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APPLICATION OF NON-DESTRUCTIVE TECHNIQUES IN QUALITY ASSESSMENT OF FRUITS AND VEGETABLES DURING POST-HARVEST STORAGE

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1. INTRODUCTION

The global demand for quality fruits and vegetables has created a need for efficient and reliable postharvest quality assessment methods (Costa and Lima, 2013; Valenzuela et al., 2023). Traditional approaches, such as measuring firmness, weight loss, or soluble solids content (SSC), are often destructive, time-consuming, and unsuitable for large-scale, real-time monitoring, leading to product waste and inconsistent quality control (Fodor et al., 2024; Palumbo et al., 2022). Non-destructive techniques address these limitations by enabling rapid, cost-effective, and continuous evaluation of entire batches, improving sorting, reducing spoilage, and extending shelf life (Abasi et al., 2018; Aline et al., 2023).

Near-Infrared (NIR) spectroscopy and machine vision systems are among the promising optical techniques. NIR spectroscopy evaluates internal quality by measuring light absorption in the 700–2500 nm range, providing information on attributes like SSC and firmness (Nicolaï et al., 2007; Tian and Xu, 2022). Laser Light Backscattering Imaging (LLBI) evaluates backscattered light to characterize internal tissue structure and surface properties (Baranyai & Zude, 2009; Qing et al., 2008). On the other hand, digital imaging with machine vision captures external attributes such as color, size, and defects (Bhargava & Bansal, 2021; Nguyen et al., 2021). These techniques are favored for industrial applications due to lower cost, faster acquisition, and adaptability compared to hyperspectral imaging (Mollazade et al., 2012; Wieme et al., 2022).

Despite their advantages, non-destructive methods face challenges, including the heterogeneous nature of fruits and vegetables, where overlapping spectral signals complicate analysis (Assaad, 2020; Paz et al., 2008). To overcome this, spectral preprocessing (e.g., Savitzky-Golay filters) and advanced wavelength selection methods (e.g., genetic algorithms) are applied (Nicolaï et al., 2007; Yao et al., 2023). When these methods are combined with chemometric models such as partial least squares regression (PLSR) and support vector machines (SVM) the accuracy of quality predictions is significantly enhanced (Yao et al., 2023; Zhang et al., 2018). These techniques are widely applied to predict various quality attributes of fruits and vegetables (Aline et al., 2023; Kashef, 2021). For instance, Liu et al. (2021) also applied PLSR to evaluate weight loss (R^2 = 0.96, RMSEP = 1.432%) and firmness (R^2 = 0.60, RMSEP = 2.453 N) in Chinese mini cabbage. Qing et al. (2007) demonstrated that LLBI combined with PLSR could predict fruit firmness with R^2 = 0.81 and RMSEP = 5.44 N. Thus, NIR spectroscopy, LLBI, and calibration models were applied to assess the postharvest quality of popular Hungarian fruits and vegetables, including asparagus, plums, and apples

2. RESEARCH OBJECTIVES

The objective of the work was to apply non-destructive techniques to assess quality changes in fruits and vegetables during post-harvest storage. The following goals were established:

1. To develop classification and prediction models using optimized and full NIR spectra to detect quality changes during storage
   - Applying different linear and non-linear models using the full spectral range provided by the handheld near-infrared (NIR) spectrometer (900–1700 nm).
   - Optimizing the full NIR spectra by analyzing the standard deviation (SD) of the normalized spectra and selecting high-SD wavelengths for multispectral analysis.
2. To compare different mathematical models in Laser light backscattering imaging (LLBI) for describing the signal and utilizing model coefficients for classification and prediction models
   - Emitting multispectral laser diodes (532–1064 nm) onto the sample surface and acquiring backscattering images.
   - Extracting features and characterizing peaks using various theoretical mathematical models.
   - Optimizing wavelengths based on the analysis of variance (ANOVA) of the extracted model coefficients.
   - Comparing the performance of both beam and line-based LLBI systems at a specific wavelength
3. To evaluate the applicability of the developed techniques for assessing quality changes in asparagus, plum, and apple during post-harvest storage
   - Applying reference measurement methods to investigate changes in quality attributes such as weight loss, firmness, SSC, and color in samples stored under different time and temperature conditions.
   - Applying the developed LLBI and NIR techniques to monitor quality changes in asparagus, plum, and apple during post-harvest storage.

3. MATERIALS AND METHODS

3.1 Materials

This study evaluated the postharvest quality of three horticultural products of plum, asparagus, and apple were collected from commercial orchards located in Csengőd, Kiskőrös, and Dunaszentmiklós, Hungary. After harvest, the fruits and vegetables were packed in polypropylene crates and transported to the Laboratory of the Department of Food Measurement and Process Control, Institute of Food Science and Technology, at the Hungarian University of Agriculture and Life Sciences. Upon arrival, all samples were inspected for uniform size, ripeness, and defects.

Initially, a total of 1,300 samples were used. This included 120 green asparagus spears (Eros') with an average mass of 36.88 ± 4.59 g, length of 20.42 ± 0.58 cm, diameter of 11.94 ± 3.52 mm, and firmness at the base, middle, and tip of 15.01 ± 2.78 N, 12.86 ± 3.64 N, and 10.86 ± 1.09 N, respectively. Additionally, 1,020 plums (510 per cultivar) were analyzed, with average firmness of 45.76 ± 6.97 N ('Stanley') and 44.74 ± 5.83 N ('Elena'), and SSC of 14.50 ± 1.03% and 14.95 ± 0.52%, respectively. Furthermore, 160 'Granny Smith' apples were evaluated, with SSC of 10.75 ± 1.09%, an average height of 72.97 ± 3.66 mm, a width of 66.25 ± 4.36 mm, and a starch index of 4.81 ± 0.83.

Storage conditions were tailored for each product. Asparagus samples were randomly divided into three groups, packed in low-density polyethylene (LDPE) plastic bags with ventilation holes. They were stored at 2 °C, 10 °C, and 15 °C for 12 days. Each plum cultivar was divided into four groups and stored at 1 °C, 5 °C, 10 °C, and 15 °C for 24 days. Apples were divided into two groups and stored at 2 °C for up to 27 weeks and at 22 °C for 5 weeks.

Relative humidity (RH) in the storage was measured using a Sain Lang humidity meter and DL-120TH Voltcraft data loggers. Cold storage conditions (1–10 °C) were 90–95% RH, while ambient storage (22 °C) was 60–65% RH. Some samples in each treatment were removed from the experiment before the scheduled measurement due to decay. Decayed fruits were excluded from the groups in accordance with Regulation (EU) No 543/2011 (Article 3, Annex I, Part A).

3.2 Measurement of Quality Attributes

3.2.1 Ethylene Production

Ethylene production was measured by placing a standardized quantity of produce (typically 1 kg) in a hermetically sealed container. The container was sealed for one hour, after which the accumulated ethylene gas concentration was recorded using an ICA-56 hand-held ethylene analyzer (International Controlled Atmosphere Ltd., United Kingdom). The results were expressed as the volume of ethylene produced per kilogram of produce per hour (µL/kg·h).

