Engenharia Agrícola
ISSN: 1809-4430 (online)
www.engenhariaagricola.org.br | www.scielo.br/j/eagri

*Scientific Paper*
DOI: http://dx.doi.org/10.1590/1809-4430-Eng.Agric.v45e20250003/2025

# ESTIMATION OF TOMATO FRUIT FIRMNESS USING DIGITAL IMAGING

**Anderson G. Costa[1*], Layana A. da Silva[1], João C. L. de Carvalho[1], Túlio de A. Machado[2]**

[1*]Corresponding author. Programa de Pós-Graduação em Engenharia Agrícola e Ambiental/Universidade Federal Rural do Rio de Janeiro/Seropédica - RJ, Brasil. E-mail: acosta@ufrrj.br | ORCID ID: https://orcid.org/0000-0003-0594-8514

**KEYWORDS**

computer vision, colorimetric indices, tomato production, multivariate analysis.

**ABSTRACT**

Computer vision systems have proven to be a promising alternative for assessing fruit quality attributes in a non-invasive, instantaneous, and accurate manner. This study aimed to use colorimetric characteristics extracted from digital images to estimate tomato fruit firmness through multivariate modeling. Images of 80 tomato fruits at four ripening stages were acquired using two digital cameras, enabling the extraction of average intensity values for the red, green, blue, and near-infrared bands, followed by the calculation of colorimetric indices. Reference firmness values were measured using a digital fruit penetrometer. Colorimetric indices were employed to estimate fruit firmness using principal component regression. Principal component analysis enabled the dimensionality to be reduced to a single principal component (explanatory percentage of the data variance of 97.06%), which was used to generate firmness estimation equations. The application of the model to the validation dataset yielded an $R^2$ = 0.937 and a mean standard error (SE) of 2.05 N, demonstrating that the protocol based on colorimetric characteristics extracted from digital images is suitable for estimating tomato firmness.

## INTRODUCTION

The advancement of digital agriculture has generated an increasing demand for automated equipment applicable in crop fields, agro-industries, and retail markets (Lezoche et al., 2020). These technologies are essential for improving crop management efficiency, reducing postharvest losses, and achieving more rigorous quality control standards for agricultural products (Ranjani et al., 2024).

The relationship between quality attributes and colorimetric characteristics for fruits and vegetables has been highlighted as an alternative for developing methods and technologies that enable the monitoring of quality-related attributes that change throughout the ripening process (Rizzo et al., 2023).

In this context, one of the most widely consumed crops worldwide is tomato (*Solanum lycopersicum*), which has a high demand for technologies that optimize management processes and support the quality control of the marketed product (Silva et al., 2025). Tomato fruits are delicate and prone to injury and, therefore, susceptible to quality loss during production, especially when subjected to mechanical harvesting, postharvest sorting, and transport. Thus, monitoring key parameters is essential to achieve greater control and establish quality standards, providing valuable information to predict quality before, during, and after harvest.

These quality attributes are generally evaluated using destructive, costly, and labor-intensive instrumental and chemical methods (Tian & Xu, 2022). Pulp firmness stands out among the various physicochemical attributes associated with tomato quality, as it is a physical parameter indicative of fruit ripening and is closely associated with changes caused by injuries resulting from mechanical impacts (Komarnicki & Kuta, 2021).

Tomatoes undergo physiological and biochemical changes during ripening, including ethylene production, which accelerates the ripening process and pectin degradation in the cell wall, thereby reducing fruit firmness (Nie et al., 2024). Simultaneously, the fruits change color, transitioning from green to yellow, pink, and finally red (Hu et al., 2024). Fruits that reach physiological maturity

[1] Programa de Pós-Graduação em Engenharia Agrícola e Ambiental/Universidade Federal Rural do Rio de Janeiro/Seropédica - RJ, Brasil.
[2] Programa de Pós-Graduação em Olericultura/ Instituto Federal Goiano/Campus Morrinhos - GO, Brasil.

Area Editor: Gizele Ingrid Gadotti
Received in: 1-8-2025
Accepted in: 6-3-2025

typically exhibit a red color and tend to be less firm due to greater pectin degradation and increased enzymatic activity associated with ripening.

Non-invasive methods based on computer vision that allow for instantaneous measurement have been applied to estimate fruit quality attributes in general, such as pH in oranges (Sabzi & Arribas, 2018), firmness in apples (Fathizadeh et al., 2021), oil content in macaúba fruits (Costa et al., 2023), and pear volume (Saikumar et al., 2025).

Recent studies conducted in the tomato crop using digital images have been successfully developed for evaluating the ripening stage (Bello et al., 2020), selecting fruit based on injuries (Phan et al., 2023), detecting defects (Ireri et al., 2019), determining optimal harvest maturity (Benavides et al., 2020), and developing real-time automated selection and harvesting systems (Jun et al., 2021).

This study aims to present a protocol based on colorimetric characteristics obtained from digital images to estimate tomato fruit firmness, with a focus on application in automated systems for harvesting and fruit sorting, as well as complementary use with laboratory methods for measuring quality attributes.

## MATERIAL AND METHODS

### Experimental design

Roma tomatoes (*Solanum lycopersicum* 'Roma'), grown in a controlled environment located in the south-central region of the state of Rio de Janeiro, Brazil, in the municipality of Paty do Alferes (22°25′10″ S and 43°25′21″ W, at an average altitude of 610 m), were used for this experiment.

