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Non-Destructive Sugar Assessment in Cashew Apples Using Reflectance Spectra

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Abstract

Sugar content in cashew apples is a critical indicator of fruit quality and maturity, directly influencing processing and market value. This study explores the use of spectral indices derived from reflectance data for the non-destructive prediction of sugar content (˚Brix) in cashew apples. Two multivariate modeling approaches were evaluated: Partial Least Squares Regression (PLSR) and Random Forest (RF). The PLSR model, optimized with 8 components, achieved high predictive performance, with $R^2 = 0.9313$, RMSE = 0.4720, and MAE = 0.3526, demonstrating excellent linear modeling capability. The RF model, assessed via 10-fold cross-validation, provided robust performance with $R^2 = 0.8819$, RMSE = 0.6189, and MAE = 0.4653, effectively capturing potential non-linear relationships. These results highlight the effectiveness of reflectance-based spectral indices combined with multivariate regression as a reliable, rapid, and non-invasive tool for assessing sugar content in cashew apples. This methodology supports precision agriculture by enabling accurate *in-situ* quality evaluation of fruits.

Keywords

Cashew Apple, Sugar Content Prediction, Reflectance Spectroscopy, Spectral Indices, Non-Destructive Measurement

1. Introduction

The cashew apple (*Anacardium occidentale* L.), a pseudo-fruit of significant economic and nutritional value, plays an increasingly important role in the agro-industrial sector of tropical regions, particularly in West Africa. Rich in reducing sugars, vitamin C, amino acids, and minerals, the cashew apple is increasingly exploited for juice production and other high-value food derivatives [1] [2]. The soluble sugar content, expressed in degrees Brix (˚Brix), is a primary determinant of fruit sweetness, maturity, and consumer acceptance, and thus directly impacts processing efficiency and market competitiveness. Accurate evaluation of ˚Brix is therefore essential for optimizing harvest scheduling, improving postharvest management, and supporting the development of quality-based marketing strategies [3] [4].

Conventional ˚Brix measurement methods, based on juice extraction and refractometry, are destructive, labor-intensive, and unsuitable for large-scale or in-field applications [5] [6]. In contrast, optical spectroscopy and remote sensing have emerged as powerful, non-invasive alternatives for fruit quality assessment. By analyzing reflectance in the visible and near-infrared (VNIR) ranges (400 - 1000 nm), it is possible to infer the biochemical and structural characteristics of plant tissues through spectral indices [7]-[9]. These indices capture variations in pigment concentration, cellular structure, and physiological status, all of which are influenced by fruit maturity and sugar accumulation [10].

Among the wide range of vegetation indices developed for plant monitoring, several indices, including the Simple Ratio (SR), the Normalized Difference Index ($NDI_{750-700}$), the Modified Normalized Difference 705 (mND705), NDVI705, the Modified Chlorophyll Absorption in Reflectance Index (MCARI), the Photochemical Reflectance Index (PRI), the Carotenoid Reflectance Index (CRI1), the Anthocyanin Reflectance Index (ARI1), and the Normalized Pigment Chlorophyll Index (NPCI), have demonstrated significant potential for the non-destructive assessment of internal fruit composition. These indices are sensitive to variations in pigment content, physiological status, and tissue structure, which are closely associated with fruit maturation processes and soluble sugar accumulation, thereby enabling the indirect prediction of sugar content [11]-[15]. For example, multispectral imaging and deep learning have achieved $R^2 > 0.9$ for sugar prediction in grapes [16], while VNIR spectroscopy has proven effective in estimating total soluble solids (TSS) in berries [17]. Similarly, remote reflectance data combined with neural networks have been successfully applied to evaluate sugar, acidity, and vitamin C content in cashew apples [18].

In this context, spectral reflectance-based indices offer a promising foundation for developing quantitative models of cashew apple quality. The integration of these indices with multivariate regression algorithms, such as Partial Least Squares Regression (PLSR) and Random Forest (RF), provides complementary advantages: PLSR efficiently captures linear relationships between spectral variables and ˚Brix values, while RF models can handle complex non-linear interactions and improve prediction robustness [19] [20]. The synergy of these techniques thus enables accurate, rapid, and non-destructive estimation of sugar content directly in field conditions, supporting decision-making in precision agriculture.

