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Modelling and nondestructive quality prediction of Guanxi Honey Red Pomelo (*Citrus grandis* (L.) Osbeck) based on shape characteristics and bitterness

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RESEARCH ARTICLE

Abstract

Currently, it is difficult to distinguish the inner quality of pachycarpous fruits using nondestructive instruments, and trace nutrients and flavor compounds are rarely considered in fruit sorting. In this study, the external features and internal quality indices of an extensively farmed citrus fruit, the Guanxi honey red pomelo, were measured. The correlation between the inner and external quality was analyzed using Pearson correlation, canonical correlation, and grey correlation analyses. This research innovatively introduced bitter substances and revealed that the height-diameter ratio could serve as a predictor for ultra-size fruits, which partially reflects inner quality indices. Several grey formulas were developed to express these correlations and were fitted to a matrix, which demonstrated accuracies at all level 1 ($C < 0.35$, $P > 0.95$). Based on the matrix, fruit quality analysis of white and red pomelo showed high prediction accuracy in TSS and bitter substance indices ($R^2 = 0.6 – 0.8$) and indicated that mature and symmetrical pomelo (height-diameter ratio of 0.9 – 1.1) exhibit a similar quality pattern. This study achieved rapid quality assessment using easy measurable shape characteristics and explored the application of characteristic bitter substances in the quality evaluation model, providing theoretical references and potential application guidance for pachycarpous fruit sorting, as well as introducing a new idea to incorporating characteristic quality into modeling index.

Keywords: bitterness; canonical correlation analysis; grey correlation analysis; guanxi honey red pomelo; internal quality indices; shape characteristics

Introduction

Fruit sorting is a postharvest operation that typically categorizes fruit based on quality characteristics such as external features (shape, size, color) or internal quality indices (total soluble solids [TSS], firmness, acidity, maturity) (Han *et al.*, 2024; H. G. Wang *et al.*, 2023). The fruit industry is pivotal in the global food supply chain, contributing to the production, distribution, and consumption of millions of tons of fruit annually. Postharvest fruit quality testing and sorting are essential for enhancing the commercial value of fruit. Efficient and effective sorting aids in the optimal distribution and rational utilization of resources (e.g., food processing, natural product extraction, or direct sales), reduces unnecessary storage, prevents quality degradation, decreases waste in the supply chain, and minimizes labor and time expenditures (Desai *et al*., 2023; Gao *et al*., 2024; Tian *et al*., 2023; Wang *et al*., 2023).

A rapid and efficient sorting approach could be beneficial for fruit growers and processors by helping them determine the quality of their products and improve profitability (Bhargava & Bansal, 2021; Gao *et al*., 2024). Traditional fruit sorting relies on manual examination or weight measurement, which can lead to unpredictable inconsistencies and bias (Akter *et al*., 2024). Additionally, unique quality indicators specific to each fruit especially small active molecules are becoming important parameters for assessing overall food quality and market preferences. However, these molecules are often overlooked in sorting processes (Saikumar *et al*., 2023; Sasikumar *et al*., 2021; Tian *et al*., 2023). Currently, advanced nondestructive techniques such as near-infrared reflectance spectroscopy (NIRS), hyperspectral imaging (HSI), X-ray detection, and machine vision, when combined with appropriate accessories or stoichiometry software packages, can rapidly assess the quality and hierarchically classify fruit based on both internal and external quality indices (Chen *et al*., 2021; Jie *et al*., 2021; Yu & Yao, 2022). These techniques have been further extended to applications such as mixed fruit recognition (Nuruzzaman *et al*., 2021), fruit segmentation (Miranda *et al*., 2023), and quality detection (Cheng *et al*., 2022). In practical applications, machine vision typically determines physical characteristics and is often combined with other testing methods. X-ray detection offers advantages in imaging internal structural characteristics but can be potentially harmful and may not provide high accuracy for specific internal components. NIRS is an indirect analytical technique that depends on conventional chemical analysis methods, sometimes using small data sets that may not be representative and requiring a high degree of instrument stability. HSI, while effective at simultaneously collecting spectral and machine vision data for quality evaluation, is complicated to operate, has long sample identification times, and is mainly suited for static laboratory testing, limiting its application in online pipeline detection (Akter *et al*., 2024; Jie *et al*., 2021; Tian *et al*., 2023; Wang *et al*., 2024).

Overall, these methods require large-scale equipment and specialized professionals, making them unsuitable for on-site detection. They are costly, time-consuming, involve complex procedures, and necessitate the use of imaging. Researchers have explored the relationship between infrared spectra and quality indices (e.g., total soluble solids, color) to predict the quality of fresh fruit without causing deterioration (Nordey *et al*., 2017; Yuan *et al*., 2020). However, the infrared spectra alone are insufficient for inspecting pachycarpous fruit due to interference from thick rinds. Additionally, the need for a stable operating environment and high accuracy in mathematical models further limits their application in fruit sorting. Therefore, developing a comprehensive, nondestructive classification approach for pachycarpous fruit to enhance sorting efficiency and stability is of significant importance (Jie & Wei, 2018; Wang *et al*., 2023).

As one of the largest pachycarpous fruits in the Citrus family, pomelo is primarily classified through manual sorting or by measuring its sugar-acid ratio (Cheng *et al*., 2021). Phuangsombut *et al.* (2021) developed discriminant analysis and partial least squares regression models to assess the maturity and internal quality of red-fleshed pomelo by analyzing the relationship between resonant frequency and sugar-acid ratio. Masoudi *et al.* (2021) employed a Gaussian process regression model (GPRM) to screen citrus fruit, finding that the model based on the projected area was effective in sorting fruit by different volumes and masses. Han *et al.* (2024) combined external appearance images with internal X-ray images to determine pomelo volume and flesh thickness, using a grayscale and thickness fitting method (GTFM) to assess flesh content. These studies highlight crucial factors in evaluating the quality of pomelo fruits.

