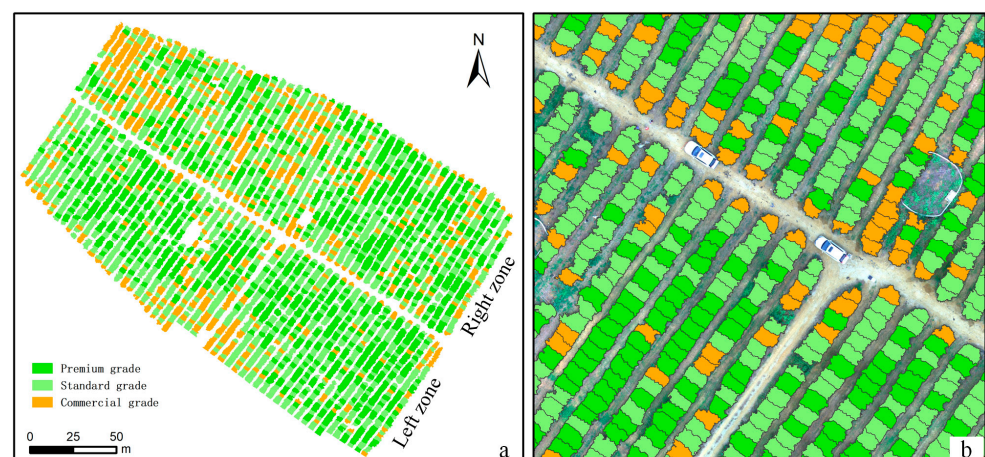


Figure 13. Citrus tree canopy scale fruit production potential assessment: (a) overall effect of citrus fruit production potential assessment; (b) detailed effect of citrus fruit production potential assessment.

4. Discussion

4.1. Advantages of Single-Tree Canopy Extraction Technology

Extracting individual tree crown information has been a focus of remote sensing research. Various studies have utilized the watershed algorithm, either independently or in combination with other techniques, to extract forest canopy information. For instance, Jing et al. [54] introduced a multi-scale segmentation method that combines Gaussian filtering with the watershed algorithm, achieving 65% accuracy in broadleaf tree crown extraction. Guo et al. [55] applied a marker-controlled watershed segmentation method to high-resolution remote sensing images, resulting in extraction accuracies of 87.8% in sparse forests and 65.5% in dense forests. In 2021, Ma et al. [56] developed a vegetation point cloud density model and integrated it with an improved watershed algorithm to extract tree height and canopy area in northern China, achieving an overall extraction accuracy above 85%. Also in 2021, Shu et al. [57] employed UAV digital imagery and the watershed algorithm to segment individual citrus trees, reporting a single-tree recognition accuracy exceeding 93%, a recall rate above 95%, an average F-score of 96.52%, and a coefficient of determination (R^2) between the projected and manually delineated crown areas ranging from 0.78 to 0.94, with an RMSE between 0.57 and 1.73 m². These studies demonstrate that remote sensing technology, when combined with the watershed algorithm, is effective for extracting individual trees. In this study, under complex growth conditions such as contiguous orchard planting in hilly areas, unclear individual tree canopy boundaries, and rampant weeds, a remote sensing technique that integrates planting agronomy with a marker-controlled watershed algorithm was used to identify fruit trees. This method achieves a precision (P) of 98.75%, a recall rate (R) of 98.47%, an F-score of 98.61%, a coefficient of determination (R^2) for extracted canopy area of 0.869, and an RMSE of 0.489 m². The accuracy of fruit tree count identification surpasses that of previous studies, while the accuracy of individual tree crown projection area is consistent with the technical standards established in prior research. It fully demonstrates the innovation of the research method and effectively addresses the problem of low accuracy in identifying individual trees in sloping orchard areas where canopy differentiation is not obvious. This method provides a new technique for extracting individual trees from contiguous citrus planting areas in hilly regions, is easy to implement, and is highly accurate.