The present study aims to evaluate the performance of reflectance-derived spectral indices for non-destructive sugar prediction in cashew apples, using PLSR and RF as comparative modeling approaches. Specifically, it investigates the predictive relevance of selected spectral indices and identifies those most strongly correlated with ˚Brix. This methodology contributes to sustainable fruit quality monitoring by providing a practical, scalable, and reliable tool for in situ maturity assessment and value chain optimization in the cashew industry.

2. Matériels et Méthodes

2.1. Study Area and Sample Collection

The study focused on cashew apples (*Anacardium occidentale* L.) collected at various maturity stages from a precisely georeferenced plantation (6˚52'14.6"N, 5˚12'14.2"W). One hundred cashew trees were selected for the experiment. Over a period of ten consecutive days, ten samples were collected daily to represent a wide range of color variations and sugar contents, ensuring a representative dataset of the fruits studied.

Each cashew apple was carefully washed, dried, and labeled with a unique identification code. Spectral measurements were taken from intact surface areas, free from spots or injuries, to minimize optical or biological biases that could affect reflectance values.

2.2. Acquisition of Spectral Data

Spectral measurements were conducted using a USB4000 FL spectrometer (Ocean Optics) integrated into an optical system comprising two instruments: a reflecting telescope coupled to the spectrometer and a refracting telescope equipped with a CCD camera. Both instruments were directed toward the fruit with a shared field of view. The entire setup was controlled by a laptop, which managed the data acquisition process.

Reflectance spectra were recorded in the 400 - 800 nm range, corresponding to the visible spectrum. For each fruit, multiple measurement points were acquired and averaged to obtain a representative spectrum and minimize local variations.

$$Reflectance = \frac{R_S - R_D}{R_B - R_D} \tag{1}$$

R_S: Reflectance spectrum of the sample;

R_B: Reflectance spectrum of the white reference standard, used to normalize the reflectance values;

R_D: Reflectance spectrum of the dark background.

The spectra were then normalized to correct for illumination variations, thereby ensuring comparability between measurements (**Figure 1**).

The reflectance spectra of unripe, ripe, and overripe fruits exhibit similar overall spectral shapes across the visible to near-infrared range (400 - 800 nm), with noticeable differences in reflectance intensity depending on the maturity stage. In the visible region (400 - 550 nm), all spectra show relatively low reflectance, which can be attributed to strong absorption by pigments such as chlorophyll. As the wavelength increases, a marked rise in reflectance is observed between 550 and

650 nm, corresponding to changes in pigment composition during fruit maturation.