Small molecular compounds, such as the bitter substances naringin, limonin, and nomilin, have been identified as important factors in pomelo flavor and quality due to their contribution to an undesirable taste when present in high concentrations (Wei *et al*., 2021). Previous studies have indicated that the content of these bitter substances is often correlated with quality factors such as fruit shape, total soluble solids (TSS), sucrose content, and sugar-acid ratio (Zhong *et al*., 2021). However, sensory qualities like bitterness are challenging to detect using nondestructive testing equipment, leading to an incomplete assessment of fruit quality (Nagy *et al*., 2022; Tian *et al*., 2023). These correlations suggest the potential to develop formulas to predict internal quality indices based on shape characteristics. Although the relationship between shape characteristics and bitter substance content remains unclear—primarily due to a focus on their biosynthesis or accumulation (Wei *et al*., 2021)—it is noteworthy that smaller pomelo tend to have higher concentrations of bitter substances. This is likely because smaller fruits accumulate less sugar and experience greater environmental stress (Kim *et al*., 2021; Volschenk, 2021).

Based on representative measurable index data from agricultural product samples, a well-designed mathematical model can be established to evaluate and monitor product quality, thereby improving the quality and safety of agricultural products (Sanganamoni *et al*., 2024). An effective sorting model can also reduce subjective errors, improve classification efficiency, and avoid secondary damage to fruits. To enhance the accuracy of quality evaluation, researchers conduct correlation studies of fruit characteristic information and use multi-information fusion to improve precision, facilitating rapid evaluation of easily measurable indicators. Correlation analysis methods, such as Pearson correlation, canonical correlation, and grey correlation analysis, can address bivariate correlations, intergroup variable correlations, and correlations among phenomena with uncertain internal information (Deng, 1982; Sasikumar *et al*., 2021). However, detailed studies on these methods for evaluating pomelo quality are still lacking. Therefore, understanding the relationships between shape characteristics and internal quality indices of pomelo, particularly bitter substances, and applying appropriate correlation analysis methods may lead to the development of fast, accurate, and economical sorting approaches.

In this study, the shape characteristics (mass, volume, H-D ratio) and internal quality indices (TSS, naringin, limonin, and nomilin content) of Guanxi honey red pomelos were assessed using Pearson correlation analysis, canonical correlation analysis (CCA), and grey correlation analysis (GCA). Mathematical analysis was used to correlate the internal and external quality indices. The study considered the content of bitter substances, characteristic of citrus fruits, to provide a more comprehensive quality analysis. By using external indicators to represent internal quality, we aim to develop a rapid and easily measurable quality evaluation model, offering a new reference for sorting fruits with thick rinds.

Materials and Methods

Material and reagents

Guanxi honey red pomelos were harvested on October 25, 2020, from Xiaoxi Town in Pinghe County (altitude range of 100-300 meters). A total of 440 mature pomelos were collected, transported to the laboratory within 2 hours, and stored at 4 ± 1°C with 90 ± 5% relative humidity until analysis.

Standard naringin, limonin, and nomilin (purity > 98%) were purchased from Yuanye Bio-Technology Co., Ltd. (Shanghai, China). HPLC-grade acetonitrile (purity > 99.99%) was obtained from Sigma-Aldrich (St. Louis, MO). Ultra-pure water was prepared using a Milli-Q water purification system (Millipore, Bedford, MA, USA).

Fruit shape characteristics

The shape characteristics of Guanxi honey red pomelos, including mass, volume, and H-D ratio, were measured as shown in Figure 1.

Fruit inner quality indices

The total soluble solids (TSS) and pH value of the pulp juice were measured using a digital refractometer (WYT-4, Quanzhou Optical Co., Ltd., China) and a pH meter (PB-10, Sartorius Co., Ltd., Germany), respectively.

The contents of bitter substances (naringin, limonin, and nomilin) were quantified using a Thermo Ultimate 3000 UPLC with Chromeleon 7.0 software. The bitter compounds in the pulp juice were enriched using a C18 solid phase extraction column. For this process, a 1 mL sample volume was used, and the enrichment solvent consisted of 60% acetonitrile and acetonitrile. The procedure was as follows: the column was first activated with 4 mL of methanol, then equilibrated with 4 mL of ultra-pure water. After injecting 1 mL of the sample, the column was washed with 2 mL of ultra-pure water. The column was then eluted with 2 mL of the enrichment solution (1:1 acetonitrile and 60% acetonitrile), and the final extraction solution was brought to 2 mL with 60% acetonitrile. A 10 μL aliquot of the enriched sample was loaded onto a Shim-pack GIS C18 column (4.6 mm × 250 mm, 5 μm). The elution was performed with a mobile phase consisting of 45% acetonitrile and 55% ultra-pure water at a flow rate of 1 mL/min for 25 minutes, with the column temperature set at 30°C.

Canonical correlation analysis

CCA was employed to examine the relationships between two sets of indices using the PROC CANCORR procedure in SPSSAU 2021 (https://www.spssau.com).