4.2. Optimization of Canopy Fruit Extraction

In recent years, using drone technology to monitor fruit quantity and yield has become increasingly popular. Apolo-Apolo et al. [58] used drones to obtain side photos of citrus fruit trees at close range and estimated the yield and size of oranges based on the R-CNN deep learning model, with an average standard error (SE) of 6.59% between visual counting and model fruit detection. The long short-term memory (LSTM) model estimated the yield of a single fruit tree and a whole orchard, and the yield error per plant (SE) was about 4.53%, the standard deviation (SD) was 0.97 kg, and the total yield error of the model (SE) was 7.22%, and SD was 4083.58 kg. Kim et al. [25] used UAV and hyperspectral sensor data to estimate Wenzhou citrus fruit in three locations in Jeju Island based on the support vector machine method, and the overall accuracy and kappa coefficient of citrus fruit identification were 98.87% and 0.83, respectively, and the difference between the estimated yield and the actual yield was 5.00%~13.30%. Kwon et al. [26] converted a UAV RGB image into an HSV image and then used the principal component analysis index for Wenzhou mandarin orange and found that to reliably estimate the fruit size, the image resolution should reach more than 5 pixels/cm, and a flight altitude of 30 m and below had a better effect on fruit identification. Liang et al. [59] developed an improved algorithm, YOLOv7-MSRS, for detecting lychee fruits, achieving an average accuracy (mAP) of up

to 96.1%. The resolution of the UAV image obtained in this paper is 3 pixels/cm, which is higher than the image resolution used by Kwon [25]. Using the NPCI threshold to identify citrus fruits, the recognition accuracy (P), recall R , and F-score were 94.74%, 86.24%, and 90.29%, respectively. The determination coefficient R^2 is 0.869, and the root mean square error $RMSE$ is 0.019 m². This study achieved relatively good overall accuracy in extracting canopy fruits. Although the accuracy is slightly lower than that of Kim [25], Liang [59], and others, the method is more lightweight and significantly reduces the impact of interfering objects, such as shadows and leaves, which have relatively low NPCI values. By appropriately increasing the NPCI threshold, interference from non-fruit objects can be reduced. Fruits that are heavily obscured by leaves may be partially missed, but a small number of missed detections does not significantly affect the assessment of the orchard's production potential. For applications in fruit counting and yield estimation, relying solely on the NPCI index for fruit identification may still leave room for improvement in accuracy. Accuracy can be improved by lowering the flight altitude and using a combined deep learning and vegetation index approach for citrus fruit recognition.

4.3. Optimization of the Selection of Evaluation Metrics

Nutritional quality indicators of citrus fruits, such as SS, VC, TSS, TA, and ER, are very important for evaluating fruit quality. However, in this experiment, Pearson's correlation analysis was used to examine the relationship between nutritional quality indicators and vegetation indices, and it was found that the 30 selected vegetation indices did not show significant correlations with SS, VC, or TSS. This does not mean there is no potential connection between vegetation indices and nutritional quality indicators; rather, it is more likely due to the nonlinear nature of their relationship, which exceeds the detection capability of Pearson's correlation analysis. Pearson's correlation analysis is a classic statistical method used to measure the linear correlation between two continuous variables. It is intuitive, easy to interpret, simple to calculate, and widely applicable, but it cannot identify nonlinear relationships such as curves or segmented patterns. It is possible that the selected vegetation indices and nutritional quality indicators have nonlinear characteristics. It is recommended that researchers, when conducting variable correlation analysis, first use Pearson's correlation for preliminary screening. If no significant linear relationship is found, nonlinear modeling methods can then be explored. Therefore, subsequent studies will adopt nonlinear methods (such as polynomial regression, generalized additive models, nonlinear least squares fitting, etc.) and machine learning approaches (such as random forest, support vector machine, XGBoost, etc.) to explore the relationship between the two, as well as incorporate more novel or composite vegetation indices specifically designed for citrus nutritional quality. By integrating multi-dimensional and multi-method analyses, the limitations of traditional linear correlation analysis can be overcome, further optimizing non-destructive evaluation indicators for premium citrus production potential and more comprehensively reflecting the production potential of fruit trees.