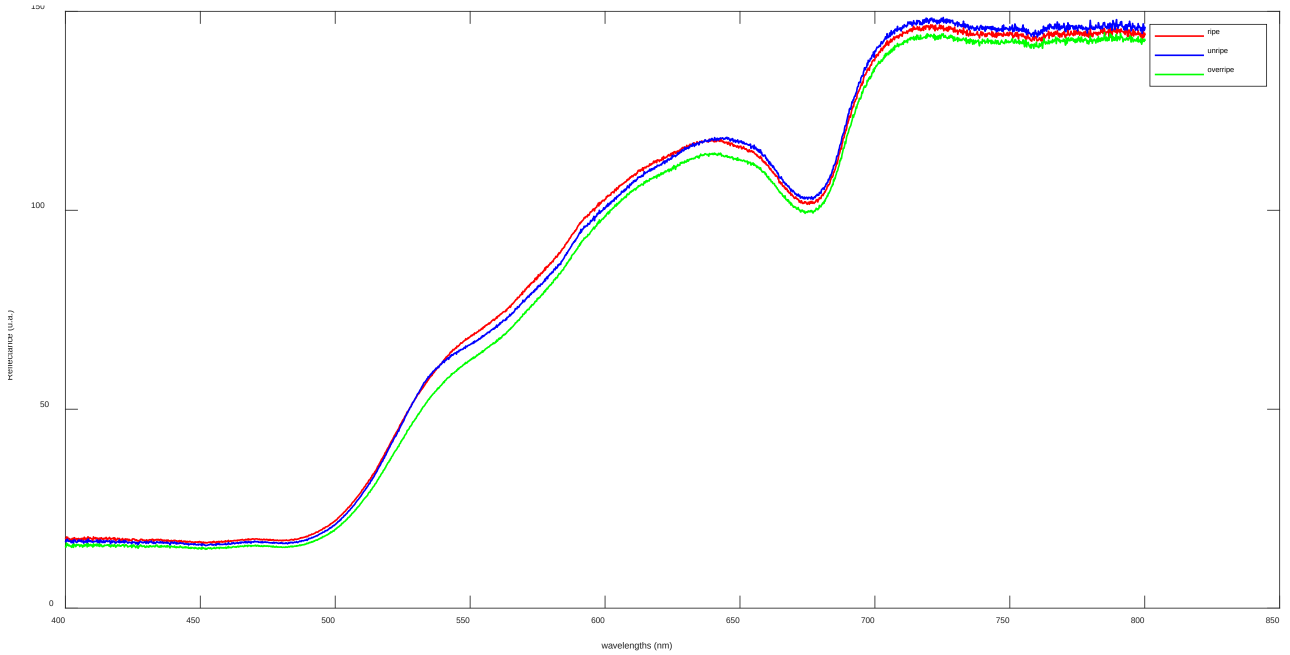

Figure 1. Mean reflectance spectrum of unripe (blue), ripe (red), and overripe (green) fruits.

A pronounced absorption feature is observed around 670 nm, likely associated with chlorophyll absorption, followed by a sharp increase in reflectance in the near-infrared region (>700 nm). In this region, unripe fruits exhibit the highest reflectance values, followed by ripe fruits, while overripe fruits show the lowest reflectance. This behavior may be related to structural changes in the fruit tissue and variations in water content as ripening progresses.

Overall, the spectral differences observed among the three maturity stages indicate that reflectance spectroscopy is sensitive to fruit ripeness and can be effectively used to discriminate between unripe, ripe, and overripe fruits.

2.3. Laboratory Analysis of Sugar Content

After spectral acquisition, the samples were subjected to a destructive reference analysis. The total sugar content (˚Brix) was determined using a laboratory digital refractometer, following the standard protocol described by [18]. This measurement validated the correlation between the spectral measurements and the actual sugar content.

2.4. Calculation of Spectral Indices

From the normalized spectra, thirteen spectral indices were calculated to characterize the biochemical and structural variations associated with fruit ripening and sugar accumulation (**Table 1**).

Table 1. Spectral indices.

Index	Description	
	General formula	Objective/relevance
SR	R_{NIR}/R_{Red}	Sensitivity to relative reflectance variations
$NDI_{750\text{-}700}$	$(R_{750}-R_{700})/(R_{750}+R_{700})$	Detects structural and pigment-related changes in the fruit
mND705	$(R_{750}-R_{705})/(R_{750}-R_{705}-R_{445})$	Estimates chlorophyll content and tracks fruit maturation
NDVI705	$(R_{705}-R_{Red})/(R_{705}+R_{Red})$	Monitors chlorophyll degradation and sugar accumulation
MTCI	$(R_{754}-R_{709})/(R_{709}-R_{681})$	Evaluates chlorophyll content and maturation progression
MCARI	$[(R_{700}-R_{670})-0.2\times(R_{700}-R_{550})]\times(R_{700}/R_{670})$	Quantifies chlorophyll absorption while minimizing background effects
PRI	$(R_{531}-R_{570})/(R_{531}+R_{570})$	Detects pigment variations (mainly carotenoids)
CRI1	$\left(\frac{1}{R_{510}}-\frac{1}{R_{550}}\right)$	Estimates carotenoid content
ARI1	$\left(\frac{1}{R_{550}}-\frac{1}{R_{700}}\right)$	Estimates anthocyanin concentration
NPCI	$(R_{680}-R_{430})/(R_{680}+R_{430})$	Reflects chlorophyll-to-carotenoid ratio variations
GI	R_{554}/R_{677}	"Greenness" index of the fruit surface
REP	$700+40\times((R_{670}+R_{780})/2-R_{700}/(R_{740}-R_{700}))$	Red-edge position related to fruit maturity
RATIO	R_{750}/R_{700}	Indicates sugar accumulation or pigment shifts

2.5. Statistical Modeling Procedures

For spectral data analysis, two multivariate modeling approaches were used: Partial Least Squares Regression (PLSR) and Random Forest (RF).