The fruits were manually harvested 85 days after planting and visually classified according to color associated with the ripening stage as unripe (green fruits), painting (green-orange fruits), colored (orange-red fruits), and ripe (red fruits) (CEAGESP, 2003). A total of 80 tomatoes were used in this experiment, consisting of 20 fruits at each ripening stage (Figure 1).

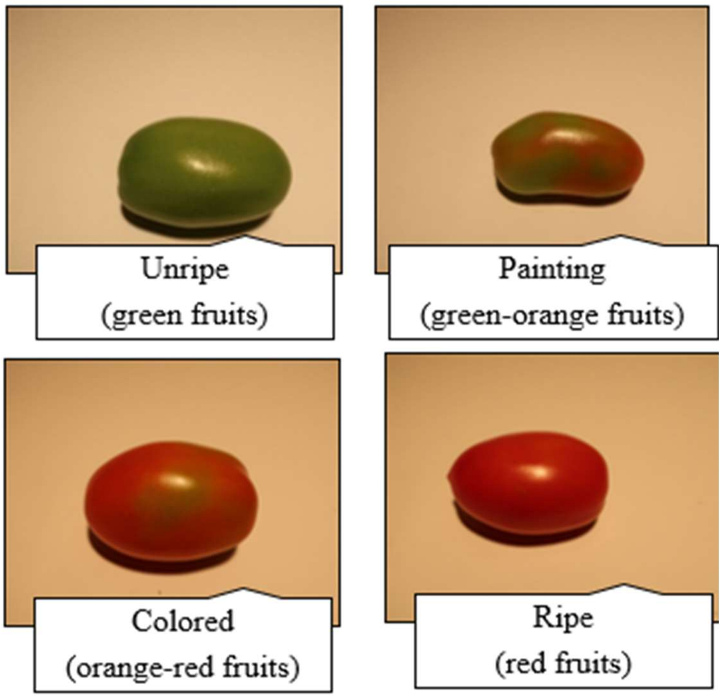


FIGURE 1. Tomato classification according to fruit ripening stages.

The experimental setup for image acquisition consisted of a Canon PowerShot G9 X RGB camera capable of capturing images in the red (R), green (G), and blue (B) bands, a MAPIR Survey 3.0 RGNIR camera with acquisition capability in the red (R), green (G), and near-infrared (NIR) bands, two 100 W halogen lamps, tripod mounts, and a computer for image processing and generation of estimation models.

The RGB and RGNIR cameras were positioned at 0.15 m and 0.25 m, respectively, above a white-background table where the tomatoes were placed for image capture. The camera settings (focus, ISO, zoom, and white balance) were kept consistent throughout the experiment to ensure standardized experimental conditions. The lamps were placed 0.85 m above the table to illuminate the image acquisition environment.

The images were processed using ImageJ software to obtain the average intensities of the red (R), green (G), and blue (B) bands captured in the visible spectral region, and the average intensities of the red (R), green (G), and near-infrared (NIR) bands obtained from the multispectral images. Intensity values ranged from 0 (black, no reflected intensity from the analyzed band) to 255 (white, full reflected intensity from the analyzed band).

According to the color space conversion models described by Gonzalez & Woods (2017), the average RGB band intensities were used to calculate hue (H), with values ranging from 0° to 360°, based on the HSI color model. The RGB values were also converted to the CIELAB color model, allowing the calculation of the lightness L (ranging from 0 to 100), and the two chromaticity coordinates a and b, which represent color ranges from green to red and blue to yellow, respectively (−128 to +128). Colorimetric indices were calculated based on the average band intensities and the parameters obtained from the color models, as described in Table 1.

TABLE 1. Colorimetric indices calculated from the RGB and RGNIR images of tomato fruits.

| Colorimetric indices | Equation |
|---|---|
| Normalized difference red index | $NDVI = \frac{NIR - R}{NIR + R}$ |
| Normalized difference green index | $NDVI - G = \frac{NIR - G}{NIR + G}$ |
| Red-to-near-infrared ratio | $RNIR = \frac{R}{NIR}$ |
| Green-to-near-infrared ratio | $GNIR = \frac{G}{NIR}$ |
| Plant pigment ratio | $PPR = \frac{G - B}{G + B}$ |
| Normalized difference green-red index | $NDGRI = \frac{G - R}{G + R}$ |
| Hue angle | H (Gonzalez & Woods, 2017) |
| Degreening index | $DI = \frac{a}{b * L}$ |
| Yellowing index | $YI = \frac{142.86 * b}{L}$ |
| Color index | $CI = \frac{1000 * a}{b * L}$ |

R = red band; G = green band; B = blue band; NIR = near-infrared.

The qualitative parameter of fruit firmness was measured using an Instrutherm PTR-300 digital penetrometer equipped with an 8-mm probe tip. The probe was pressed with constant force perpendicularly into the equatorial region of the fruit until penetration occurred. The force required to overcome the fruit's resistance to penetration was measured in Newtons (N). Each fruit was measured in triplicate, and an average value per fruit was calculated. The firmness values were used as reference measurements for the subsequent analyses.

**Data analysis**

Initially, an analysis of variance (ANOVA) and Tukey's test at the 5% significance level were performed to compare the mean firmness values among the different ripening stages.