4.4. Optimization of Evaluation Metric Weights

In the experiment, experts in the citrus field unanimously agreed that the importance of nutritional quality indicators is higher than that of tree health, while tree health is more important than canopy area and canopy fruit area. However, differences in opinion arose during the specific scoring process. To avoid subjective bias in constructing judgment matrices and considering that the evaluation of production potential should examine the overall capacity of the tree—meaning that nutritional quality, health, canopy, and fruit area all need to be optimal to produce more premium-quality fruit—this study adopts an approach of equal weighting for comprehensive assessment. Although this method does

not fully reflect the actual importance differences among indicators, it is simple to operate and can provide an overall reflection of a tree's production potential, effectively meeting the needs of farmers and buyers for a quick prediction of orchard output levels. Nevertheless, scientific research should strive for greater precision to better align with biological realities, and future work will improve the mechanisms for determining weights. On the one hand, it will examine the strength of the association between each evaluation indicator and the number of 'above-commercial fruit per tree,' quantifying their contributions. On the other hand, it will integrate expert knowledge to construct judgment matrices, combining data-driven and domain experience to scientifically optimize the weight distribution of evaluation indicators, thereby better aligning the model with actual production patterns.

4.5. Reliability of Assessment Methods

Existing studies mainly obtain close-up fruit images using drones or other experimental equipment and measure single-fruit weight, peel thickness, fruit diameter, sugar, acid, Vc, flavonoids, phenolic acids, and other appearance, nutritional, and flavor qualities in the laboratory. Methods such as correlation analysis, PCA, heatmap clustering, and machine learning are then used for a comprehensive evaluation of fruit quality [6]. Hari Krishna and others [60], based on UAV hyperspectral imaging, developed a framework for preprocessing, feature optimization, and deep learning to evaluate the quality of apples and oranges, achieving 99.11% and 99.17% accuracy and precision in quality assessment, respectively. Lin et al. [61] proposed a novel method for automatically detecting spherical or cylindrical fruits using a combination of color, depth, and shape information to analyze fruit and vegetable quality, achieving high recall rates (0.762 to 0.889) and precision (0.864 to 0.888) on guava, eggplant, and chili datasets. Zhang et al. [62] used visible–near-infrared (Vis-NIR) hyperspectral reflectance imaging technology to detect surface anomalies in oranges. By combining mean principal component images with an enhanced watershed segmentation method, principal component analysis (PCA) was able to achieve overall classification, reaching an accuracy of 97.73% in distinguishing normal and defective oranges. This study is fundamentally different from the aforementioned research. It focuses on individual citrus trees, integrating nutritional quality, tree health status, canopy, and canopy fruit indicators to construct a model of the potential for premium fruit production. It allows for prediction of the quality production potential of each citrus tree before fruit maturation and harvest, with an overall accuracy of 85.11%. For premium-grade fruits, the accuracy (P) is 85.71%, recall (R) is 92.31%, and F-score 88.89%; for standard-grade fruits, P is 83.33%, R is 78.95, and F-score is 81.08%; for commercial-grade fruits, P , R , and F-score are all 86.67%. Overall assessment accuracy is good, meeting the needs of farmers and buyers for rapid orchard yield predictions, providing a basis for farmers to evaluate selling price, harvesting schedule, and tree management and providing buyers with accurate information on premium fruits, addressing the mismatch between premium citrus and price. The methodology presented in this paper can be applied in citrus orchards in the hilly regions of southern China, including orah mandarin, Maoguo citrus, oranges, and pomelos. It is recommended to conduct evaluations 1 to 2 months before harvest, with accuracy increasing as the harvest approaches. However, it is not recommended to use it in orchards with small-fruited citrus such as sugar tangerines and honey tangerines, because counting the fruits is time-consuming due to their small size, and the error in fruit recognition using NPCI has not yet been evaluated.

This paper presents new ideas for assessing the potential for premium citrus production in orchard areas of hilly regions in southern China. However, there is still room for improvement in the reliability and general applicability of the methods. This study conducted an experiment using a single-phase remote sensing image of a orah mandarin

orchard in Wuming District, Guangxi, and verified the production potential with only 47 citrus trees. The sample size did not meet the commonly required ‘three replicates’ standard for agricultural experiments, which may lead to instability in the selection of evaluation indicators and threshold divisions, thereby affecting the accuracy and representativeness of the results. To enhance the robustness and precision of the assessment technology, future research will expand to multiple orchards, integrate hyperspectral data and multi-temporal time-series images, significantly increase the sample size, and optimize the modeling process using machine learning methods to strengthen the model’s robustness and generalization. It is recommended that other researchers conducting similar experiments refer to the technical framework of this study while localizing and adjusting the thresholds of key parameters such as DSM, NDVI, and NPCI, as well as grading standards for evaluation indicators, according to specific regional environments, variety characteristics, and data conditions, to improve the applicability and scientific validity of their assessment results.