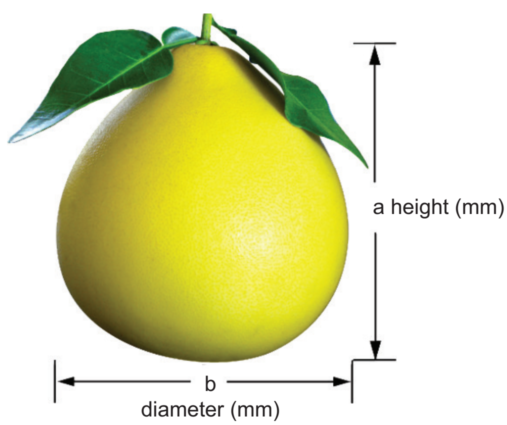

Figure 1. The dimensions of Guanxi honey red pomelo. The height (a) and diameter (b) of each pomelo were measured using a ruler with 1 mm accuracy to calculate the H-D ratio. The mass of each pomelo was recorded using a digital electronic scale with ± 1.0 g accuracy. The volume of each pomelo was determined using the water displacement method.

The canonical variates for the two sets U^T and V^T, are defined in equation (1) and (2).

$$U^T = \alpha_1 X_1 + \alpha_2 X_2 + \cdots + \alpha_p X_p \quad (1)$$

$$V^T = \beta^1 Y_1 + \beta_2 Y_2 + \cdots + \beta_p Y_p$$

In the equations, shape characteristics were included in the first variable set (X_i), while the second set of variables (Y_i) consisted of inner quality indices. For the vectors X and Y, the population means and (co)variances were Cov (U^T, V^T). Since U^T and V^T had an expectation of zero, their variances were shown as Var (U^T) and Var (V^T). The correlation coefficient (ρ (U, V)) between U^T and V^T was described as follows:

$$\rho(U,V) = \frac{Cov(U^T, V^T)}{\left[Var(U^T) \times Var(V^T)\right]^{1/2}} \quad (3)$$

Grey correlation analysis

The inner quality index data were used as reference sequences and served as the dependent variable in the formula. The shape characteristics selected from CCA constituted the comparison sequences and were included in the formula as the independent variable. After the collected data were normalized, the grey incidence coefficients were calculated based on the absolute difference and weight between the reference and comparison sequences. The grey incidence coefficients (K) were calculated using equation (4) and then averaged in equation (5) to obtain the degree of grey coefficient (r):

$$\zeta_i(k) = \frac{min_i min_k \left|x_0(k) - x_i(k)\right| + \rho \; max_i max_k \left|x_0(k) - x_i(k)\right|}{\left|x_0(k) - x_i(k)\right| + \rho \; max_i max_k \left|x_0(k) - x_i(k)\right|} \quad (4)$$

$$r = \frac{\sum_{i=1}^{n} k}{n} \quad (5)$$

The posterior difference ratio (C) was a criterion to evaluate the accuracy of the prediction results. Taking x as the measured data index and X as the predicted data index, the calculation formula of C was:

$$C = \frac{\sum_{i=0}^{n} x^{(0)}(k) - \frac{\sum_{i=0}^{n} x^{(0)}(k)}{n}}{\sum_{i=0}^{n} X^{(0)}(k) - \frac{\sum_{i=0}^{n} X^{(0)}(k)}{n}} \quad (6)$$

The small error probability (P) was another criterion to assess the reliability of the grey formula. A large P value implied high accuracy of the formula. The P value calculated should satisfy equation (7):

$$P = P\{\left|X(k) - \overline{X}\right| > 0.95\} \quad (7)$$

Calculation of buffer operator

$X = (x(1), x(2), \ldots, x(n))$ was a data sequence of measured inner quality indices, and $Z = (z(1), z(2), \ldots, z(n))$ was a data sequence of preliminarily predicted inner quality indices, given by $Z = ai_1 + bi_2 + ci_3$. The conversion value between the two sets used a strengthening buffer operator *(t),* and the compute of buffer operators was consistent with the formula (Wu *et al.*, 2018):

$$t = \frac{\sum_{i=1}^{n} \frac{z_i}{x_i}}{n} \quad (8)$$

Expression of prediction formula

The grey formula for predicting the inner quality index of Guanxi honey red pomelo is expressed as follows:

$$K = t \times (ai_1 + bi_2 + ci_3) \quad (9)$$

where K represents the inner quality indices; a, b, and c are the degree of grey coefficients between the inner quality indices and shape characteristics; i_1, i_2, i_3 represent the shape characteristics that are closely related to the inner quality index; t is the buffer operator.

Matrix format

According to the standardized data in the GCA process, the sequence operators for each inner quality index value were obtained based on grey theory and averaged to create a revering operator to predict the system's characteristic sequence. These revering operators were then used to supplement the grey formula (Liu *et al.*, 2009). Each inner quality index in GCA was predicted using three shape characteristics: mass, volume, and H-D Ratio. Linear expressions were combined into a matrix, which was referred to as SeqGC after excluding the unqualified grey formula.

Matrix equation is expressed as:

$$M_{ik} = \begin{bmatrix} t_1 \\ t_2 \\ \cdots \\ t_n \end{bmatrix} \begin{bmatrix} a_1 & b_1 & c_1 \\ a_2 & b_2 & c_2 \\ \cdots & \cdots & \cdots \\ a_n & b_n & c_n \end{bmatrix} \begin{bmatrix} i_1 \\ i_2 \\ i_3 \end{bmatrix} = \begin{bmatrix} K_1 \\ K_2 \\ \cdots \\ K_n \end{bmatrix} \quad (10)$$

Statistical analysis

CCA was conducted using SPSSAU 2021 (Version 21.0, Online Application Software, Qingsi Technology Co., Ltd., Beijing, China), with the Shapiro-Wilk test used to assess normality. GCA was performed using Excel 2016 (Microsoft Corp, Redmond, WA, USA), following the data test equations (5–6). Pearson correlation analysis ($P < 0.05$) was completed using Origin 2021 (Origin Lab, Northampton, MA, USA). All experiments were repeated three times. Validation experiments for the nondestructive prediction of bitterness content were carried out by randomly sampling 50 fresh Guanxi honey red pomelos.