Subsequently, Pearson correlation coefficients were calculated between fruit firmness and each colorimetric index. The colorimetric indices that showed a correlation greater than 0.80 (or less than −0.80) with fruit firmness were selected for principal component analysis (PCA).

Principal component analysis (PCA) was performed based on the linear combination of the correlation matrix of the colorimetric indices, enabling the extraction of principal components (PCs) and their respective explanatory powers of variance (Jolliffe & Cadima, 2016). The correlation between the colorimetric indices and PCs was also evaluated. The dispersion of fruit samples in a two-dimensional plane formed by the two most relevant principal components was analyzed to assess sample clustering and the influence of the colorimetric indices at each ripening stage.

A multiple linear regression (MLR) model, generated from the relationship between firmness values obtained from the reference method (digital penetrometer) and the most representative PCs (cumulative explanatory variance above 70%), was used to estimate fruit firmness. This model was developed using a training dataset composed of 40 fruits, with 10 fruits from each ripening stage.

The PCs selected for inclusion in the model were subjected to an analysis of variance (ANOVA) and a significance test for model coefficients at the 5% significance level. The performance of the trained regression model was evaluated using the standard error (SE) and the coefficient of determination ($R^2$) between the estimated firmness values and the reference values obtained by the destructive penetrometer method.

The trained model was applied to a validation dataset (20 fruits, with five fruits from each ripening stage) to assess its capability in estimating the firmness of tomato fruits. The model's performance on the validation dataset was measured using the coefficient of determination ($R^2$), validation standard error (SE), and mean squared error (MSE), based on the linear relationship between the estimated firmness values and the reference values.

Figure 2 shows the analysis workflow of the proposed protocol designed to estimate the quality attributes of tomatoes based on the fruit colorimetric characteristics.

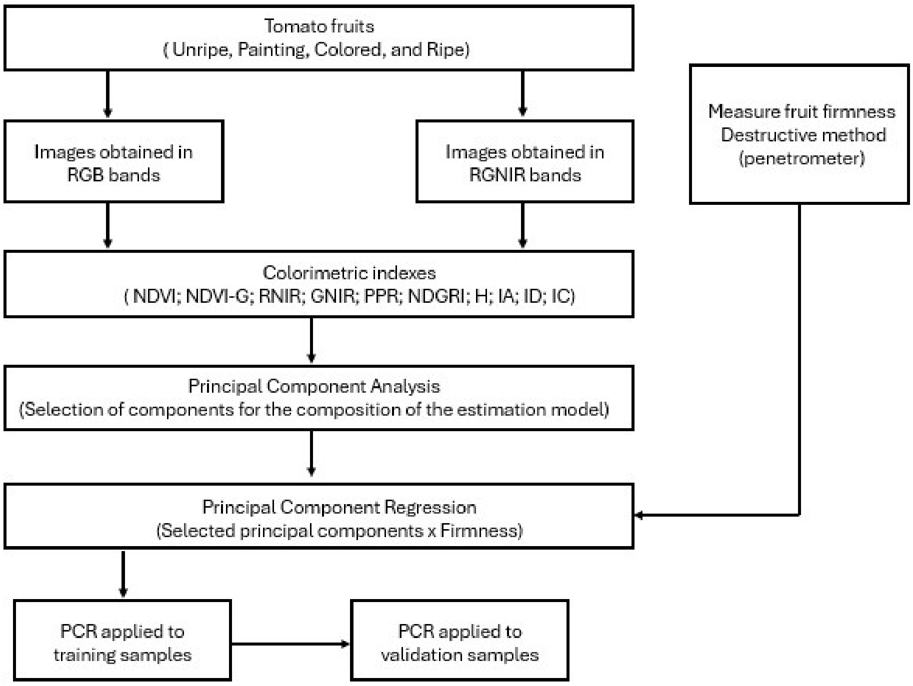


FIGURE 2. Steps for applying the PCR regression model developed to estimate tomato fruit firmness based on digital imaging.

## RESULTS AND DISCUSSION

The tomato fruit firmness across the different ripening stages (Figure 3) showed a decrease as ripening progressed. This behavior is expected for fruits in general, as the approach to physiological maturity is accompanied by a reduction in the amount of insoluble pectin and, consequently, a decrease in the resistance of the cell walls to penetration (Nie et al., 2024). The colored and ripe stages exhibited firmness levels close to those of physiological maturity, making it impossible to distinguish between these stages.

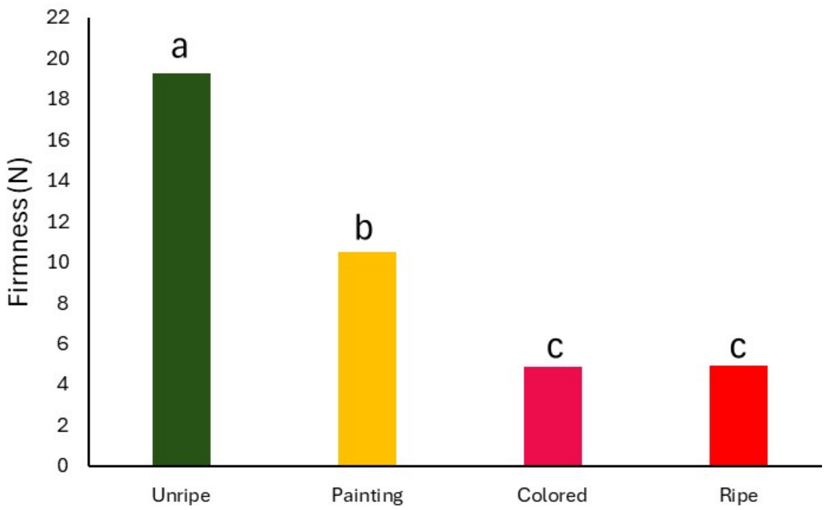


FIGURE 3. Comparison between means of firmness of tomato fruits at different ripening stages.