2.5.1. Cross-Validation

10-fold cross-validation was used to evaluate the performance of the models. This method helps minimize overfitting bias by dividing the data into 10 subsets, each subset being used as a test set while the others are used for training.

2.5.2. Selection of Latent Variables for PLSR

For the PLSR model, the optimal number of latent components was determined by minimizing the Root Mean Square Error (RMSE) obtained during cross-validation. The number of latent components was set to 8 after evaluating the model's performance with different numbers of components. This choice provided an optimal balance between model complexity and prediction accuracy.

3. Result

3.1. Importance of Spectral Indices

The analysis of feature importance in the Random Forest (RF) model revealed the spectral indices that most strongly influence the prediction of sugar content

(˚Brix) in cashew apples.

As shown in **Figure 2**, REP (Red-Edge Position) and RATIO emerged as the most influential indices, followed by SR, $NDI_{750-700}$, and NPCI. Indices related to chlorophyll and secondary pigments, such as MCARI, PRI, and ARI1, contributed comparatively less.

These results confirm that the red-edge position (REP) and band ratios, which are sensitive to biochemical and structural variations, are robust indicators of fruit maturity and sugar accumulation. The SR and $NDI_{750-700}$ indices, which capture reflectance variations in the near-infrared and red-edge regions, are particularly responsive to changes associated with chlorophyll degradation and pigment evolution, as highlighted by [18] [21]-[23].

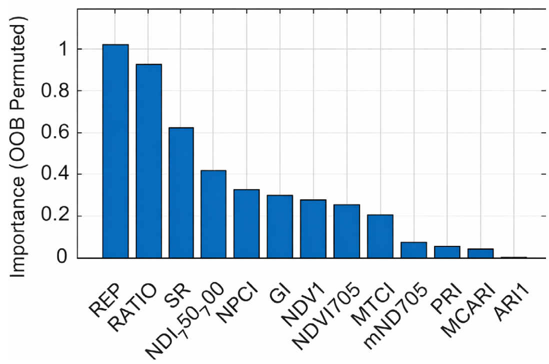

Figure 2. Relative importance of spectral indices in the Random Forest model.

3.2. Performance of the PLSR Model

The relationship between measured and predicted ˚Brix values using Partial Least Squares Regression (PLSR) is presented in **Figure 3**.

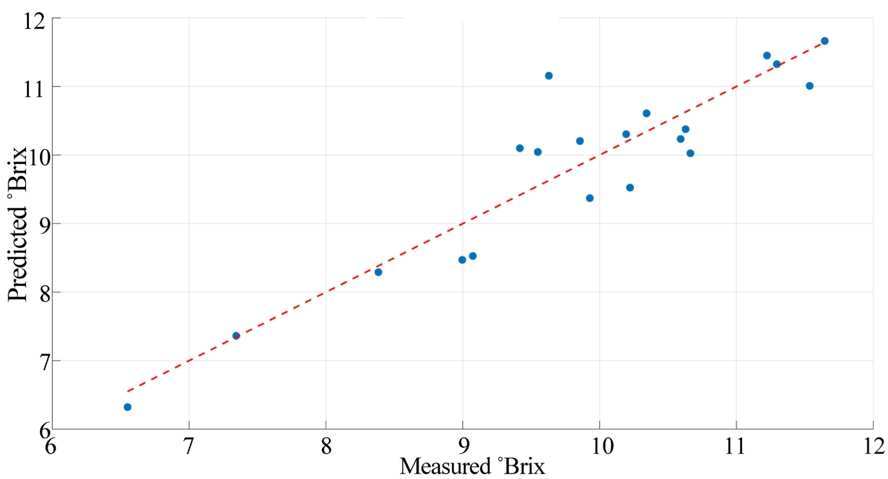

Figure 3. Relationship between measured and predicted ˚Brix using the PLSR model.