Results and Discussion

Determination of shape characteristics and inner quality indices

The shape characteristics data of Guanxi honey red pomelo are presented in Table 1. The mean values for mass, volume, and H-D Ratio were 1.65 ± 0.30 kg, 2.27 ± 0.46 dm^3, and 1.03 ± 0.07, respectively. Notably, the mass and volume of Guanxi honey red pomelo are approximately 10%-30% larger than those of other varieties (Paudyal and Haq, 2008; Yang *et al.*, 2020). For the inner quality indices, the mean values for TSS and pH were 10.62 ± 1.44% and 3.92 ± 0.42, respectively, indicating that Guanxi honey red pomelo is generally sweeter (approximately 10% higher in TSS) compared to other pomelos (Nayak *et al.*, 2020; Rehman *et al.*, 2020; Yin *et al.*, 2023). The content of bitter substances, including naringin, limonin, and nomilin, were 12.10 ± 3.70 mg kg^{-1}, 12.24 ± 3.46 mg kg^{-1}, and 4.69 ± 1.74 mg kg^{-1}, respectively, averaging roughly 30%-50% lower compared to other varieties (F. S. Wang *et al.*, 2016). Overall, the Guanxi honey red pomelo is noted for its attractive flavor and satisfying shape, contributing to its popularity worldwide.

Correlation analysis between shape characteristics and inner quality indices

In verifying the canonical correlation model, canonical correlation represented the degree of relevance between two groups, while canonical variates reflected the optimal linear combinations of dependent and independent variables. As shown in Figure 2, the relationship between shape characteristics and inner quality indices was analyzed using CCA. This analysis revealed that TSS, naringin, and limonoids were negatively correlated with both volume and mass, with the correlation being stronger with volume than with mass. Model 1, which had the highest canonical correlation value, was the focus of interpretation in this study. Standardized canonical coefficients, or canonical weights, for the U^T and V^T variables represented their relative contributions to the related variates. The cross-loading denotes the simple correlation coefficient between a specific variable and each variable within an alternative set of variables, and high cross-loading corresponded to the high canonical loading. The canonical variate for inner flavor factors V^T had highly positive coefficients from the H-D Ratio, while the coefficients of mass and volume in the variate V^T were negative. The estimated canonical correlations between the pairs of canonical variates were found to be 0.995, with their probabilities (P-values) of significance from the likelihood ratio test being less than 0.000 (Table 2). This indicates a significant difference between the two sets, suggesting that Model 1 was suitable for verifying the correlation between inner quality and shape. Sasikumar *et al.* (2021) established a model for blood orange (*Haemetocarpus validus*) by correlating flavor

Table 1. The mean values, standard deviation (SD) and coefficient of variation (CV) of morphological and biochemical characteristics measured in Guanxi red honey pomelo.

	Maximum	Minimum	Mean	SD	CV (%)
Mass (kg)	2.48	0.96	1.65	0.30	0.18
Volume (dm^3)	3.80	1.10	2.27	0.46	0.20
Height (mm)	220	130	174	1.65	0.09
Diameter (mm)	210	135	169	1.31	0.08
H-D Ratio	1.26	0.79	1.03	0.07	0.07
TSS (%)	14.00	8.00	10.62	1.44	0.13
pH	4.21	3.71	3.92	0.42	0.09
Naringin in pulp* (mg kg^{-1})	21.96	4.01	12.10	3.70	0.31
Limonin in pulp* (mg kg^{-1})	19.30	4.67	12.24	3.46	0.28
Nomilin in pulp* (mg kg^{-1})	7.40	1.15	4.69	1.74	0.37

*fresh weight.

with physical properties, finding that ellipsoidal blood oranges had higher flavonoid content, which contributed to a bitter flavor. This verified that the shape characteristics of citrus fruits are closely related to inner quality indices. Combined with the loading in CCA, the shape characteristics of mass, volume, and H-D Ratio were found to be closely related to the inner quality indices of Guanxi honey red pomelo, providing a basis for subsequent analysis.

Relevance between shape characteristics and TSS

In this study, the relevance of TSS and shape characteristics was investigated using Pearson correlation analysis (Figure 3A). Mass, volume, and H-D Ratio showed a statistically significant correlation ($P < 0.05$) with TSS, with Pearson correlation coefficients (*Rs*) of 0.98, 0.98, and 0.94, respectively. As an important index for evaluating flavor, TSS primarily refers to soluble sugar content, which contributes to a pleasant taste (Beckles, 2012; Sun *et al*., 2020). Khodabakhshian *et al*. (2021) measured shape characteristics in pomegranates and found that the sugar content increased with the weight of the ripening pomegranates. Similarly, our data confirm that TSS is strongly correlated with shape characteristics.