Tomato ripening is a physiological process that affects quality attributes and influences the final fruit quality (Nie et al., 2024). These attributes are essential for determining the optimal harvest time and sorting fruits during postharvest handling to ensure quality and commercial value. Color is the main indicator of the physiological maturity stage of tomatoes (Zuo, 2022). Tomato fruit is primarily composed of lycopene (a red pigment) and a fraction of carotene (a yellow pigment). The final red color of the fruit results from lycopene accumulation and chlorophyll degradation (Hu et al., 2024).

Ethylene emission during fruit ripening, in addition to inducing red coloration through lycopene accumulation and chlorophyll degradation, also affects enzymes such as polygalacturonase and pectinesterase, which degrade cell walls, leading to reduced fruit firmness and increased transpiration and water loss (Nie et al., 2024).

The correlation analysis between firmness and colorimetric indices (Figure 4) showed that the indices GNIR, NGDRI, and H had the highest positive correlations with firmness (greater than 0.80), while the indices NDVI-G, DI, YI, and CI exhibited the strongest negative correlations (less than −0.80). Thus, these colorimetric indices were selected to compose the multivariate model based on principal components.

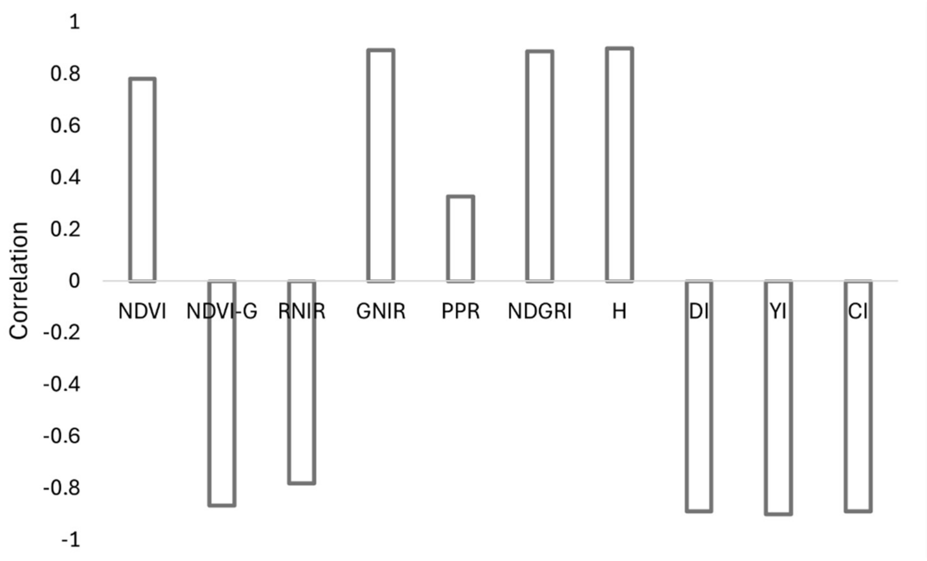


FIGURE 4. Pearson correlation coefficients between tomato fruit firmness and colorimetric indices.

Color is fundamental for discriminating objects based on their reflectance values. Differences that are imperceptible to the human eye can be instantly and numerically detected by optical devices that measure color (Bustamante et al., 2021). Colorimetric characteristics in tomatoes have been successfully used to distinguish ripening stages (Bello et al., 2020) and correlate with physicochemical attributes.

Applying principal component analysis (PCA) to the set of colorimetric indices revealed that PC1 accounted for 97.06% of the variance explained by the ripening stages (Table 2). The variance of 5.83, which is greater than 1.0, indicates that PC1 is a robust metric for differentiating tomato fruit ripening stages, and this variation can be effectively represented by a single component. PC2 contributed slightly to the data variation (2.41%), indicating that the analysis can be well represented using these two components, with a cumulative explanatory power of 99.47%.