3.2.2 Respiration Rate

The respiration rate was determined by placing produce (typically 1 kg) inside a sealed polymethyl methacrylate (plexiglass) container equipped with FY A600-CO2H carbon dioxide (CO_2) sensors connected to an Almemo 3290-8 data logger (Ahlborn Mess- und Regelungstechnik GmbH, Germany). The container was sealed to maintain a controlled environment, and CO_2 levels were recorded after one hour. Results were expressed as the volume of CO_2 produced per kilogram of produce per hour (mL/kg·h).

3.2.3 Weight Loss

Weight loss of fresh produce was determined using a digital balance (WLC 2/A2, RADWAG, Radom, Poland). The initial weight of each sample was recorded, followed by subsequent measurements over time. Weight loss was calculated as the percentage difference between the current and initial weights, relative to the initial value. The weighing method varied by produce type: green asparagus and Granny Smith apples were weighed individually, while plums were weighed in groups (20 fruits per group).

3.2.4 Firmness

Asparagus

The firmness of asparagus samples was measured using a texture analyzer (TA-XTplus, Stable Microsystems, Surrey, UK) equipped with a blade cutter (HDP/BSK). The test speed was set to 1 mm/s with a 0.01 s data acquisition delay. Ten asparagus spears were tested at every 4-day interval per storage temperature group. Maximum force (N) was recorded at three positions: base, middle, and tip.

Plum

Firmness was measured using a portable fruit firmness tester (FT 327, T.R. Turoni srl, Forlì, Italy) equipped with a 7.9 mm cylindrical probe. The probe penetrated the peeled plum tissue to a depth of 2 mm. Maximum force (N) was recorded on two opposite sides of each fruit. Twenty fruits were measured every 4 days across four storage temperature groups

Apple

Apple firmness was measured using a handheld fruit firmness tester (FT 327, T.R. Turoni srl, Forlì, Italy) mounted on a vertical stand for stability. A 7.9 mm cylindrical probe penetrated the peeled apple tissue to a depth of 10 mm. Maximum force (N) was recorded at three equatorial positions on each fruit. Twenty apples were measured every 9 weeks under cold storage (2 °C) and every 2 weeks at room temperature (22 °C)

3.2.5 Soluble Solid Content (SSC)

SSC was measured using a handheld refractometer (PAL-1, Atago Co. Ltd., Tokyo, Japan; 0–53% range). Juice was extracted from each fruit, clarified of pulp, and one drop was placed on the prism to record °Brix. Twenty plums were measured every 4 days across four storage temperatures, while twenty apples were sampled from each temperature group every 2 weeks at room temperature and every 9 weeks under cold storage.

3.2.6 Peel Color

Minolta Chroma Meter

Plum peel color was measured using a Minolta Chroma Meter CR-400 (Minolta Corporation, Osaka, Japan) calibrated with a standard white plate (CR-A43). Measurements were taken at two opposite equatorial points per fruit. CIE parameters (L*, a*, b*) were recorded. Chroma (C*) was calculated as $\sqrt{(a^2+b^2)}$, and hue angle as $\tan^{-1}(b^*/a^*)$.

Computer Vision

A computer vision (CV) system was used to monitor peel color changes in asparagus and apples during storage. The system consisted of a high-performance color digital camera (Hitachi HV-C20 3CCD, Tokyo, Japan) operated in manual mode with default settings. The color temperature was 3200 K and was used for image acquisition. The camera was mounted 60 cm above the sample chamber, positioned perpendicular to the surface of the samples to ensure consistent top-down imaging and eliminate perspective distortion. LED lights (1m/1m LED light strips, 30LEDs, 2.8W) were arranged in a circular configuration around the inner ceiling of the chamber, providing uniform and diffuse illumination. This setup minimized shadows and reflections, ensuring consistent lighting across all samples. The color change in asparagus and apples during storage was evaluated. Four to five samples were placed on a white background, which also served as a color reference. Images were captured at a resolution of 768 × 576 pixels and processed using Scilab software (version 2024.0.1), following the image analysis method described by Nguyen et al. (2021). The IP_hue spectra were extracted from each image and used to quantitatively evaluate color changes at different storage times and temperatures. It is a weighted histogram of hue angle and a summary of saturation over the captured image. The color change of the samples is represented by the displacement of the peaks. The root mean square error (RMSE) was calculated between the IP_hue spectra curve of consecutive measurement days using the following formula:

$$RMSE_{A-B} = \sqrt{\frac{\sum_{i=1}^{n}(A_i - B_i)^2}{n}}$$

where A_i and B_i represent the saturation values at the i^{th} hue degree for two consecutive measurement days, and n is the total number of hue degrees (typically 360).

3.3 Non-destructive measurement techniques

3.3.1 NIR spectroscopy (NIR)

NIR Spectra Acquisition

A handheld near-infrared (NIR) spectrometer (NIR-S-G1, InnoSpectra Co., Hsinchu, Taiwan) was used to collect absorption spectra in the 900–1700 nm wavelength range, with a spectral resolution of 4 nm. The device is based on digital light processing (DLP) technology and operates in reflectance mode. It features compact optics and is equipped with both Micro USB and Bluetooth Low Energy (BLE) interfaces, allowing data transfer either via USB or wirelessly to smartphones, tablets, or personal computers. Spectral acquisition was performed using the manufacturer's software (NIRScan) under ambient laboratory conditions. The device is internally calibrated and does not require an external white reference tile, as calibration is automatically managed by the internal system. During measurement, asparagus spears were positioned horizontally, and spectra were collected from three distinct locations along each spear: the base, middle, and tip. This approach was used to capture spatial variation in tissue composition along the spear. For plums and apples spectral data were collected from both opposite sides at the equatorial region. At each measurement location, two scans were taken for asparagus and three for plums and apples to ensure repeatability and reliability. During scanning, the measurement window was fully covered by the sample surface to maintain a consistent contact area and minimize external light interference.

Pre-processing of NIR spectra

The spectral data were pre-processed using several techniques to correct physical and chemical effects, such as non-zero baselines and scatter. These methods included Savitzky-Golay (SG) smoothing (i.e., polynomial, n=3 and window size, m =21) to reduce noise and Standard Normal Variate (SNV) to correct for scatter effects. These pre-processing techniques were applied to green asparagus, plums, and apple experiments to improve the quality of the spectra for subsequent analysis.

Selection of sensitive wavelengths

In this study, sensitive wavelengths were selected using a filter-based variable selection approach. The acquired spectra were pre-processed using SNV to remove the noise that is potentially produced by specular reflection and the device. The standard deviation of the normalized spectra was calculated column-wise to identify local maxima values, and significant wavelengths were manually selected. These wavelengths were considered important because they corresponded to changes in quality parameters such as WL, firmness, and SSC. Their relevance was further confirmed by calculating quality indices, including the normalized difference index (NDI) and quality index (QI), at the selected wavelengths. The reference wavelength was chosen based on the minimum standard deviation of the normalized full spectrum.

$$NDI = \frac{A_{selected} - A_{reference}}{A_{selected} + A_{reference}}, \qquad QI = \frac{A_{selected}}{A_{reference}}$$

Where $A_{selected}$ is NIR absorbance at the selected wavelength(s), $A_{reference}$ is NIR absorbance of the reference wavelength. These indices were linked to quality parameters such as weight loss (WL), firmness, and SSC.