Moreover, the effect of shape characteristics (i_0) was measured in the following order based on the H-D Ratio (i_3) > mass (i_1) > volume (i_2) based on the GCA, indicating that the H-D Ratio (i_3) was the most relevant factor to TSS (K_{TSS}). A significant correlation was considered if the *r* value between the reference and comparison sequence was above 0.6 (Tsai and Hsu, 2010). The formula was deemed qualified when the *C* value was less than 0.35 and the *P* value was greater than 0.95, predicting the highest accuracy at level 1. Furthermore, the degree of grey coefficient (*r*) between the H-D Ratio and TSS was also the highest (0.71). This might be due to the expansion of juice sac cells caused by sugar accumulation, which led to abdomen swelling, and a decrease in the H-D Ratio during the ripening period. The obtained strengthening buffer operator was 3.17, which adjusted the difference between predicted values and measured values to strengthen the predicted trend of shape characteristics relative to sugar content. The formula was deduced to be $K_{TSS} = 3.17 \times (0.69i_1 + 0.64i_2 + 0.71i_3)$. The posterior difference ratio $C = 0.07$ and $P = 1$ indicated that the prediction accuracy was at level 1 ($C < 0.35$, $P > 0.95$). This formula could satisfy the prediction of TSS based on shape characteristics in Guanxi honey red pomelo.

Relevance between shape characteristics and naringin

The relevance of shape characteristics and naringin content of Guanxi honey red pomelo was also investigated and shown in Figure 3B. Mass, volume, and H-D Ratio

Table 2. Canonical correlation between U^T and V^T of variables, eigenvalues, and their probabilities.

	Canonical correlation	Eigen values	*F* value	Degree of freedom	*P* value
1	0.995	97.423	22.622	65	<0.001
2	0.634	0.667	3.513	65	0.118
3	0.531	0.394	2.051	65	0.412

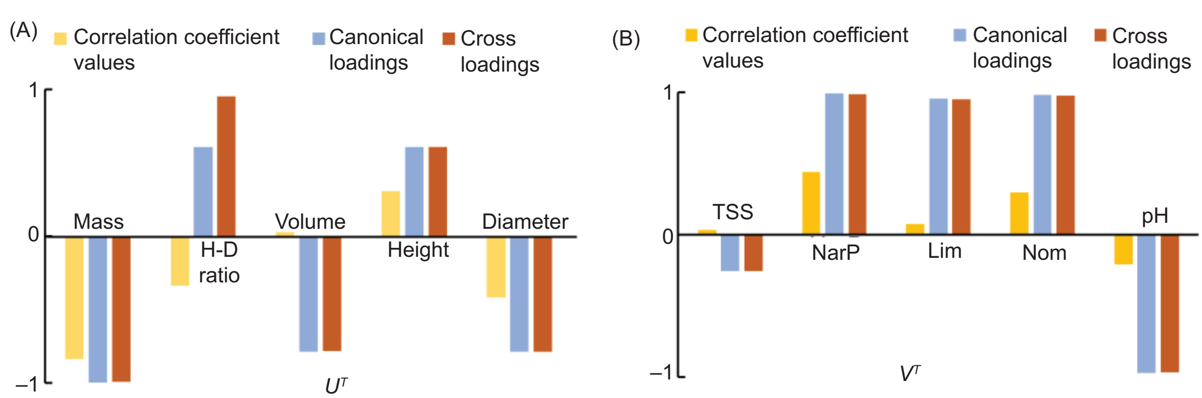

Figure 2. CCA between shape characteristics U^T and inner quality indices V^T. (A) Correlation coefficient values, canonical loadings and cross loadings for shape characteristics U^T in model 1. (B) Correlation coefficient values, canonical loadings and cross loadings for bitter substance contents V^T in model 1.