5. Conclusions

This study conducted a non-destructive assessment of the production potential of premium citrus fruit in orchards in Wuming District, Guangxi, China, using UAV multispectral remote sensing and ground-based measurement techniques. By using PAMWA, high-precision identification of individual trees was achieved, with an accuracy (P) of 98.75%, recall (R) of 98.47%, F1 score of 98.61%, and coefficient of determination (R^2) for canopy extraction area of 0.869, with a root mean square error (RMSE) of 0.489 m², effectively overcoming technical challenges posed by dense planting and blurred canopy boundaries in citrus orchards in southern hilly regions. On this basis, a production potential assessment model was developed using five indicators: NDVI (health status), TCAVI, REOSAVI, tree canopy area, and canopy fruit area, achieving an overall assessment accuracy of 85.11%, with the best recognition performance for premium grades and the next best for commercial grades. This study provides a feasible approach for remote sensing assessment of premium citrus production potential in southern hilly areas, though there remains room for optimization in indicator selection, weight assignment, and grade classification. Future work will focus on refining the indicator system and modeling methods to enhance the stability, scientific validity, and replicability of the technology, promoting its practical application in orchard management on a larger scale.

Author Contributions: Technical method design: G.X. and Q.H.; experimental data organization: C.M. and X.H.; single-tree canopy information extraction: Y.L. and C.L.; evaluation index selection: S.Y. and S.W.; production potential assessment: G.X., W.N. and Q.H.; accuracy verification: Z.Q. and C.M.; paper writing: G.X. and W.N. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Science and Technology Major Program of Guangxi Science and Technology Department (AA22036002), the “Empowerment” Action Plan (Guangxi Key Research and Development Program) of Guangxi Science and Technology Department (FN2504240015), Special Program on Talent Training for Agriculture and Rural Revitalization of Guangxi Agriculture and Rural Affairs Department (GXQNTJ242121), and Science and Technology Development Fund of Guangxi Academy of Agricultural Sciences (2026YT172 and 2024YP065).

Data Availability Statement: The UAV data and statistical data included in this study are available upon request by contact with the corresponding author.

Acknowledgments: The authors would like to thank team members who assistance with field measurements and UAV data processing.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

NPCI	Normalized pigment chlorophyll index
UAV	Unmanned aerial vehicle
NDVI	Normalized difference vegetation index
TCAVI	Transformed chlorophyll absorption in reflectance index
REOSAVI	Red-edge optimal soil-adjusted vegetation index
DSM	Digital surface model
RMSE	Root mean square error
R^2	R-squared
LAI	Leaf Area Index
MSE	Mean Square Error
MAE	Mean Absolute Error
NDRE	Normalized difference red-edge index
MSAVI	Modified soil-adjusted vegetation index
CI	Chlorophyll index
HLB	Huanglongbing
TVI	Triangular vegetation index
CNC	Canopy nitrogen content
API	Agricultural practice information
VIs	Vegetation indices
HSI	Hyperspectral imaging
FSL	Few-shot learning
PAMWA	Planting agronomy and the marker-control watershed algorithm
SS	Soluble sugars
VC	Vitamin C
TSS	Total soluble solids
TA	Titrateable acidity
ER	Edible rate
RGB	Red, green, blue
RE	Red-edge
NIR	Near-infrared
ROI	Region of interest
PCA	Principal component analysis