3.3.2 Laser light backscattering imaging (LLBI)

In this method, a laser light illuminates a point and line on the fruit's surface in a dark chamber, and the resulting light scattering provides valuable information about the fruit's mechanical and textural properties

Laser Module and Camera Specifications

Beam-based LLBI

A laser beam imaging system with a 12-bit/pixel monochrome CMOS camera (MV1-D1312, Photon Focus, Lachen, Switzerland) with default settings was used to generate diffusely reflected signals. Laser diodes (3 mW) emitting at 532, 635, 780, 808, 850, and 1064 nm were used. The incident angle of the laser beams was set to 15°, focused within a circular area of Ø1 mm. Image acquisition was performed in a dark chamber to minimize external light interference and improve the signal-to-noise ratio. The system captured images at a resolution of 0.113 mm/pixel and a size of 512 × 512 pixels. The images were stored in raw binary format for analysis.

Line-Based LLBI

A line laser imaging system was implemented to monitor quality changes in samples during post-harvest storage. The system comprised a dark chamber, a monochrome industrial camera (DMK38GX540-a, 1.2-inch Sony CMOS, GigE Interface (RJ45), Imaging Source, Bremen, Germany), and a 635 nm LM Laser KH93242 single-line laser module (1 mW power, 1 mm line thickness). The laser module was used to illuminate the samples, generating diffusely reflected signals for imaging. The camera lens was positioned 27 cm from the sample surface, and a laser module was mounted at an incident angle of 20° within a dark chamber to reduce direct reflections and geometric distortion. Digital images were captured at a resolution of 0.0325 mm per pixel, to ensure the spatial accuracy and minimize curvature-related distortions.

Description of LLBI profiles

An image processing algorithm was developed using Scilab (version 2024.1.0). Raw RGB image files were transformed into greyscales, resulting in a two-dimensional (2D) matrix of pixels with intensity values ranging from 0 to 255 . The incident (center) point was determined by calculating the intensity-weighted average of pixel positions. A 5-pixel-wide band crossing the incident point was selected as the region of interest (ROI). The 1D profiles were obtained from the intensity values within the ROI. Then, the profiles were modeled using the modified Cauchy distribution (CD) function (Eq. a) and modified Gaussian distribution (GD) function (Eq. b), which are mathematically expressed as follows:

$$I_C = z_{1c} + \frac{z_{2c}\, {z_{3c}}^2}{(x - z_{4c})^2 + {z_{3c}}^2} \qquad \text{(a)}$$

$$I_G = z_{1g} + z_{2g} \exp\left(-\frac{(x - z_{4g})^2}{2\, {z_{3g}}^2}\right) \qquad \text{(b)}$$

Where I_C and I_G denotes estimated light intensity; x denote the picture width ; z_{1c} and z_{1g} are the baseline intensity; z_{2c} and z_{2g} are amplitude; z_{3c} and z_{3g} are shape factors; and z_{4c} and z_{4g} are the locations of the peaks of the CD and GD functions. The coefficient parameters of the intensity profile were extracted using a signal approximation approach based on modified Cauchy distribution and Gaussian distribution function models. The coefficients derived from the model demonstrated strong performance in characterizing intensity profiles and were used to develop models for monitoring quality changes.

Image processing and feature extraction

The collected laser signal images were processed using a developed algorithm using Scilab software (version 2024.1.0, Dassault Systèmes, Vélizy-Villacoublay, France). The coefficient parameters of the intensity profile were extracted using a signal approximation approach based on modified Cauchy distribution and Gaussian distribution function models. The coefficients derived from the model demonstrated strong performance in characterizing intensity profiles and were used to develop models for monitoring quality changes.

3.4. Experimental design

3.4.1 Quality assessment of green asparagus during post-harvest storage

Storage treatment

The LDPE-packed green asparagus spears (Eros') were stored at three different temperatures (2 - 10 ℃ with 90-95 RH% and 15 ℃ with default RH%). Measurements were taken at 4-day intervals, with 10 samples tested from each group at each time point. The samples were kept at room temperature for 12 h to maintain the surface temperature of the samples the same as the room temperature. First, non-destructive measurements were performed on each spear at three positions of the base, middle, and tip. Afterward, destructive analyses were conducted on the same tested spears, which were then removed from the sample pool.

Measurement

The weight loss and firmness of the green asparagus spears were measured using the methods described in Sections 3.2.3 and 3.2.4, respectively. The device used for NIR and the system for LLBI evaluations are detailed in Sections 3.3.1 and 3.3.2

NIR spectroscopy

NIR spectra were collected non-destructively from three positions (base, middle, tip) of each spear. Spectra were preprocessed with SG and SNV, the standard deviation was computed of the normalized spectra, and peak wavelengths were manually selected. NDI and QI were calculated to assess sensitivity. The dataset (684 samples) covered four storage times (0, 4, 8, 12 days) and three temperatures (2 °C, 10 °C, 15 °C), split into 80% training and 20% validation. Classification models (PLS-DA, LDA) and prediction models (PLSR, SVM) were built using full and selected spectra. Model performance was evaluated using accuracy, sensitivity, specificity, precision, F-score, R^2, RMSE, and RPD, with reliability confirmed by 100 bootstraps.

Line LLBI

Line-based LLBI was conducted at the wavelength of 635 nm, capturing three LLBI images from the base, middle, and peak of each asparagus spear. The Cauchy curve fitting method extracted LLBI parameters (i.e, amplitude, shape and FWHM) from the LLBI profile. A total of 344 observations were collected from asparagus spears stored at 2 °C, 10 °C, and 15 °C. MVR and MARS models were developed to predict weight loss and firmness, while LDA was applied to evaluate quality changes in the asparagus. The dataset was randomly split into two subsets, with 80% used for training and 20% for validation. Bootstrapping with 100 repetitions was performed to evaluate model performance, generating statistical metrics such as mean and 95% confidence intervals for R^2, RMSE, and RPD.

3.4.2 Quality assessment of Plums during post-harvest storage

Storage treatment

Two plum cultivars (Stanley' and 'Elena') were used in the study. A total of 510 fruits were selected for each cultivar, of which 30 were used for initial measurements. The remaining 480 fruits were randomly divided into four temperature groups (1 -10 °C with 90-95 RH%, and 15 °C) and stored for 24 days. Storage duration was recorded in days. On each measurement day, 20 fruits were taken from each temperature group, and they were kept for 12 h before the measurement to maintain the sample's surface temperature the same as the room temperature. Moreover, some groups were terminated early due to decay.