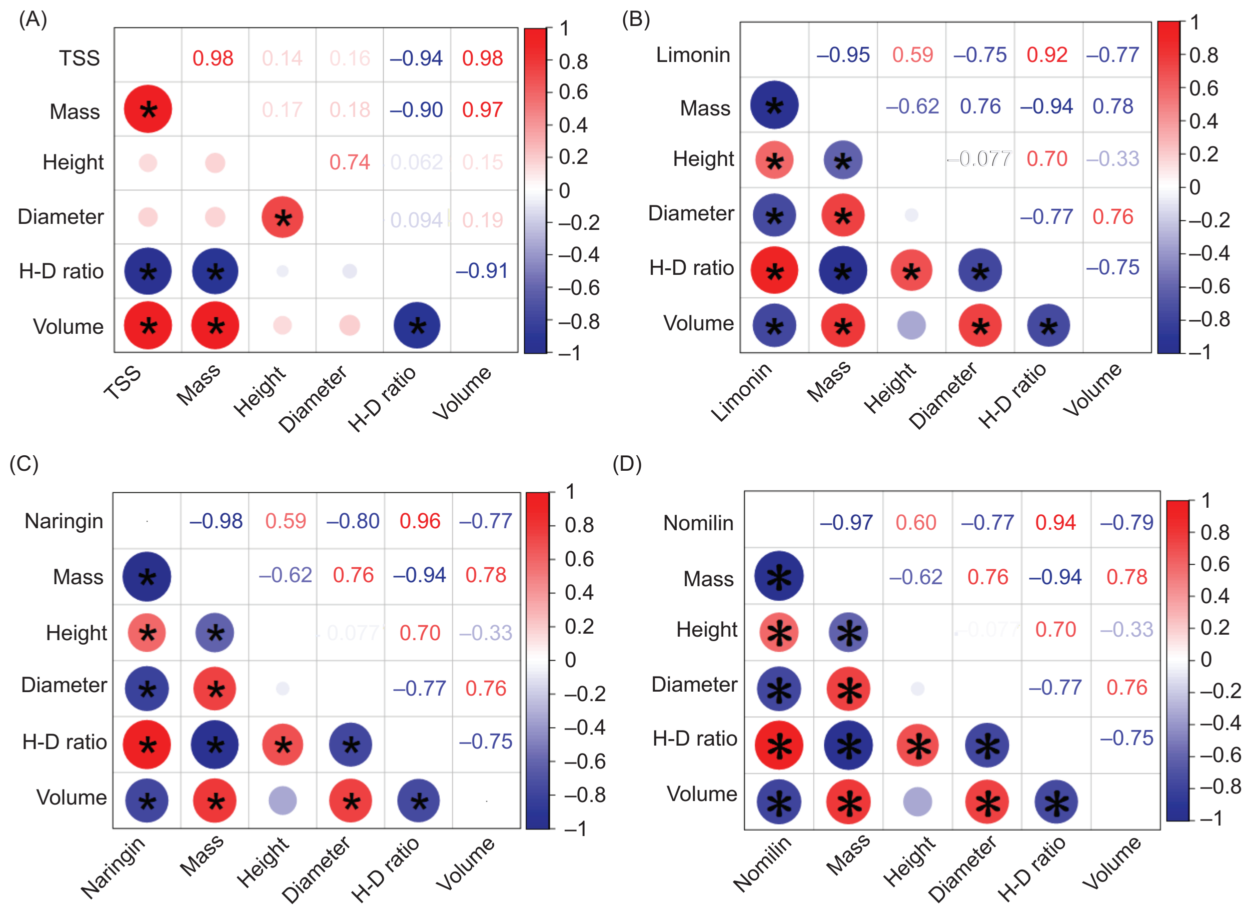

Figure 3. Pearson correlation analysis of inner quality indices and measured shape properties. (A) TSS and shape characteristics. (B) Naringin content and shape characteristics. (C) Limonin content and shape characteristics. (D) Nomilin content and shape characteristics. Note: The correlation values range from –1.00 (blue) to 1.00 (red); *FDR-adjusted *P*-value ($P < 0.05$).

appeared to have significant correlations ($P < 0.05$) with naringin content, and the Pearson correlation coefficients (*Rs*) were - 0.98, - 0.77, and 0.96, respectively, suggesting naringin content was highly correlated with shape characteristics. As the mass and volume increase, both the H-D Ratio and naringin content decrease. Naringin, an immediate bitter substance, constitutes a significant proportion (30%) of the polyphenols in Guanxi honey red pomelo, directly impacting its bitterness (Nhi *et al.*, 2020; Pawelczyk *et al.*, 2023). Previous studies have shown that polyphenols, including naringin, are less abundant in larger Yuzu (*Citrus junos* Sieb.) (Moon *et al.*, 2015), which supports our findings.

Based on the GCA, the effect of shape characteristics (i_0) was ranked in the following order: volume (i_2) > mass (i_1) > H-D Ratio (i_3), indicating that the naringin content (K_{Nar}) was most closely related to volume (i_2). The calculated strengthening buffer operator was 3.42 by adjustment. The formulate was deduced to be $K_{Nar} = 3.42 \times (0.72i_1 + 0.75i_2 + 0.70i_3)$. The lower the posterior difference ratio, the more credible the prediction results (Wang *et al.*, 2020). With a posterior difference ratio $C = 0.14$ and $P = 1$, the prediction accuracy was at level 1, indicating successful fitting in forecasting the naringin content from shape characteristics through mathematical analysis.

Relevance between shape characteristics and limonoids

Limonoids are ubiquitous delayed bitter substances that can negatively affect the pulp flavor of *Citrus* families and cause pomelo to become bitter during storage (Dea *et al.*, 2013; Wang *et al.*, 2018). As shown in Figure 3C and 3D, mass (i_1), volume (i_2), and H-D Ratio (i_3) were all significantly affected by limonin and nomilin content ($P < 0.05$). Limonoids decreased during the ripening stage and then increased, attaining its maximum accumulation at the dehydration stage. This variation was related to the granulation degree of the pomelo, which might affect the expansion of the fruit, as reflected in the variations in mass, volume, and height-diameter ratio (Wang *et al.*, 2017).

In the GCA, buffer operators were also calculated, and the formula for limonin content (K_{Lim}) is expressed as $K_{\text{Lim}} = 3.60 \times (0.69\, i_1 + 0.67 i_2 + 0.71 i_3)$ ($C = 0.14$, $P = 1$). The formula for nomilin content (K_{Nom}) is given by $K_{\text{Nom}} = 1.42 \times (0.64 i_1 + 0.64 i_2 + 0.68 i_3)$ ($C = 0.26$, $P = 1$). The accuracy of both formulas was level 1. Thus, we included the delayed bitter substances as inner quality indices in the evaluation system to reasonable classify Guanxi honey red pomelo based on mathematical statistics.

Matrix development and Predictive model validation

In our study, the H-D Ratio was introduced as a shape characteristic, and bitter substances were creatively incorporated into the evaluation criterion. This approach led to the development of a comprehensive evaluation matrix for sorting Guanxi honey red pomelo, based on both CCA and GCA.

$$M_{ik} = \begin{bmatrix} 3.17 \\ 3.42 \\ 3.60 \\ 1.42 \end{bmatrix} \begin{bmatrix} 0.69 & 0.64 & 0.71 \\ 0.72 & 0.75 & 0.70 \\ 0.69 & 0.67 & 0.71 \\ 0.64 & 0.64 & 0.68 \end{bmatrix} \begin{bmatrix} i_1 \\ i_2 \\ i_3 \end{bmatrix} = \begin{bmatrix} K_{TSS} \\ K_{Nar} \\ K_{Lim} \\ K_{Nom} \end{bmatrix} \quad (11)$$

Pomelo has traditionally been evaluated based on its appearance, while inner factors such as sugar content and bitter substances, which affect taste and flavor, present practical challenges for quality assessment (Gao *et al.*, 2024; Sun *et al.*, 2020). Previous models typically relied on complex chemical detections, including TSS or sugar-acid ratio (Salihah *et al.*, 2015; Xu *et al.*, 2021), and generally used simple correlation coefficient analysis and principal component analysis to examine the relationship between shape characteristics and individual inner quality indices (Rungpichayapichet *et al.*, 2017). Consequently, these established models are limited in their ability to evaluate overall fruit quality.