The optimized model with eight latent components (optComp = 8) achieved high predictive performance, with R^2 = 0.9313, RMSE = 0.4720 ˚Brix, and MAE =

0.3526 ˚Brix.

The strong alignment of the points along the (y = x) line demonstrates a close match between observed and predicted values.

The PLSR model showed excellent linear modeling capability, indicating that most of the variation in sugar content can be explained through a linear combination of spectral indices [24]-[26]. This strong performance stems from PLSR's ability to extract the most informative latent variables from highly collinear data while minimizing noise and redundancy [24] [25]. Comparable results have been reported for non-destructive ˚Brix prediction in mango and papaya [27] [28].

3.3. Performance of the Random Forest Model

The Random Forest (RF) model, a non-linear ensemble learning approach, also provided reliable predictive performance (Figure 4).

With R^2 = 0.8819, RMSE = 0.6189 ˚Brix, and MAE = 0.4653 ˚Brix, RF achieved slightly lower accuracy than PLSR but demonstrated strong robustness and the ability to capture non-linear relationships between spectral indices and sugar content.

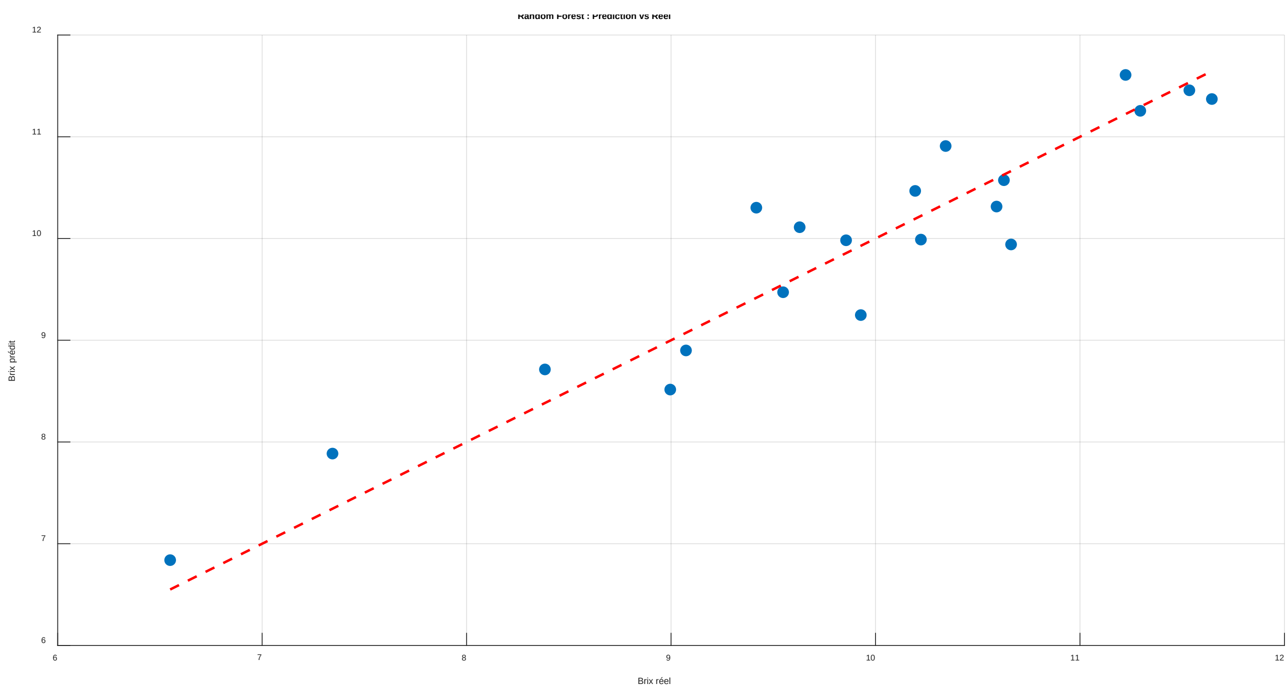

Figure 4. Relationship between measured and predicted ˚Brix using the Random Forest model.