Measurements

The physiological and quality changes of the plums were measured using the methods described in Sections 3.2.1 to 3.2.6. The device used for NIR and the system for LLBI evaluations are detailed in Sections 3.3.1 and 3.3.2.

NIR spectroscopy

Spectral data were collected from both sides of each fruit with three consecutive scans. Full raw spectra were preprocessed using SNV. The standard deviation of the normalized spectra was calculated to identify local maxima, and the prominent wavelengths were manually selected for model development. NDI and QI indices were also calculated for these wavelengths to validate their sensitivity. PLSR and SVM models were developed and compared using both full spectra and selected wavelengths to predict WL and SSC. The data set consisted of a total of 2965 observations, including 1649 observations for 'Stanley' and 1316 observations for 'Elena'. Each dataset (i.e, two-cultivar and cultivar-specific) was randomly split into two subsets, with 80% used for training and 20% for validation. Bootstrapping with 100 repetitions was applied to evaluate model performance, providing statistical metrics such as the mean and 95% confidence intervals for R^2, RMSE, and RPD.

Beam LLBI

Beam-based LLBI was applied to the surface of plum fruits, capturing two LLBI images from both sides of each fruit across six wavelengths (532, 635, 780, 808, 850, and 1064 nm). The optimized wavelengths were identified through ANOVA and Tukey's post hoc analysis, which highlighted the wavelengths most sensitive to quality variations. A total of 1,276 observations were collected, comprising 569 observations from the 'Stanley' cultivar and 707 observations from the 'Elena' cultivar. LDA models were applied to classify samples based on storage time, effectively detecting quality changes throughout the storage period. Additionally, MVR models, utilizing two LLBI parameters at optimized wavelengths, were used to predict firmness, soluble solids content (SSC), and skin color for both cultivars. Bootstrapping with 100 repetitions ensured robust performance metrics (R^2, RMSE, and RPD) with 95% confidence intervals, demonstrating reliable model stability.

3.4.3 Quality assessment of apple during post-harvest storage

Storage treatment

Similar to green asparagus and plums, the assessment of quality changes in ‘Granny smith’ using NIR spectroscopy and LLBI techniques during postharvest storage was performed. A total of 160 apple samples were randomly divided into two groups. The first part was stored at room temperature (22 °C with 60-65 RH%) for 5 weeks and sampled at 2-week intervals. The second part apples were stored under cold conditions (2 °C with 90-95 RH%) for 26 weeks, followed by 1 week at 22 °C for shelf life, with sampling conducted at 9-week intervals.

Measurement

The physiological and quality changes of the ‘Granny Smith apples were measured using the methods described in Section 3.2.1. to 3.2.6 The device used for NIR and the system for LLBI evaluations are detailed in Sections 3.3.1 and 3.3.2

NIR Spectroscopy

A handheld NIR spectrometer (900–1700 nm) collected spectra from two opposite locations around the equator of each apple, with three consecutive scans per location. Spectra were preprocessed using SG smoothing and SNV. The significant wavelengths were identified from column-wise standard deviations. Additionally, NDI and QI indices for these wavelengths were calculated to confirm their sensitivity. PLSR and SVM models were developed using both the full spectra and the selected wavelengths, and their performance was compared. A total of 834 observations were collected. This dataset was randomly divided into two sheets, with 80% used for training and 20% for validation. Bootstrapping with 100 repetitions was employed to assess model performance, providing statistical metrics such as the mean and 95% confidence intervals for R^2, RMSE, and RPD, ensuring robust and reliable evaluation of the models.

Line LLBI

In the line-based system, LLBI images were captured from two opposite locations at the equatorial surface of each apple. The LLBI profile at 635 nm was fitted with the modified Cauchy Distribution (CD) model, and three parameters (i.e., amplitude, shape, and FWHM) were extracted from both the beam- and line-based systems. These parameters were used to develop the MVR and SVM models. A total of 643 observations were collected from both systems (line: n = 382; beam: n = 261). The dataset was randomly divided into two subsets, with 80% used for training and 20% for validation. Bootstrapping with 100 repetitions was performed, and model performance metrics (R^2, RMSE, and RPD) were evaluated using t-tests with 95% confidence intervals.

3.5 Data analysis

The data analysis provides a comprehensive framework for the spectral analysis of horticultural products, employing both classification and prediction techniques to effectively assess and manage fruit quality. This integration of advanced spectral analysis with multivariate statistical methods enables precise control and improvement of post-harvest handling and processing procedures. In this dissertation, basic descriptive statistics on the quality parameters of the fresh produce during treatments were presented in plots, Analysis of Variance (ANOVA) was used to evaluate the effects of the treatments on these parameters. Moreover, classification and prediction models were applied to assess the association between quality parameters and the laser and NIR spectral variables. Partial Least Squares Discriminant Analysis (PLS-DA) and Linear Discriminant Analysis (LDA) were established to classify the samples based on their treatment groups, utilizing the 'plsdepot' (version 0.2.0) and 'mda' (version 0.5-3) packages. Additionally, Partial Least Squares Regression (PLSR), Multivariate Regression (MVR) Support Vector Machine Regression (SVM) and Adaptive Regression Splines (MARS) were built to predict the quality attributes of the samples using the 'pls' (version 2.8-2), 'aquap2' (version 0.4.2), 'e1071' (version 1.7-13), 'earth' (version 5.3.3) packages, respectively. All statistical analyses were performed using R software (version 4.2.3, R Foundation for Statistical Computing, Vienna, Austria).

4. RESULTS

4.1 Quality assessment of green asparagus during post-harvest storage

This section presents the results of NIR spectroscopy and line-based LLBI techniques used to monitor quality changes in green asparagus during storage. For NIR spectroscopy analysis, a total of 684 observations were generated by acquiring spectral data at three positions (base, middle, and peak) on each spear, using two scans per position. The collected spectra were preprocessed using standard normal variate (SNV), and five prominent wavelengths were manually selected based on the standard deviation of the normalized spectra. Normalized difference index (NDI) and quality index (QI) were calculated to validate the sensitivity of these wavelengths. Classification models (PLS-DA, LDA) and prediction models PLSR and SVM were developed using both full spectra and the spectra at selected wavelengths to evaluate changes in asparagus quality. PLS-DA was implemented using the 'plsdepot' package (version 0.2.0), while LDA was performed using the 'mda 'package (version 0.5-3) in R. For LLBI, 344 observations were obtained by capturing images at 635 nm from the same three positions on each spear. LLBI parameters (i.e., amplitude, shape and FWHM) were extracted using Cauchy curve fitting. MVR using 'pls' (version 2.8-2), and MARS with 'earth' (version 5.3.3) package in R. The models were developed to predict weight loss and firmness, while LDA was used to detect quality changes over time for the samples stored at different storage temperature groups. All datasets were randomly split into training (80%) and validation (20%) subsets. Model performance was evaluated using bootstrapped metrics (R^2, RMSE, RPD) with 95% confidence intervals

4.1.1 Weight loss

The influence of storage temperature and duration on weight loss in green asparagus was significant. As storage time increases from 0 to 12 days, weight loss rises across all temperature groups, with the highest losses observed at 15 °C, followed by 10 °C, and the lowest at 2 °C. This trend indicates that higher temperatures accelerate moisture loss, likely due to increased respiration and transpiration rates. ANOVA also confirmed that the effects of both storage temperature (F-value = 655.347) and time (F-value = 2014.46) were significant ($P < 0.001$). The weight loss increased progressively during storage and is mainly attributed to water loss by transpiration due to differences in water vapor pressure between the atmosphere and the asparagus surface.