Our matrix differs from other fruit quality evaluation models in that it utilizes multiple correlation analyses rather than relying solely on Pearson correlation analysis for the entire model. The model we have developed offers a new approach to preliminarily predicting the inner quality of pomelo using a simple nondestructive method, as opposed to complex component detection or measurements requiring precision equipment (Ma *et al.*, 2023; Shicheng *et al.*, 2021).

Meanwhile, the relevant internal and external quality indicators of Guanxi honey red pomelo and white pomelo (n=30 for each) were determined for the same period. Fifteen samples from each type were chosen randomly to obtain the prediction values for relevant intrinsic indicators, verifying the accuracy and applicability of the prediction model. The pomelos were numbered R1-R15 (R represents red-fleshed) and W1-W15 (W represents white-fleshed). Table 3 presents the relative errors between the actual values and the predicted scores, and Figure 4 displays the fitted curves. According to the measured data, the validation model for shape characteristics and TSS had determination coefficients of 0.7982 and 0.7571 (Figure 4A and 4C), demonstrating that the model is broadly applicable to both red and white pomelos. A comparison of bitter substances was also undertaken, with limonin serving as the representative compound (Figure 4B and 4D). The observed differences in the variety and characteristics of bitter substances may account for the less accurate prediction of bitter substances for white pomelo based on the red pomelo data. These results indicate that the predictive model can accurately forecast intrinsic qualities of pomelo, including TSS and bitter substances, by analyzing appearance quality characteristics. Additionally, the findings validate that mature and symmetrical pomelo fruits (with an H-D Ratio of about 0.9 – 1.1, weight of 1.2 – 2.2 kg, and volume of 1.8 – 2.8 dm^3) exhibit a consistent quality pattern over time.

Existing pomelo sorting methods primarily focus on shape characteristics such as weight and volume or depend on sugar and acid content (Salihah *et al.*, 2015; Xu *et al.*, 2023; Xu *et al.*, 2021). However, our study integrates both shape characteristics and internal quality to establish a more holistic evaluation matrix for pomelo. By introducing bitter substances as an additional sorting index alongside the H-D ratio, we highlight the importance of including trace substances in the sorting process. This approach allows for a more comprehensive evaluation of pomelo quality.

Conclusions

In summary, we established a matrix that integrates shape characteristics and internal quality indices using three correlation analysis methods. Bitter substances were incorporated into the fruit sorting system to assess fruit quality, and the H-D ratio was identified as a predictor of inner quality indices. Mature and symmetrical pomelos (with an H-D Ratio of about 0.9 – 1.1) exhibit a consistent quality pattern over time. The matrix can predict inner quality indices, particularly the content of bitter substances, from easily measured shape characteristics without destruction, based on four grey formulas. All grey correlation degrees were above 0.6, and the prediction accuracies were all rated as level 1, demonstrating the reliability of the formulas. Our work achieves rapid and cost-effective quality evaluation, introduces characteristic bitter substance indicators into the model, and provides a theoretical reference for pomelo sorting and

Table 3. Analysis of the prediction results of quality evaluation model.

Sample number	Prediction value		Actual value		Relative errors (%)	
	K_{TSS}	K_{Lim}	TSS (%)	Limonin (mg kg^{-1})	TSS	Limonin
R1	8.79	11.74	8.50	12.69	3.29%	–8.04%
R2	10.43	12.21	10.00	12.83	4.09%	–5.13%
R3	10.72	12.56	11.00	11.26	–2.59%	10.39%
R4	10.49	12.28	10.00	12.51	4.63%	–1.88%
R5	10.76	12.61	11.00	11.25	–2.26%	10.78%
R6	12.37	15.03	13.00	14.93	–5.10%	0.68%
R7	9.86	14.39	10.00	13.77	–1.42%	4.28%
R8	10.22	11.97	10.00	12.77	2.13%	–6.66%
R9	9.98	11.67	10.00	12.63	–0.22%	–8.27%
R10	9.63	13.62	9.50	12.83	1.35%	–8.27%
R11	10.03	13.89	10.00	14.40	0.32%	–3.64%
R12	9.80	10.37	9.00	9.31	8.17%	10.24%
R13	8.75	10.97	8.00	9.22	8.53%	15.95%
R14	9.91	11.58	11.00	11.09	–11.01%	4.24%
R15	10.20	11.90	11.50	9.87	–12.73%	17.05%
W1	10.80	14.51	10.50	16.42	2.76%	–13.16%
W2	10.94	12.81	10.10	17.94	7.66%	–40.03%
W3	9.92	12.79	10.10	12.41	–1.78%	2.96%
W4	9.79	11.19	10.00	14.26	–2.13%	–27.47%
W5	10.15	11.87	10.50	8.64	–3.48%	27.19%
W6	10.22	14.29	10.00	10.23	2.18%	28.36%
W7	11.13	11.36	11.00	8.71	1.16%	23.36%
W8	10.40	12.16	10.20	15.54	1.88%	–27.72%
W9	9.90	19.75	10.00	18.90	–0.98%	4.31%
W10	10.65	11.36	11.00	8.71	–3.28%	23.36%
W11	11.97	14.36	11.80	17.57	1.44%	–22.34%
W12	9.68	16.24	9.90	18.32	–2.24%	–12.80%
W13	10.37	16.24	9.90	18.32	4.49%	–12.80%
W14	11.25	14.03	11.00	8.06	2.20%	42.57%
W15	9.85	13.81	9.80	18.94	0.54%	–37.13%