References

1. Wang, S.; Xie, W.; Yan, X. Effects of Future Climate Change on Citrus Quality and Yield in China. *Sustainability* **2022**, *14*, 9366. [CrossRef]
2. Food and Agriculture Organization of the United Nations. FAO Statistical Databases 2019. Available online: <https://www.fao.org/faostat/> (accessed on 10 July 2022).
3. World Production of Citrus Fruits in 2020, by Region. Available online: <https://www.statista.com/statistics/264002/production-of-citrus-fruits-worldwide-by-region/> (accessed on 10 July 2022).
4. Lin, C.; Wang, M.; Su, B. Analysis of citrus production efficiency and inter-provincial variability in China under the constraints of non-point source pollution. *Ciência Rural* **2024**, *54*, e20230147. [CrossRef]
5. Xie, G.; Huang, Q.; Qin, Z.; Lan, Z.; Liang, Y.; Wen, G.; Yang, S.; Ning, X. Risk Assessment of Citrus Huanglongbing with the Support of Remote Sensing Technology. *J. Henan Agric. Sci.* **2024**, *53*, 141–149. [CrossRef]
6. Zhang, W.; Lin, M.; Wang, T.; Sun, L.; Feng, X.; Yao, Z.; Xu, C.; Wang, Y. Comprehensive evaluation of citrus fruit quality based on principal component and cluster analysis. *J. Fruit Sci.* **2023**, *40*, 902–918. [CrossRef]
7. Zeng, X. Studies on the Effects of Habitats to Sweet Orange Fruit Texture. Ph.D. Thesis, Sichuan Agriculture University, Chengdu, China, 2007.
8. Zhang, H.; Zhang, L.; Wu, H.; Wang, D.; Ma, X.; Shao, Y.; Jiang, M.; Chen, X. Unmanned-Aerial-Vehicle-Based Multispectral Monitoring of Nitrogen Content in Canopy Leaves of Processed Tomatoes. *Agriculture* **2025**, *15*, 309. [CrossRef]