4.1.2 Firmness

The firmness of asparagus spears from the base section increased notably over time across all storage temperatures (2°C, 10°C, and 15°C). Initially, at day 0, the firmness values were lowest and relatively similar across all temperature treatments. However, as storage progressed, firmness increased markedly at all temperatures; moreover, the magnitude and rate of increase were more pronounced at higher temperatures. This pattern may be attributed to continued lignification and fiber development, as well as water loss and changes in cell wall structure. Furthermore, these findings were supported by ANOVA, which showed a significant effect (F-values = 862.10 and 4751.08, $p < 0.001$). In addition, significant differences in firmness were observed across spear positions ($F = 168.087$, $p < 0.001$). The base of the spears consistently exhibited the highest firmness values, particularly at 15 °C, indicating rapid lignification and moisture loss. The middle section showed intermediate firmness, increasing steadily with storage duration and temperature. In contrast, the peak remained the least firm, reflecting its naturally tender tissue and lower susceptibility to structural hardening. Therefore, it can be inferred that the degradation of organic compounds and the varying fiber content across different sections of the asparagus spear (base, middle, and tip) contribute to these observed differences

4.1.3 Peel color

The IP_hue spectra for each temperature group across their respective storage durations showed that shift of both the hue angles and saturation values. The IP_hue spectra at 2 °C are relatively close together for storage times of 4, 8, and 12 days, with only small changes observed in the peak position as storage time increased. This indicates that asparagus color remains relatively stable over time at low temperatures. In contrast, at 10 °C, there is a noticeable separation between the curves, with the peak shifting slightly and a gradual decrease in overall saturation as storage time increases. This suggests moderate color changes and some loss of visual quality at this intermediate temperature. At 15 °C, the separation between curves for different storage durations becomes much more pronounced. There is a larger decrease in saturation at hues with prolonged storage, and the peak position shifts more than at the lower temperatures. The RMSE values between consecutive measuring days further support these observations. At 2 °C, RMSE values remain very low, confirming that only minimal color changes occur during storage at this temperature. In contrast, at both 10 °C and 15 °C, RMSE values are noticeably higher, particularly over longer storage periods. This indicates that color stability is greatly reduced at higher temperatures, with asparagus losing color quality. This is attributed to the loss of its freshness.

4.1.4 NIR spectroscopy

Spectral description

The prominent wavelengths with higher standard deviations were 907 nm, 923 nm, 1069 nm, 1442 nm, and 1696 nm, reflecting quality changes in the spears. Their sensitivity was further confirmed by the Normalized Difference Index (NDI) and Quality Index (QI) parameters. For example, the NDI of 1696 nm vs 1252 nm changes its values with time and temperature, likely due to increased metabolic and enzymatic activity. Moreover, a significant correlation was observed between NIR absorbances at specific wavelengths, such as between NIR-907 and NIR-1069 ($r = 0.998$). Both NIR-907 ($r = 0.928$) and NIR-1069 ($r = 0.923$) exhibit significant correlations with firmness. Similarly, a significant correlation is observed between NIR absorbance at these wavelengths and weight loss ($r = 0.829$). The absorbance at longer wavelengths, such as NIR-1442 and NIR-1696, exhibited moderate correlations with firmness ($r = 0.453$ and $r = 0.607$, respectively) and weaker correlations with weight loss ($r = 0.233$ and $r = 0.439$, respectively). This can be attributed to the ability of longer wavelengths to penetrate deeper into the tissue, capturing more complex structural changes, as well as their exposure to spectral overlap within the absorption bands.

Quality change detection over storage time

The comparative evaluation of partial least squares discriminant analysis (PLS-DA) and linear discriminant analysis (LDA) models for detecting quality changes in green asparagus stored at 15 °C, assessed at four-day intervals (0, 4, 8, and 12 days). Both models were constructed using five latent variables; however, PLS-DA utilized the full NIR spectral range, while LDA was developed using a set of selected wavelengths. The LDA model demonstrated superior performance compared to PLS-DA, achieving detection accuracies of 76.9% at 15 °C, 74.3% at 10 °C, and 60.4% at 2 °C. The improved performance of the LDA model is attributed to feature selection, which reduces spectral noise and highlights the most discriminative wavelengths. However, detection accuracy declined at lower storage temperatures (e.g., 2 °C), likely because slower physiological changes in asparagus produced less distinct spectral differences between storage intervals.

Quality detection over temperature-induced variation

On the other hand, the quality detection efficiency of the PLS-DA and LDA models for green asparagus stored at three different temperatures (2°C, 10°C, and 15°C) on the 12th day of storage. Both models were constructed using five latent variables (LV = 5). The PLS-DA model, which used the full NIR spectrum, achieved a mean accuracy of 42.8%. In contrast, the LDA model, constructed using a set of selected wavelengths, demonstrated enhanced performance. The LDA model achieved an accuracy of 87.7%.

Prediction of Weight Loss and Firmness

The performance of PLSR and SVM models using the full NIR spectra and spectra at selected wavelengths for predicting weight loss (%) and firmness (N) in green asparagus. The SVM model showed relatively improved predictive accuracy when using selected wavelengths compared to the PLSR model for both parameters. For weight loss, the model achieved R^2 = 0.768, RMSE =5.690 %, and RPD = 2.080. For the firmness, the model achieved R^2 = 0.829, RMSE = 5.380 N, and RPD =2.322. These results indicate that focusing on informative spectral regions combined with nonlinear regression models enhances model performance.

4.1.5 Laser light backscattering imaging (LLBI)

LLBI Profile Description

The amplitude, shape, and FWHM parameters of the LLBI profile were extracted using the Cauchy model. The average curve-fitting efficiency across all sample images (n = 344) demonstrated that the modified Cauchy model achieved R^2 = 0.78 and RPD = 2.29, performing better than the Gaussian model, which exhibited lower efficiency with R^2 = 0.53 and RPD = 1.96. The LLBI parameters extracted from the modified Cauchy model were used for further analysis. The amplitude and shape parameters consistently increase with both time and temperature. Amplitude values indicate scattering intensity, while the shape parameter reflects the light distribution size within the asparagus tissue. These changes would be related to physiological processes like water loss, cell wall degradation, and tissue senescence. ANOVA results also indicated significant effects of storage time on amplitude ($F = 641.172$, $p < 0.001$) and shape ($F = 431.757$, $p < 0.001$). Pearson's correlation analysis shows strong correlations between amplitude and shape ($r = 0.816$), amplitude and weight loss ($r = 0.809$), and shape with firmness ($r = 0.928$).