RF offers the advantage of being less affected by multicollinearity and can model complex interactions among variables, making it particularly suitable for heterogeneous datasets influenced by illumination or textural variations [29] [30] [31]. Moreover, the built-in variable importance analysis provides a powerful feature-selection tool, helping to identify the most relevant indices for model optimization [29] [32].

4. Discussion

This study confirms the strong potential of reflectance-based spectral indices combined with multivariate modeling techniques for the non-destructive estimation of sugar content (˚Brix) in cashew apples. The results demonstrate that biochemical changes occurring during fruit ripening are effectively captured by spectral information derived from the visible and near-infrared regions, particularly through spectral indices rather than full spectra [33].

The prominent role of the red-edge position (REP) observed in this study is physiologically coherent. The red-edge region (approximately 680 - 750 nm) is well known for its sensitivity to variations in chlorophyll concentration and internal tissue structure [15]. As cashew apples mature, chlorophyll degradation occurs concurrently with sugar accumulation, leading to a systematic shift of the red-edge toward longer wavelengths, a phenomenon widely documented in fruit ripening studies [34]. Comparable relationships between red-edge dynamics and total soluble solids or maturity indices have been reported for tropical fruits such as mango and grape, confirming the robustness of REP as an indicator of internal fruit quality [35].

The strong contribution of ratio-based indices such as RATIO and $NDI_{750-700}$ further supports the effectiveness of simple band combinations for estimating internal quality attributes. By combining information from both visible and near-infrared wavelengths, these indices capture pigment-related changes as well as structural modifications in fruit tissues [36]. The importance of SR and NPCI suggests that sugar accumulation is indirectly associated with the balance between chlorophyll and carotenoids and with changes in cellular organization during ripening [15].

Regarding modeling approaches, Partial Least Squares Regression (PLSR) achieved higher predictive accuracy ($R^2 = 0.93$) than the Random Forest model ($R^2 = 0.88$), indicating that the relationship between spectral indices and ˚Brix in the present dataset is predominantly linear. PLSR is particularly suitable for spectroscopic data because it efficiently handles multicollinearity and extracts latent variables that maximize covariance between predictors and response variables [24] [25]. Similar performances of PLSR for non-destructive prediction of soluble solids have been widely reported in fruit quality assessment studies using spectral data [33].

Nevertheless, the Random Forest model demonstrated robust performance and provided valuable complementary insights. Its ability to model non-linear interactions and rank variable importance makes it especially relevant under heterogeneous field conditions, where illumination variability, surface texture, and biological diversity may introduce non-linear effects [29]. The slightly lower accuracy observed in this study may be explained by the relatively limited sample size and the dominance of linear trends in sugar accumulation during cashew apple ripening [29].

From an application perspective, the proposed non-destructive approach offers significant opportunities for precision agriculture and quality-oriented cashew value chains. Rapid, in situ estimation of sugar content can support optimized harvest timing, reduce postharvest losses, and enable differential sorting based on fruit maturity. This is particularly relevant in West African contexts where cashew apples remain underutilized despite their high nutritional and economic potential [33]. Furthermore, the use of spectral indices instead of full spectral signatures reduces computational complexity and facilitates integration into low-cost multispectral sensors, portable spectrometers, and drone- or smartphone-based platforms, thereby enhancing scalability and adoption by smallholder farmers and agro-industrial stakeholders [36].

5. Conclusions

This study demonstrates that reflectance-based spectral indices combined with multivariate modeling provide an efficient and reliable approach for the non-destructive estimation of sugar content in cashew apples. The predominance of red-edge and ratio-based indices confirms their physiological relevance in capturing the biochemical and structural changes associated with fruit ripening.

Partial Least Squares Regression achieved the highest predictive accuracy, highlighting the predominantly linear relationship between selected spectral indices and ˚Brix, while the Random Forest model provided complementary robustness and interpretability through variable importance analysis. Together, these results emphasize the methodological consistency and applicability of the proposed framework.

Overall, the approach offers a scalable and practical solution for fruit quality monitoring, with strong potential for integration into low-cost sensing technologies. This work contributes to the development of precision agriculture tools tailored to tropical fruit production and supports the improved valorization of cashew apples within quality-oriented supply chains.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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