9. Lee, K.; Sudduth, K.A.; Zhou, J. Evaluating UAV-Based Remote Sensing for Hay Yield Estimation. *Sensors* **2024**, *24*, 5326. [\[CrossRef\]](#)
10. Xu, C.; Wang, C.; Liu, L.; Yan, X.; Liu, X.; Chen, H.; Cheng, M.; Fan, Y. The Research on Precise Monitoring Methods for Grain Planting Areas Based on High-precision UAV Remote Sensing Images. *J. Geod. Geoinf. Sci.* **2024**, *7*, 94–109. [\[CrossRef\]](#)
11. Zhang, Y.; Ta, N.; Guo, S.; Chen, Q.; Zhao, L.; Li, F.; Chang, Q. Combining Spectral and Textural Information from UAV RGB Images for Leaf Area Index Monitoring in Kiwifruit Orchard. *Remote Sens.* **2022**, *14*, 1063. [\[CrossRef\]](#)
12. Anthony, D.; Elbaum, S.; Lorenz, A.; Detweiler, C. On Crop Height Estimation with UAVs. In Proceedings of the 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems, Chicago, IL, USA, 14–18 September 2014; pp. 4805–4812.
13. García-Martínez, H.; Flores-Magdaleno, H.; Ascencio-Hernández, R.; Khalil-Gardezi, A.; Tijerina-Chávez, L.; Mancilla-Villa, O.R.; Vázquez-Peña, M.A. Corn Grain Yield Estimation from Vegetation Indices, Canopy Cover, Plant Density, and a Neural Network Using Multispectral and RGB Images. *Agriculture* **2020**, *10*, 277. [\[CrossRef\]](#)
14. Liang, L.; Di, L.; Huang, T.; Wang, J.; Lin, L.; Wang, L.; Yang, M. Estimation of leaf nitrogen content in wheat using new hyperspectral indices and a random forest regression algorithm. *Remote Sens.* **2018**, *10*, 1940. [\[CrossRef\]](#)
15. Peng, L.; Xin, H.; Lv, C.; Li, N.; Li, Y.; Geng, Q.; Chen, S.; Lai, N. Inversion of nitrogen and phosphorus contents in cotton leaves based on the Gaussian mixture model and differences in hyperspectral features of UAV. *Spectrochim. Acta Part A Mol. Biomol. Spectrosc.* **2025**, *327*, 125419. [\[CrossRef\]](#) [\[PubMed\]](#)
16. Garza, B.N.; Ancona, V.; Enciso, J.; Perotto-Baldivieso, H.L.; Kunta, M.; Simpson, C. Quantifying Citrus Tree Health Using True Color UAV Images. *Remote Sens.* **2020**, *12*, 170. [\[CrossRef\]](#)
17. Pham, T.D.; Yokoya, N.; Bui, D.T.; Yoshino, K.; Friess, D.A. Remote sensing approaches for monitoring mangrove species, structure, and biomass: Opportunities and challenges. *Remote Sens.* **2019**, *11*, 230. [\[CrossRef\]](#)
18. Lu, X.; Li, W.; Xiao, J.; Zhu, H.; Yang, D.; Yang, J.; Xu, X.; Lan, Y.; Zhang, Y. Inversion of Leaf Area Index in Citrus Trees Based on Multi-Modal Data Fusion from UAV Platform. *Remote Sens.* **2023**, *15*, 3523. [\[CrossRef\]](#)
19. Anjin, C.; Junho, Y.; Jinha, J.; Juan, L. Comparison of Canopy Shape and Vegetation Indices of Citrus Trees Derived from UAV Multispectral Images for Characterization of Citrus Greening Disease. *Remote Sens.* **2020**, *12*, 4122. [\[CrossRef\]](#)
20. Zhang, D.; Qi, H.; Guo, X.; Sun, H.; Min, J.; Li, S.; Hou, L.; Lv, L. Integration of UAV Multispectral Remote Sensing and Random Forest for Full-Growth Stage Monitoring of Wheat Dynamics. *Agriculture* **2025**, *15*, 353. [\[CrossRef\]](#)