Quality detection over storage time

To evaluate the effect of storage time on green asparagus quality, an LDA model using the three LLBI parameters was developed, considering all temperature groups. The model achieved an overall detection accuracy of 79.7%. However, performance improved when calibrated for individual temperature groups: at 2 °C, the validation accuracy was 81.4%; at 10 °C, it increased to 89.6%; and at 15 °C, it reached 93.4%.

Prediction of Weight Loss and Firmness

The comparative regression model results demonstrate the prediction of weight loss and firmness using LLBI parameters combined with both multivariate regression (MVR) and multivariate adaptive regression splines (MARS). The MARS model outperformed the MVR model in predicting both weight loss ($R^2 = 0.846$, RMSE = 6.401%, RPD = 2.558) and firmness ($R^2 = 0.927$, RMSE = 3.266 N, RPD = 3.775).

4.2 Assessment of quality changes in plums during post-harvest storage

In this section, the results obtained from physiological assessments, near-infrared (NIR) spectroscopy, and beam-based LLBI techniques are presented to evaluate the quality attributes of plum fruits during storage. For NIR spectroscopy analysis, a total of 2,965 observations were produced by acquiring spectral data from both sides of each fruit using three consecutive scans, followed by SNV preprocessing and manual selection of five prominent wavelengths. NDI and QI indices were calculated to validate spectral sensitivity. PLSR and SVM models were developed using the R packages 'pls' (version 2.8-2) and 'e1071' (version 1.7-13), respectively. These models were calibrated using both the full spectra and selected wavelengths to predict weight loss and soluble solids content in green asparagus. For LLBI, 1,276 observations were obtained by capturing images at six wavelengths (532, 635, 780, 808, 850, and 1064 nm) from both sides of each fruit. Optimized wavelengths were identified through ANOVA and Tukey's post hoc analysis. LDA and MVR models were used to detect the quality changes by classifying samples into their storage time groups and predicting firmness, SSC, and skin color, respectively. The datasets included samples from two cultivars (Stanley' and 'Elena') and were split into training and validation subsets. Model performance was evaluated using bootstrapped metrics (R^2, RMSE, RPD) with 95% confidence intervals.

4.2.1 Ethylene production

The rate of ethylene production increased with both storage temperature (F-value = 321.80 and 109.11; $P < 0.001$) and storage time (F-value = 170.42 and 69.03; $P < 0.001$) in both 'Stanley' and 'Elena' plums. However, the ethylene production of plums stored at 1 °C significantly differed from those stored at higher temperatures. The 'Stanley' plums showed a relatively higher rate of ethylene production than the 'Elena' plums.

4.2.2 Respiration rate

The respiration rate of both 'Stanley' and 'Elena' plums increased with both storage temperature (F-value = 195.04 and 565.46; $P < 0.001$) and storage time (F-value = 816.80 and 269.53; $P < 0.001$). 'Stanley' plums stored at 10 °C and 15 °C exhibited higher respiration rates compared to those stored at 1 °C and 5 °C, while 'Elena' plums showed the highest respiration at 15 °C Respiration peaked at 8 days for 'Stanley' and 12 days for 'Elena', then declined after 20 days.

4.2.3 Weight loss

The changes in plum weight loss (WL) at different storage temperatures and times. The effect of time and temperature was more pronounced in 'Stanley' plums compared to 'Elena'. ANOVA analysis confirmed that both storage time and temperature significantly impacted WL ($F = 6.06 \times 10^{28}$ and 1.88×10^{28}; $p < 0.001$), with significant differences between the two cultivars ($F = 1.21 \times 10^{28}$; $p < 0.001$). WL variation was higher after 12 days, primarily due to increased water loss as the fruit ripened. The variation in plums' weight loss is influenced by storage temperature and duration, which accelerate enzymatic activities that enhance ripening due to increased respiration rates.

4.2.4 Firmness

The firmness of the plums declined steadily over time for both plum cultivars. Samples stored at 15 °C exhibited the shortest shelf life, followed by those stored at 10 °C, indicating that higher temperatures accelerated softening. ANOVA confirmed that storage time ($F = 8992.12, p < 0.001$), storage temperature ($F = 1927.80, p < 0.001$), and cultivar differences ($F = 3142.06, p < 0.001$) all had significant effects on firmness. These findings suggest that firmness loss may be driven by storage conditions and inherent cultivar traits. The faster decline in firmness at higher temperatures reflects the acceleration of ripening and softening processes, while cooler storage slows these changes and better preserves fruit texture.

4.2.5 Soluble solid content (SSC)

Soluble solids content (SSC) increased significantly with both storage time and temperature (ANOVA: $F_{time} = 124{,}779.90$, $F_{temperature} = 4{,}632.10$, $p < 0.001$), and there were also significant differences between cultivars ($F_{cultivar} = 250{,}701.30$, $p < 0.001$). Higher storage temperatures accelerated SSC accumulation, with samples stored at 15 °C exhibiting the highest SSC values. These results indicate that SSC is influenced by both physiological changes and storage conditions. Higher SSC reflects greater sweetness and ripeness, but rapid increases at elevated temperatures may accelerate overripening and shorten shelf life. Maintaining lower storage temperatures slows SSC accumulation, extending fruit quality and shelf life, while cultivar selection affects the rate and extent of sweetness development.

4.2.6 Peel Color

Chroma and hue values from the Minolta chroma device showed that both plum cultivars changed significantly during storage, with greater deviation observed at higher temperatures. The ‘Stanley’ cultivar showed a stronger decline in chroma, and more pronounced hue changes compared to ‘Elena’, indicating greater sensitivity to temperature-related color changes. Storage at lower temperatures (1 °C and 5 °C) slowed these changes, although ‘Stanley’ exhibited a sudden hue decline at 5 °C, suggesting susceptibility to water loss and accelerated ripening under certain conditions. Two-way ANOVA confirmed that chroma was most influenced by cultivar ($F = 1498.539$), followed by storage time ($F = 1433.125$) and temperature ($F = 273.025$). Hue was primarily affected by storage time ($F = 1803.530$) and temperature ($F = 244.233$). These results suggest that color changes in plums are driven by both genetic differences and storage conditions. Higher temperatures accelerate pigment transformations and ripening, while lower temperatures help preserve visual quality.

4.2.7 NIR spectroscopy

Spectral description

Sensitive wavelengths were identified at 909, 1064, 1323, 1447, and 1650 nm, which reflected physiological and biochemical changes in plums during storage. These variations may be related to sugar accumulation, water dynamics, and structural changes in fruit tissues. Two-way ANOVA showed that NDI of the selected wavelengths relative to 1532 nm was more sensitive to both time (F-value = 93.05–251.37, $p < 0.001$) and temperature (F = 16,536.74–25,347.47, $p < 0.001$). Cultivar differences were most evident at longer wavelengths (1447 nm: F = 55.71; 1650 nm: F = 37.75; $p < 0.001$). SSC significantly correlated with WL (r = 0.868) and with absorbances at 1650 nm (r = 0.803). In contrast, it was negatively correlated with absorbance at 1447 nm (r = –0.734).