TABLE 2. Principal component analysis (PCA) for comparing ripening stages based on colorimetric indices that distinguished the fruit maturation stages.

| | PC1 | PC2 | PC3 | PC4 | PC5 | PC6 |
|---|---|---|---|---|---|---|
| Variance | 5.83 | 0.14 | 0.02 | 0.01 | 0.01 | ~ 0.000 |
| PE (%) | 97.06 | 2.41 | 0.29 | 0.17 | 0.069 | ~ 0.000 |
| CPE (%) | 97.06 | 99.47 | 99.76 | 99.93 | ~100.00 | 100.00 |
| Correlation between PCs and colorimetric indices | | | | | | |
| NDVI-G | 0.97 | −0.25 | 0.03 | −0.03 | 0.03 | ~ 0.000 |
| GNIR | −0.98 | 0.17 | 0.01 | −0.06 | 0.03 | ~ 0.000 |
| H | −0.99 | −0.04 | 0.01 | 0.07 | 0.03 | ~ 0.000 |
| DI | 0.99 | 0.14 | 0.05 | 0.02 | 0.01 | ~ 0.000 |
| YI | 0.99 | 0.09 | −0.10 | 0.01 | 0.02 | ~ 0.000 |
| CI | 0.99 | 0.14 | 0.05 | 0.02 | 0.01 | ~ 0.000 |

PE = percentage of explained variance; CPE = cumulative percentage of explained variance; NDGRI = normalized difference green-red index; H = hue angle; DI = degreening index; NDVI-G = normalized difference green index; GNIR = green-to-near-infrared ratio.

All colorimetric indices showed a correlation higher than 0.95 with PC1, demonstrating their effectiveness in characterizing variations as a function of fruit ripening. The indices NDVI-G, DI, YI, and CI showed strong direct correlations, while GNIR and H exhibited strong inverse correlations. Therefore, PC1 can be used as a response variable to represent the colorimetric variation of fruits according to their ripening stage and generate equations to estimate tomato fruit firmness.

Fruit distribution in the two-dimensional space defined by PC1 and PC2 (Figure 5) showed that the proposed protocol was effective in distinguishing tomato ripening stages based on colorimetric indices. The clustering of fruits from the same ripening stage in distinct quadrants reflects the tomato ripening transition. The PC1 direction (x-axis) highlights the tomato colorimetric shift throughout ripening, with immature fruits associated with negative values of this component, while mature fruits were associated with positive values. PC2 contributed to subtle variations among intermediate-stage fruits (painting and colored). These results demonstrate that the protocol presented in this study has potential for application in automated systems for classifying tomatoes based on their colorimetric characteristics.

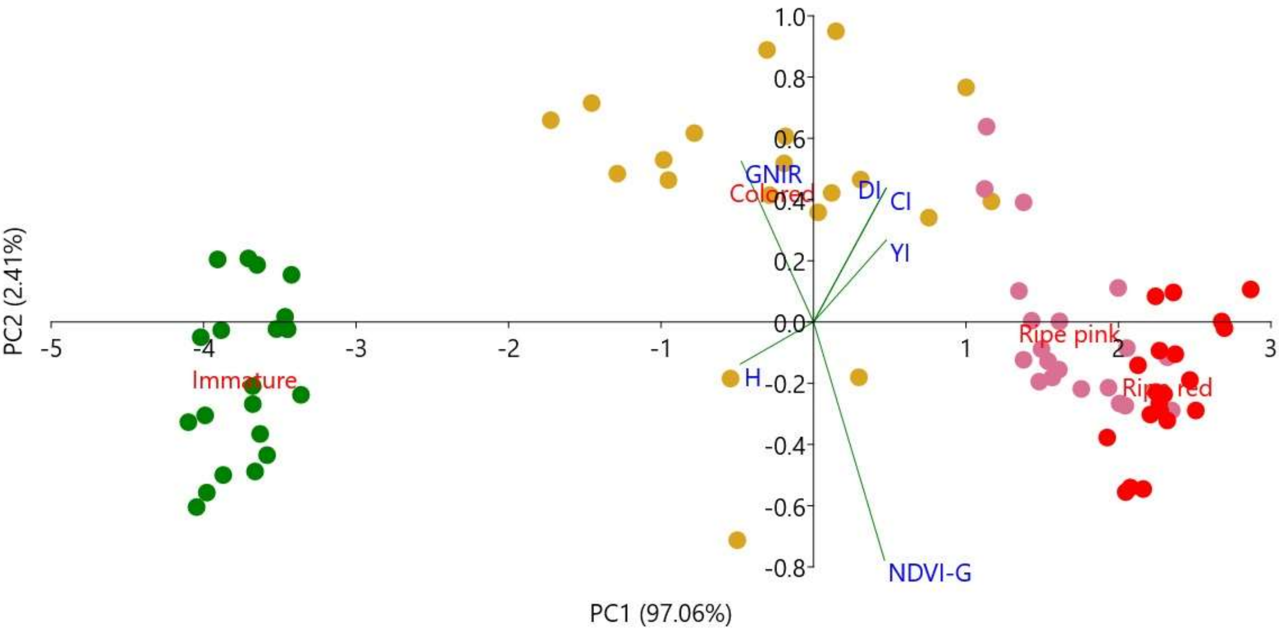


FIGURE 5. Dispersion in the two-dimensional plane (PC1 × PC2), based on the colorimetric indices of tomato fruits obtained at different ripening stages.

Immature fruits showed less dispersion within the group, indicating greater colorimetric uniformity at this stage. The painting and colored groups exhibited the greatest dispersions, characterizing the transition phase, during which fruits undergo more varied changes in their colorimetric characteristics. Fruits at the mature stage once again presented more concentrated dispersion, indicating greater colorimetric homogeneity upon reaching physiological maturity.