21. Osco, L.P.; Ramos, A.P.M.; Pereira, D.R.; Moriya, É.A.S.; Imai, N.N.; Matsubara, E.T.; Estrabis, N.; Souza, M.D.; Junior, J.M.; Gonçalves, W.N.; et al. Predicting Canopy Nitrogen Content in Citrus-Trees Using Random Forest Algorithm Associated to Spectral Vegetation Indices from UAV-Imagery. *Remote Sens.* **2019**, *11*, 2925. [\[CrossRef\]](#)
22. Zhou, L.; Meng, R.; Yu, X.; Liao, Y.; Huang, Z.; Lü, Z.; Xu, B.; Yang, G.; Peng, S.; Xu, L. Improved Yield Prediction of Ratoon Rice Using Unmanned Aerial Vehicle-Based Multi-Temporal Feature Method. *Rice Sci.* **2023**, *30*, 247–256. [\[CrossRef\]](#)
23. Karmakar, P.; Murshed, M.; Teng, S.W. Hyperspectral Imaging-Based Grain Quality Assessment With Limited Labelled Data. *arXiv* **2024**, arXiv:2411.10924. [\[CrossRef\]](#)
24. Zhang, C.; Zhu, Q.; Fu, Z.; Yuan, C.; Geng, M.; Meng, R. Estimation of Aboveground Biomass of Chinese Milk Vetch Based on UAV Multi-Source Map Fusion. *Remote Sens.* **2025**, *17*, 699. [\[CrossRef\]](#)
25. Kim, J.; Kwon, S.; Park, K.; Moon, Y. Estimation of satsuma mandarin fruit yield using a drone and hyperspectral sensor. *Hortic. Environ. Biotechnol.* **2025**, *66*, 381–392. [\[CrossRef\]](#)
26. Kwon, S.H.; Ku, K.B.; Le, A.T.; Han, G.D.; Park, Y.; Kim, J.; Taun, T.T.; Chung, Y.S.; Mansoor, S. Enhancing citrus fruit yield investigations through flight height optimization with UAV imaging. *Sci. Rep.* **2024**, *14*, 322. [\[CrossRef\]](#)
27. Rouse, J.W.J.; Haas, R.H.; Schell, J.A.; Deering, D.W. Monitoring vegetation systems in the great plains with ERTS. *NASA Spec. Publ.* **1974**, *351*, 309.
28. Gitelson, A.A.; Merzlyak, M.N. Spectral reflectance changes associated with autumn senescence of *Aesculus hippocastanum* L. and *Acer platanoides* L. leaves. Spectral features and relation to chlorophyll estimation. *J. Plant Physiol.* **1994**, *143*, 286–292. [\[CrossRef\]](#)
29. Song, H. Research on Citrus Information Extraction from UAV Multispectral Image Based on Deep Learning. Master's Thesis, Guilin University of Technology, Guilin, China, 2023. [\[CrossRef\]](#)
30. Feng, W.; Wu, Y.; He, L.; Ren, X.; Wang, Y.; Hou, G.; Wang, Y.; Liu, W.; Guo, T. An optimized non-linear vegetation index for estimating leaf area index in winter wheat. *Precis. Agric.* **2019**, *20*, 1157–1176. [\[CrossRef\]](#)
31. Ranjan, R.; Chopra, U.K.; Sahoo, R.N.; Singh, A.K.; Pradhan, S. Assessment of plant nitrogen stress in wheat (*Triticum aestivum* L.) through hyperspectral indices. *Int. J. Remote Sens.* **2012**, *33*, 6342–6360. [\[CrossRef\]](#)
32. Jordan, C.F. Deviation of leaf-area index from quality of light on the forest floor. *Ecology* **1969**, *50*, 663–666. [\[CrossRef\]](#)
33. Tucker, C.J. Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sens. Environ.* **1979**, *8*, 127–150. [\[CrossRef\]](#)
34. Ahamed, T.; Tian, L.; Zhang, Y.; Ting, K.C. A review of remote sensing methods for biomass feedstock production. *Biomass Bioenergy* **2021**, *35*, 2455–2469. [\[CrossRef\]](#)