Prediction of WL and SSC

SVM models outperformed PLSR in predicting soluble solids content (SSC) and weight loss (WL) of plums, with accuracy further enhanced by wavelength selection. For WL, SVM using a set of selected wavelengths achieved $R^2 = 0.917$, RMSE = 0.884%, RPD = 3.492, and for SSC, SVM achieved $R^2 = 0.844$, RMSE = 0.781%, and RPD = 2.499.

4.2.8 Laser Back Scattering Imaging

Amplitude and shape parameters at 532 nm and 780 nm were identified as the most sensitive indicators of postharvest plum quality (ANOVA: $F_{amplitude} = 623.86$, $F_{shape} = 2321.50$, $p < 0.001$). The modified Cauchy distribution provided superior model fitting ($R^2 > 0.96$, RPD > 4.5) compared to the Gaussian distribution ($R^2 < 0.70$, RPD < 4.5). At 532 nm, amplitude correlated with firmness (r = 0.607), and shape correlated significantly with color and firmness (r = 0.748 and 0.600, respectively). At 780 nm, amplitude correlated with firmness and chroma (r = 0.607 and 0.661) and negatively with SSC (r = –0.609), while shape correlated significantly with firmness and chroma (r = 0.720 and 0.670) and negatively with SSC (r = –0.570)

Plum Quality change detection over storage period

Linear Discriminant Analysis (LDA) models were initially developed by considering all temperature groups to detect storage time-related quality changes in ‘Stanley’ and ‘Elena’ plums using four LLBI parameters at 532 nm and 780 nm. The model detected quality changes with 61.3% accuracy for ‘Stanley’ and 77.3% for ‘Elena’. Performance improved when calibrated for individual temperature groups; at 1 °C, detection accuracy increased to 92.3% for ‘Stanley’ and 91.9% for ‘Elena’. Furthermore, LDA models for 5 °C storage achieved detection accuracy of 100% for both cultivars across all time points.

Prediction of quality parameters

Two-cultivar and cultivar-specific MVR models were established using four LLBI parameters to predict firmness, SSC, chroma, and hue. The two-cultivar model showed moderate performance for firmness (R^2 = 0.632, RMSE = 3.924 N, RPD = 1.653), whereas cultivar-specific models achieved higher accuracy, particularly for 'Stanley' (R^2 = 0.769, RMSE = 3.049 N, RPD = 2.084). SSC predictions followed a similar pattern, with cultivar-specific models outperforming the multi-cultivar model ('Elena': R^2 = 0.818, RMSE = 0.873%, RPD = 2.366). Color parameters from Minolta chroma also improved with cultivar-specific calibration, with chroma reaching R^2 = 0.866, RMSE = 0.634 in 'Elena' and hue R^2 = 0.731, RMSE = 16.62° in 'Stanley'. These results demonstrate that cultivar-specific calibration enhances the predictive accuracy of LLBI.

4.3. Assessment of quality changes of apples during post-harvest storage

This section also discusses the results of physiological measurement, NIR spectroscopy, and LLBI techniques applied to assess quality attributes of ‘Granny smith’ apples stored under different temperature conditions. In NIR spectroscopy analysis, a total of 834 observations were made by acquiring spectral data from two locations around equatorial part of each apple using three consecutive scans per location. The apples were rotated 180 degrees between scans to ensure full surface coverage. Spectral data in the 900–1700 nm range were preprocessed using SNV, and five significant wavelengths were manually selected based on the standard deviation of the normalized spectra. NDI and QI were computed to assess the sensitivity of selected wavelengths. PLSR and SVM models were developed using the R packages ‘pls’ (version 2.8-2) and ‘e1071’ (version 1.7-13), respectively. These models were calibrated using both full spectra and selected wavelengths to predict weight loss, firmness, and SSC. For LLBI, 643 observations were collected using both line-based (n = 382) and beam-based (n = 261) systems. LLBI images were captured at 635 nm, and the resulting profiles were fitted using the Cauchy Distribution model to extract amplitude and shape parameters. These parameters were used to develop MVR and SVM models for predicting weight loss and firmness. All datasets were randomly divided into training (80%) and validation (20%) subsets. Model performance was evaluated using bootstrapped metrics (R^2, RMSE, RPD) with 95% confidence intervals.

4.3.1 Ethylene production

The ethylene production rate in apples is strongly influenced by storage temperature and duration. Apples stored under cold conditions and later exposed to room temperature exhibited a continuous increase in ethylene production, whereas apples stored at room temperature initially increased in ethylene output but declined after two weeks. By the end of the storage period, apples under shelf-life conditions produced approximately 50 μL/kg·h of ethylene. ANOVA indicated that both storage temperature and time had significant effects on ethylene production ($F = 171.985$ and 111.961; $p < 0.001$). Cold storage suppresses immediate ethylene production but enhances the peel’s potential to produce ethylene upon warming, while higher storage temperatures accelerate ripening and ethylene emission.

4.3.2 Respiration Rate

The respiration rate in apples followed a similar pattern to ethylene production. Apples stored in cold storage and then exposed to room temperature showed an increasing respiration rate over time, while those stored continuously at room temperature increased initially and then declined. ANOVA indicated significant effects of storage temperature and time on respiration ($F = 83.665$ and 49.668; $p < 0.001$). The highest respiration rate was observed in apples subjected to cold storage followed by room temperature shelf life, peaking at 18.50 mL/ Kg.h after 27 weeks. Apples stored at cold temperatures had lower respiration (11.88 mL/ Kg.h), while those stored at room temperature peaked at 6.20 mL/ Kg.h after 2 weeks before declining.

4.3.3 Weight loss

The weight loss of apples during storage increased over time, with apples stored at cold temperatures showing lower weight loss than those stored at room temperature. ANOVA confirmed significant effects of storage time and temperature on weight loss (F-value = 571.58 and 216.57; $p < 0.001$). Higher temperatures accelerate respiration and water loss, leading to faster weight loss, while lower temperatures slow respiration and preserve freshness.

4.3.4 Firmness

The firmness of apples decreased over time under both cold storage and cold-to-ambient storage conditions. Apples stored under cold-to-ambient conditions experienced a faster reduction in firmness compared to those stored solely at ambient temperatures. ANOVA showed that both storage time ($F = 1469.8$) and temperature ($F = 2561.2$) significantly affected firmness ($p < 0.001$), with temperature having a greater impact. This trend is likely due to temperature-induced changes in cellular structure, including cell wall breakage and pectin degradation, as well as accelerated ethylene production and respiration rates during ripening. These metabolic changes contribute to tissue softening and reduced firmness over time.

4.3.5 Soluble solid content (SSC)

The SSC of apples increased over time and with rising storage temperatures. ANOVA indicated that both storage time ($F = 354.3$) and temperature ($F = 16.8$) significantly affected SSC ($p < 0.001$). The observed increase is primarily due to the conversion of starch into sugars during ripening. In cold storage, this conversion is slowed, while transfer to ambient temperatures accelerates respiration and ethylene production, resulting in a rapid rise in SSC.