The colorimetric indices enabled the discrimination of different tomato ripening stages by reflecting the gradual colorimetric changes occurring throughout the ripening process. The indices DI, CI, YI, and NDVI-G were associated with the characterization of fruits at more advanced ripening stages, capturing the reduction in green pigmentation and the increase in red coloration during ripening. The H index was associated with immature tomatoes, indicating the high chlorophyll content and the predominance of green color in these fruits. The GNIR index was associated with intermediate-stage fruits, especially colored fruits (orange-red fruits), reflecting the variability in these fruits in transition.

The relationship between PC1 and tomato firmness enabled obtaining the coefficients that composed the single linear regression model used to estimate tomato firmness based on the fruit colorimetric characteristics (Table 3). The coefficient associated with PC1 was statistically significant (p-value $< 0.05$), and the model yielded $R^2 = 0.78$ and standard error = 0.55 for the calibration sample set, indicating that the proposed protocol has potential for accurately and non-destructively estimating tomato firmness.

TABLE 3. Coefficients and their performance parameters in the PCR model generated from the calibration dataset for firmness estimation based on colorimetric indices.

| | Coefficient | Standard error | p-value | $R^2$ |
|---|---|---|---|---|
| Constant | 9.91 | 0.39 | 2.01E-33 | |
| PC1 | −2.30 | 0.16 | 7.00E-21 | 0.78 |

PC1: principal component 1; $R^2$: coefficient of determination.

The application of the generated model (Firmness = −2.30*PC1 + 9.91) in the set of validation samples showed a linear relationship of $R^2 = 0.937$, allowing the estimation of tomato firmness based on the colorimetric characteristics of the fruits (Figure 6). The analysis of MSE (4.22) and SE (2.05) showed that the estimated firmness values deviated from the reference values obtained by the destructive method (penetrometer) on average by 2.05 N.

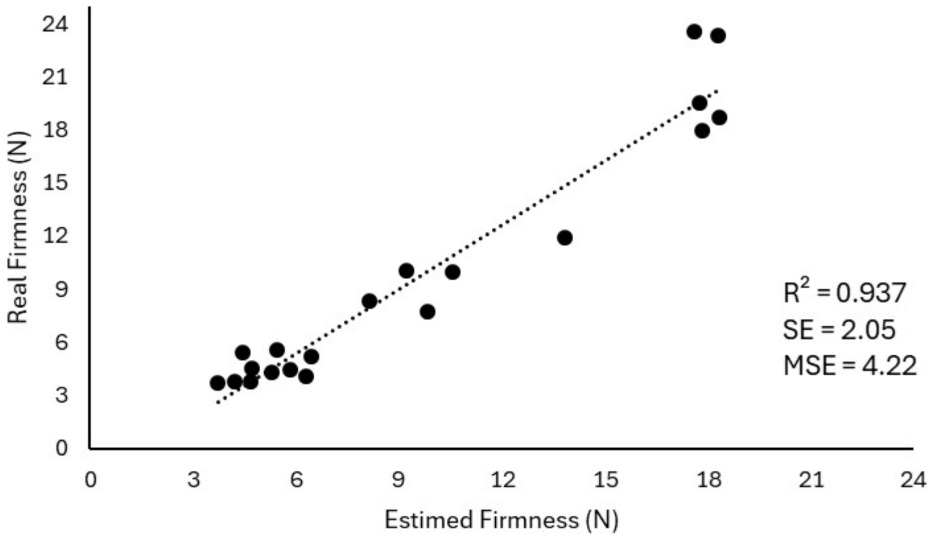


FIGURE 6. Relationship between the firmness obtained by the reference method (real firmness) and the firmness estimated from the use of digital images in the validation data and the respective performance parameters of the model: coefficient of determination ($R^2$), validation standard error (SE), and validation mean square error (MSE).

Importantly, the values estimated by the PCR model for the validation data were closer to the reference values for fruits in more advanced stages of ripening (ripe fruits), as shown in the residuals in Figure 7. Fruits in the painting and colored stages were in a transition phase, with a wider deviation, although smaller when compared to immature fruits, because of the more varied coloration. Therefore, the model can be applied to tomatoes at any stage of ripening but tends to present greater accuracy in the estimates of tomatoes with a lower level of firmness, which are generally closer to physiological maturity.

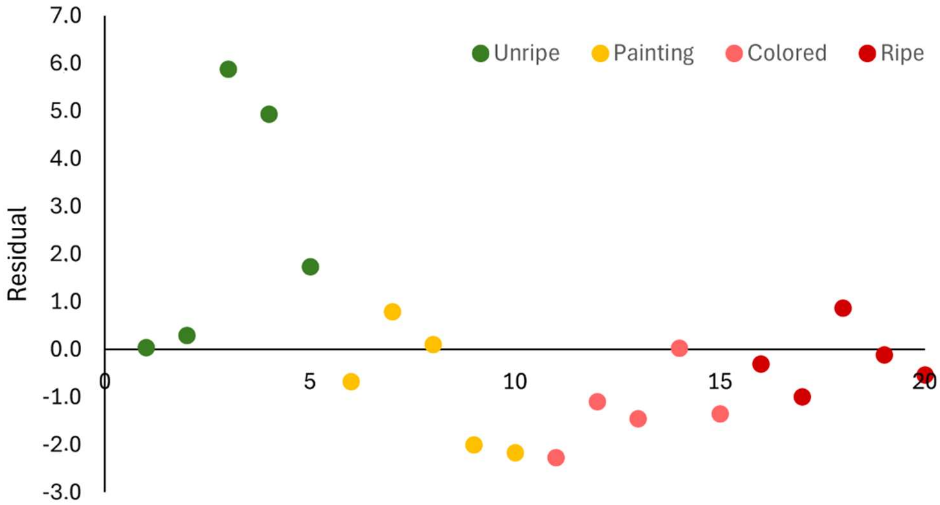


FIGURE 7. Variation of residuals obtained between the estimated and reference firmness values.