the improvement of comprehensive sorting standards. Additionally, it offers insights and implications for the fine sorting of other fruits, such as persimmons with astringent tannins, which could have potential applications in the redesign and advancement of traditional fruit processing equipment.

Author Contributions

Conceptualization, Y.Y., H.N., and F.H.; methodology, Y.Y., H.N., and F.H.; validation, J.T.; investigation, H.P., Y.X., and L.C.; resources, H.P., Y.X., L.C., and F.C.; data curation, H.P. and Y.X.; writing—original draft preparation, H.P. and Y.X.; writing—review and editing, Y.Y., H.N., J.T., and F.H.; supervision, Y.Y., H.N., and F.H.; project administration, L.L., Y.H., and Y.W.; funding acquisition, L.L., Y.H., H.N., and F.H. All authors have read and agreed to the published version of the manuscript.

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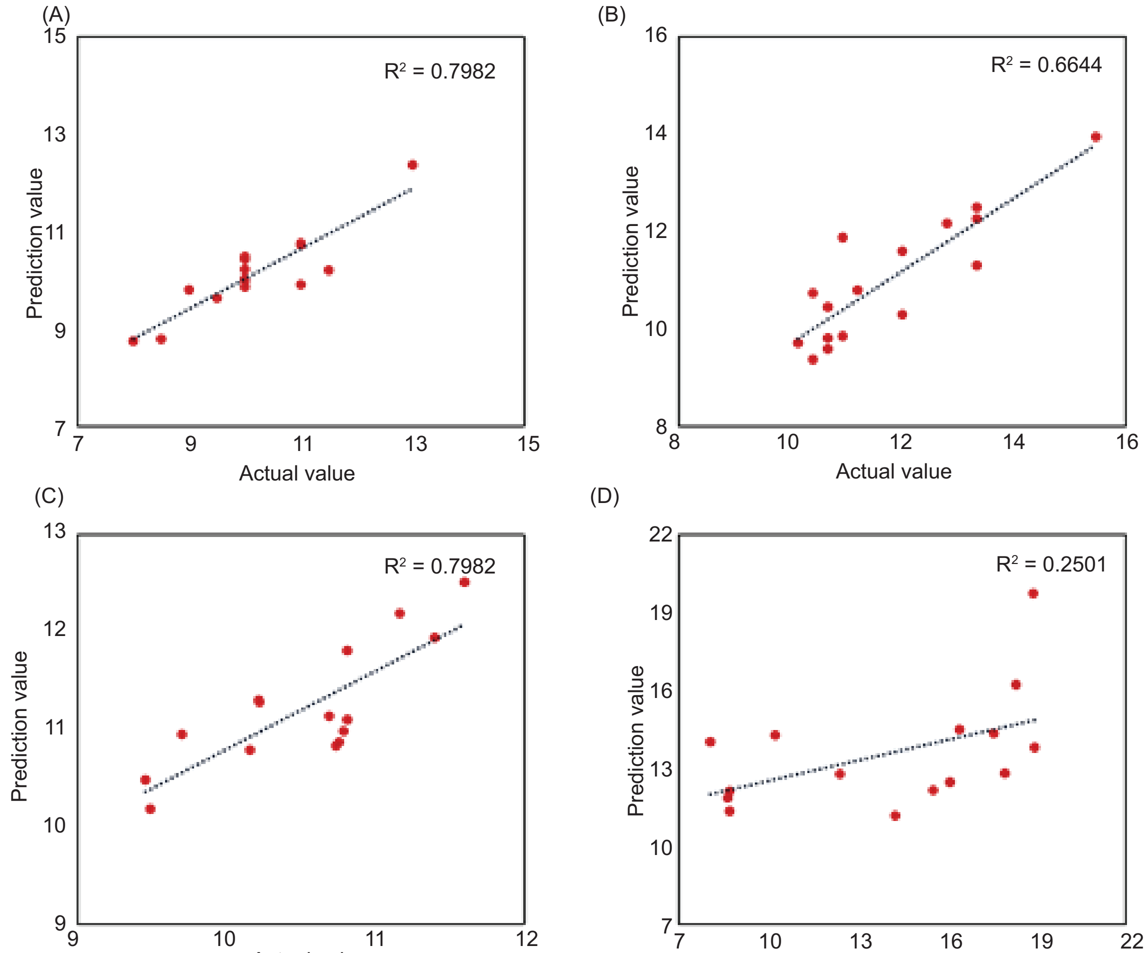

Figure 4. Quality-association validation model for Guanxi honey pomelo's shape characteristics and internal quality indices. (A) Validation model of shape characteristics and TSS for Guanxi honey red pomelo. (B) Validation model of shape characteristics and limonin for Guanxi honey red pomelo. (C) Validation model of shape characteristics and TSS for Guanxi honey white pomelo. (D) Validation model of shape characteristics and limonin for Guanxi honey white pomelo.

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Conflicts of Interest

The authors declare no conflict of interest.

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