35. Huete, A.R. A soil-adjusted vegetation index (SAVI). *Remote Sens. Environ.* **1988**, *25*, 295–309. [[CrossRef](#)]
36. Rondeaux, G.; Steven, M.; Baret, F. Optimization of soil-adjusted vegetation indices. *Remote Sens. Environ.* **1996**, *55*, 95–107. [[CrossRef](#)]
37. Gilabert, M.A.; Gonzonzález-Piqueras, J.; García-Haro, F.J.; Meliá, J. A generalized soil adjusted vegetation index. *Remote Sens. Environ.* **2002**, *82*, 303–310. [[CrossRef](#)]
38. Sripada, R. Aerial color infrared photography for determining early in-season nitrogen requirements in corn. *Agron. J.* **2006**, *98*, 968–977. [[CrossRef](#)]
39. Chen, H.; Feng, H.; Yang, Z.; Wang, N.; Li, Y. Estimation of chlorophyll content of summer maize canopy based on UAV multispectral remote sensing. *J. Drain. Irrig. Mach. Eng. (JDIME)* **2021**, *39*, 622–629.
40. Buschmann, C.; Nagel, E. In vivo spectroscopy and internal optics of leaves as basis for remote sensing of vegetation. *Int. J. Remote Sens.* **1993**, *14*, 711–722. [[CrossRef](#)]
41. Thenkabail, P.S.; Smith, R.B.; De Pauw, E. Hyperspectral Vegetation Indices and Their Relationships with Agricultural Crop Characteristics. *Remote Sens. Environ.* **2000**, *71*, 158–182. [[CrossRef](#)]
42. Hatfield, J.L.; Prueger, J.H. Value of using different vegetative indices to quantify agricultural crop characteristics at different growth stages under varying management practices. *Remote Sens.* **2010**, *2*, 562–578. [[CrossRef](#)]
43. Yu, K.; Lenz-Wiedemann, V.; Chen, X.P.; Bareth, G. Estimating leaf chlorophyll of barley at different growth stages using spectral indices to reduce soil background and canopy structure effects. *ISPRS J. Photogramm. Remote Sens.* **2014**, *97*, 58–77. [[CrossRef](#)]
44. Liu, X. Using Canopy Active Sensors to Monitor Growth Status and Develop Optional Dynamic Vegetation Indicators Modelin Winter Wheat. Master's Thesis, Nanjing Agricultural University, Nanjing, China, 2017.
45. Jasper, J.; Reusch, S.; Link, A. Active sensing of the N status of wheat using optimized wavelength combination: Impact of seed rate, variety and growth stage. In *Proceedings of Precision Agriculture '09*; Wageningen Academic: Wageningen, The Netherlands, 2009.
46. SIPI-Penuelas, J.; Baret, F.; Filella, I. Semi-empirical indices to assess carotenoids/chlorophyll a ratio from leaf spectral reflectance. *Photosynthetica* **1995**, *31*, 221–230.
47. Haboudane, D.; Miller, J.R.; Pattey, E.; Zarco-Tejadad, P.J.; Strachane, I.B. Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and validation in the context of precision agriculture. *Remote Sens. Environ.* **2004**, *90*, 337–352. [[CrossRef](#)]
48. Xu, H.Q. A study on information extraction of water body with the modified normalized difference water index (MNDWI). *J. Remote Sens.* **2005**, *9*, 589–595. [[CrossRef](#)]
49. Sims, D.A.; Gamon, J.A. Relationships between leaf pigmentcontent and spectral reflectance across a wide range of species, leaf structures and developmental stages. *Remote Sens. Environ.* **2002**, *81*, 337–354. [[CrossRef](#)]
50. Jannoura, R.; Brinkmann, K.; Uteau, D.; Bruns, C.; Joergensen, R.G. Monitoring of crop biomass using true colour aerial photographs taken from a remote controlled hexacopter. *Biosyst. Eng.* **2015**, *129*, 341–351. [[CrossRef](#)]
51. Bendig, J.; Kang, Y.; Aasen, H.; Bolten, A.; Bennertz, S.; Broscheit, J.; Gnypa, M.L.; Bareth, G. Combining UAV-based plant height from crop surface models, visible, and near infrared vegetation indices for biomass monitoring in barley. *Int. J. Appl. Earth Obs. Geoinf.* **2015**, *39*, 79–87. [[CrossRef](#)]
52. Verrelst, J.; Schaepman, M.E.; Koetz, B.; Kneubühler, M. Angular sensitivity analysis of vegetation indices derived from CHRIS/PROBA data. *Remote Sens. Environ.* **2008**, *112*, 2341–2353. [[CrossRef](#)]
53. Louhaichi, M.; Borman, M.M.; Johnson, D.E. Spatially located platform and aerial photography for documentation of grazing impacts on wheat. *Geocarto Int.* **2001**, *16*, 65–70. [[CrossRef](#)]
54. Jing, L.; Hu, B.; Noland, T.; Li, J. An individual tree crown delineation method based on multi-scale segmentation of imagery. *ISPRS J. Photogramm. Remote Sens.* **2012**, *70*, 88–98. [[CrossRef](#)]
55. Guo, Y.; Liu, Q.; Liu, G.; Huang, C. Individual tree crown extraction of high resolution image based on marker-controlled watershed segmentation method. *J. Geo-Inf. Sci.* **2016**, *18*, 1259–1266.
56. Ma, K.; Xiong, Y.; Jiang, F.; Chen, S.; Sun, H. A Novel Vegetation Point Cloud Density Tree-Segmentation Model for Overlapping Crowns Using UAV LiDAR. *Remote Sens.* **2021**, *13*, 1442. [[CrossRef](#)]
57. Shu, M.; Li, S.; Wei, J.; Che, Y.; Li, B.; Ma, Y. Extraction of citrus crown parameters using UAV platform. *Trans. Chin. Soc. Agric. Eng.* **2021**, *37*, 68–76. [[CrossRef](#)]
58. Apolo-Apolo, O.E.; Martínez-Guanter, J.; Egea, G.; Raja, P.; Pérez-Ruiz, M. Deep learning techniques for estimation of the yield and size of citrus fruits using a UAV. *Eur. J. Agron.* **2020**, *115*, 126030. [[CrossRef](#)]
59. Liang, C.; Liang, J.; Yang, W.; Ge, W.; Zhao, J.; Li, S.; Bai, S.; Fan, J.; Lan, Y. Enhanced visual detection of litchi fruit in complex natural environments based on unmanned aerial vehicle (UAV) remote sensing. *Precision Agric.* **2025**, *26*, 23. [[CrossRef](#)]
60. Hari Krishna, H.; Aradhana, D. DCP-ResNet-Based Framework for Hyperspectral Fruit Quality Estimation. *SN Comput. Sci.* **2025**, *6*, 976. [[CrossRef](#)]

61. Lin, G.; Tang, Y.; Zou, X.; Xiong, J.; Fang, Y. Color-, depth-, and shape-based 3D fruit detection. *Precis. Agric.* **2020**, *21*, 1–17. [[CrossRef](#)]
62. Zhang, H.; Chen, Y.; Liu, X.; Huang, Y.; Zhan, B.; Luo, W. Identification of Common Skin Defects and Classification of Early Decayed Citrus Using Hyperspectral Imaging Technique. *Food Anal. Methods* **2021**, *14*, 1176–1193. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.