Costa et al. (2023) also observed an increase in the performance parameters of linear models closer to the physiological maturity when estimating the oil content in macaúba fruits. The authors found a decrease in the standard error and, consequently, a better model fit when analyzing only fruits in more advanced ripening stages, which contained the highest oil contents.

This behavior, observed from the estimation of physicochemical attributes by linear models, can be attributed to the colorimetric characteristics of fruits reaching physiological maturity. The colorimetric characteristics of fruits at ripening stages are in a transition process, even influencing the homogeneity of the evaluated lots, which reduces the model performance. Although linear models present satisfactory performance metrics, non-linear models can enable an increase in the accuracy obtained in the estimates of quality attributes in fruit ripening phases.

However, linear models tend to be more adaptable to implementation in automated systems due to their simpler structure and ease of calibration (Maulud & Abdulazeez, 2020). An assessment of the real gain when using nonlinear models over linear models should be conducted, considering factors such as problem complexity, system limitations, and resources available for implementation (Korda & Mezić, 2018).

The agricultural sector faces increasing challenges, such as the need to raise production efficiency, reduce losses, and adopt sustainable technologies to meet the demand for quality food. Quality inspection of fruits and vegetables throughout the production cycle is increasingly demanded to meet the strict quality and sustainability standards required by the market (Silva et al., 2025). In the case of tomato production, fruit firmness is one of the main attributes associated with fruit quality, as perceived by the end consumer.

Thus, the search for innovative and accessible solutions, such as the measurement of tomato fruit firmness using a non-destructive, easy-to-implement, and low-cost system, can contribute to increasing the efficiency of selection and quality control processes, reduce losses, and enable greater technological accessibility for small producers.

## CONCLUSIONS

The protocol based on colorimetric characteristics obtained by digital imaging was suitable for estimating tomato fruit firmness, demonstrating potential for application in automated harvesting systems, fruit sorting, and instantaneous fruit firmness measurement.

The colorimetric indices GNIR, NGDRI, and H presented the highest direct correlations with firmness (greater than 0.80), while the NDVI-G, DI, YI, and CI indices presented the highest inverse correlations (lower than −0.80).

Principal component analysis (PCA) applied to the set of colorimetric indices demonstrated that PC1 had 97.06% of the explanatory power of the variance generated by the ripening stages. Furthermore, all colorimetric indices presented a correlation greater than 0.95, mainly with this component, which allowed us to conclude that PC1 can be used to generate equations to estimate tomato fruit firmness.

The application of the generated model (Firmness = −2.30*PC1 + 9.91) in the set of validation samples presented an $R^2$ = 0.937, allowing the estimation of the tomato firmness based on the colorimetric characteristics of the fruits. The standard error showed that the estimated firmness values deviated from the reference values obtained by the destructive method on average by 2.05 N.

The model showed potential to be applied to fruits at any ripeness stage, but tended to present greater accuracy in the firmness estimates associated with tomatoes closer to physiological maturity.

## ACKNOWLEDGEMENTS

The authors would like to thank the Coordination for the Improvement of Higher Education Personnel (CAPES), National Council for Scientific and Technological Development (CNPq) and the Carlos Chagas Filho Foundation for Research Support in the State of Rio de Janeiro – FAPERJ (Fund project: E-26/010.002732/2019).

## REFERENCES

Benavides, M., Cantón-Garbín, M., Sánchez-Molina, J. A. & Rodríguez, F. (2020). Automatic tomato and peduncle location system based on computer vision for use in robotized harvesting. *Applied Sciences, 10*(17), 5887. https://doi.org/10.3390/app10175887

Bello, T. B., Costa, A. G., Silva, T. R. S., Paes, J. L. & Oliveira, M. V. M. (2020). Tomato quality based on colorimetric characteristics of digital images. *Revista Brasileira de Engenharia Agrícola e Ambiental, 24*(8), 567-572. https://doi.org/10.1590/1807-1929/agriambi.v24n8p567-572

Bustamante, P., Acosta, I., León, J. & Campano, M. A. (2021). Assessment of color discrimination of different light sources. *Buildings*, *11*(11), 527. https://doi.org/10.3390/buildings11110527

Companhia de Entrepostos e Armazéns Gerais de São Paulo. (2003). *Normas de classificação do tomate: Centro de Qualidade em Horticultura*. https://ceagesp.gov.br/wp-content/uploads/2015/07/tomate.pdf

Costa, A. G., Oliveira, M. C., Carvalho, J. C. L., Pinto, F. A. C. & Motoike, S. Y. (2023). Bioenergetic cultures: Estimate of oil content in macaw palm via computer vision. *Engenharia Agrícola*, *43*(spe), e20220105. https://doi.org/10.1590/1809-4430 Eng.Agric.v43nepe20220105/2023

Fathizadeh, Z., Aboonajmi, M. & Hassan-Beygi, S. R. (2021). Nondestructive methods for determining the firmness of apple fruit flesh. *Information Processing in Agriculture,* *8*(4), 515-527. https://doi.org/10.1016/j.inpa.2020.12.002

Gonzalez, R. C. & Woods R. E. (2017). *Digital image processing*. Pearson.

Hu, J., Wang, J., Muhammad, T., Yang, T., Li, N., Yang, H., Yu, Q. & Wang, B. (2024). Integrative analysis of metabolome and transcriptome of carotenoid biosynthesis reveals the mechanism of fruit color change in tomato (*Solanum lycopersicum*). *International Journal of Molecular Sciences, 25*(12), 6493. https://doi.org/10.3390/ijms25126493

Ireri, D., Belal, E., Okinda, C., Makange, N. & Ji, C. (2019). A computer vision system for defect discrimination and grading in tomatoes using machine learning and image processing. *Artificial Intelligence in Agriculture, 2*, 28-37. https://doi.org/10.1016/j.aiia.2019.06.001

Jolliffe, I. T. & Cadima, J. (2016). Principal component analysis: A review and recent developments. *Philosophical Transactions of the Royal Society: A Mathematical, Physical and Engineering Sciences, 374*(2065), 20150202. https://doi.org/10.1098/rsta.2015.0202

Jun, J., Kim, J., Seol, J., Kim, J. & Son, H. I. (2021). Towards an efficient tomato harvesting robot: 3D perception, manipulation, and end-effector. *IEEE Access*, *9*, 17631 - 17640. https://doi.org/10.1109/ACCESS.2021.3052240

Korda, M. & Mezić, I. (2018). Linear predictors for nonlinear dynamical systems: Koopman operator meets model predictive control. *Automatica*, *93*, 149-160. https://doi.org/10.1016/j.automatica.2018.03.046

Komarnicki, P. & Kuta, Ł. (2021). Evaluation of picker discomfort and its impact on maintaining strawberry picking quality. *Applied Sciences*, *11*(24), 11836. https://doi.org/10.3390/app112411836

Lezoche, M., Hernandez, J. E., Diaz, M. M. E. A., Panetto, H. & Kacprzyk, J. (2020). Agri-food 4.0: A survey of the supply chains and technologies for the future agriculture. *Computers in Industry, 117*, 103187. https://doi.org/10.1016/j.compind.2020.103187

Maulud, D. & Abdulazeez, A. M. (2020). A review on linear regression comprehensive in machine learning. *Journal of Applied Science and Technology Trends, 1*(2), 140-147. https://doi.org/10.38094/jastt1457

Nie, H., Yang, X., Zheng, S. & Hou, L. (2024). Gene-based developments in improving quality of tomato: Focus on firmness, shelf life, and pre-and post-harvest stress adaptations. *Horticulturae, 10*(6), 641. https://doi.org/10.3390/horticulturae10060641

Phan, Q. H., Nguyen, V. T., Lien, C. H., Duong, T. P., Hou, M. T. K. & Le, N. B. (2023). Classification of tomato fruit using yolov5 and convolutional neural network models. *Plants, 12*(4), 790. https://doi.org/10.3390/plants12040790

Ranjani, M., Soumiya, K., Dhanalakshmi, S. & Narola, A. (2024). Advances in non-destructive techniques for fruit quality assessment: A comprehensive review. *International Journal of Agriculture and Food Science, 6*(1), 40 - 42. https://doi.org/10.33545/2664844X.2024.v6.i1a.164

Rizzo, M., Marcuzzo, M., Zangari, A., Gasparetto, A. & Albarelli, A. (2023). Fruit ripeness classification: A survey. *Artificial Intelligence in Agriculture*, *7*, 44-57. https://doi.org/10.1016/j.aiia.2023.02.004

Sabzi, S. & Arribas, J. I. (2018). A visible-range computer-vision system for automated, non-intrusive assessment of the pH value in Thomson oranges. *Computers in Industry*, *99*, 69 - 82. https://doi.org/10.1016/j.compind.2018.03.016

Saikumar, A., Sahal, A., Mansuri, S. M., Hussain, A., Junaid, P. M., Nickhil, C., Badwaik, L. S. & Kumar, S. (2025). Assessment of physicochemical attributes and variation in mass-volume of Himalayan pears: Computer vision-based modeling. *Journal of Food Composition and Analysis, 137*: 106955. https://doi.org/10.1016/j.jfca.2024.106955

Silva, R. D., Amarante, C. V. T., Hermes, C. A., Marcuzzo, L. L. & Steffens, C. A. (2025). Grafting compatibility and yield in tomato genotypes under potted and aquaponic cultivation systems in the off-season. *Ciência Rural, 55*(3): e20230033. https://doi.org/10.1590/0103-8478cr20230033

Tian, S. & Xu, H. (2022). Nondestructive methods for the quality assessment of fruits and vegetables considering their physical and biological variability. *Food Engineering Reviews*, *14*(3), 380-407. https://doi.org/10.1007/s12393-021-09300-0

Zuo, H. (2022). Analysis and detection of tomatoes quality using machine learning algorithm and image processing. *International Journal of Advanced Computer Science and Applications*, *13*(12), 410-419. http://dx.doi.org/10.14569/IJACSA.2022.0131250