4.3.6 Peel color

The hue spectra of 'Granny Smith' apples were monitored over the storage period. During early ripening (0, 2, 4, 5 weeks), RMSE values between intervals were low, with the maximum being 0.003068 (week 2 vs. week 5), indicating gradual color changes. Long-term storage (0, 8, 17, 26 weeks) showed higher RMSE values, particularly between 0–26 weeks (0.003847) and 17–26 weeks (0.002359), reflecting more pronounced spectral shifts and hue transformations. Late storage (9–27 weeks) had a maximum RMSE of 0.004004, demonstrating dynamic color changes during extended storage. These results indicate that apple color changes are gradual during early storage but become more pronounced over long-term storage, with significant shifts in hue and saturation corresponding to aging, pigment changes, and loss of freshness. Higher storage temperatures accelerate these color changes, while prolonged storage leads to greater variability in hue.

4.3.7 NIR spectroscopy

The sensitive wavelengths were identified as 908, 1080, 1358, 1450, and 1650 nm. Their sensitivity was further evidenced by NDI and QI values relative to 1531 nm as a reference. Both NDI and QI at 908–1650 nm were significantly affected by storage time and temperature, with 1650 nm showing the strongest sensitivity (NDI $F = 4346.35$; QI $F = 4579.41$; $p < 0.001$). Early in storage, NDI exhibited high variability, which decreased as the apples became more uniform. Correlation analysis confirmed that the NDI of 1650 nm vs 1531 nm was strongly associated with weight loss ($r = -0.87$), firmness ($r = 0.818$), and SSC ($r = -0.843$).

Prediction models

Comparison of PLSR and SVM models using bootstrapped validation shows that wavelength selection substantially improves prediction accuracy over full spectra. SVM consistently outperformed PLSR for weight loss, firmness, and SSC. For weight loss, PLSR with selected wavelengths achieved $R^2 = 0.893$, RMSE = 1.116%, and RPD = 3.046, while SVM further improved predictions to $R^2 = 0.955$, RMSE = 0.708%, and RPD = 4.85. For firmness, PLSR yielded $R^2 = 0.823$, RMSE = 4.545 N, and RPD = 2.39, whereas SVM achieved $R^2 = 0.958$, RMSE = 2.201 N, and RPD = 5.09. For SSC, PLSR reached $R^2 = 0.791$, RMSE = 0.440%, and RPD = 2.20, while SVM significantly outperformed it with $R^2 = 0.937$, RMSE = 0.250%, and RPD = 3.93. These results indicate that SVM combined with selected wavelengths provides better predictive accuracy for apple quality parameters, outperforming both PLSR and full-spectrum approaches.

4.3.8 Laser light backscattering imaging (LLBI)

The modified Cauchy distribution (CD) function provided good curve-fitting performance for extracting LLBI parameters, achieving $R^2 = 0.970$ and RPD = 6.08 for the beam system, and $R^2 = 0.884$ and RPD = 3.145 for the line system.

Prediction models

The three LLBI parameters extracted from modified Cauchy fitting of both line and spot illumination systems, combined with SVM models, demonstrated strong predictive performance for weight loss ($R^2 > 0.96$) and firmness ($R^2 > 0.91$). Specifically, weight loss prediction was highest with line illumination ($R^2 = 0.971$, RMSE = 0.608%, RPD = 6.035), reflecting greater sensitivity to surface changes, while firmness prediction was best with spot illumination ($R^2 = 0.940$, RMSE = 2.626 N, RPD = 4.100), due to deeper light penetration.

5. NEW SCIENTIFIC RESULTS

This study evaluated the application of non-destructive techniques to monitor quality changes in green asparagus, plums, and apples during post-harvest storage. The main scientific results from each practical experiment are presented as follows:

1. An optimum set of wavelengths (907, 923, 1069, 1442, and 1696 nm) was selected for the quality assessment of green asparagus during storage and shelf life. Linear Discriminant Analysis (LDA) using the selected wavelengths successfully detected the quality change in 4 days storage interval. The model achieved classification accuracies of 60.4% at 2 °C, 74.3% at 10 °C, and 76.9% at 15 °C. After 12 days, temperature-induced changes were detected with 87.7% accuracy. The SVM model demonstrated enhanced predictive accuracy compared to the PLSR model when calibrated using NIR spectra at selected wavelengths for predicting weight loss and firmness. The SVM model achieved R^2 = 0.768, RMSE = 5.690%, and RPD = 2.080 for weight loss, while for firmness, it achieved R^2 = 0.829, RMSE = 5.380 N, and RPD = 2.322.

2. Line-based Laser Light Backscattering Imaging (LLBI) analysis with a single laser module emitting at 635 nm was applied, and diffusely illuminated surfaces were captured from three positions (base, middle, tip) on asparagus spears. LLBI parameters of amplitude, shape, and FWHM were extracted using Cauchy curve fitting. The LDA model based on LLBI parameters detected quality changes in asparagus spears after 4 days across all temperature groups with 79.7% accuracy. For individual temperatures, accuracy was 81.4% at 2 °C, 89.6% at 10 °C, and 93.4% at 15 °C. MVR and MARS models were developed to predict weight loss and firmness. MARS outperformed MVR, and predicted weight loss with R^2 = 0.846, RMSE = 6.401%, RPD = 2.558, and firmness with R^2 = 0.927, RMSE = 3.266 N, RPD = 3.775.

3. An optimum set of wavelengths (909, 1064, 1323, 1447, 1650 nm) was selected for quality assessment of plum fruits during storage and shelf life. Using these wavelengths, PLSR predicted weight loss with R^2 = 0.738, RMSEP = 1.582%, and RPD = 1.953, and SSC with R^2 = 0.740, RMSEP = 0.980%, and RPD = 1.991. However, performance improved with the SVM model, which achieved R^2 = 0.917, RMSEP = 0.844%, and RPD = 3.492 for weight loss, and R^2 = 0.844, RMSEP = 0.780%, and RPD = 2.498 for SSC.

4. The beam based LLBI technique with a Cauchy distribution function fitted on the signal of 532 nm and 780 nm was able to detect quality changes of plum. Plums stored at 1 °C showed detectable quality changes within 4 days interval, with LDA models achieving classification accuracy of 92.3% for 'Stanley' and 91.9% for 'Elena'. For storage at 5 °C, the models reached 100% accuracy across all time points and cultivars. Cultivar-specific regression models outperformed combined models. The best cross-validation results were observed for 'Elena' (Minolta chroma-based chroma: R^2 = 0.866, RMSE = 0.634; SSC: R^2 = 0.818, RMSE = 0.873%) and 'Stanley' (firmness: R^2 = 0.769, RMSE = 3.049 N; Minolta chroma-based hue angle: R^2 = 0.731, RMSE = 16.62°).This

showed the potential of LLBI combined with multivariate models (i.e. LDA, MVR) for real-time quality assessment in postharvest handling and cold chain management.

5. Optimized wavelengths (908, 1080, 1358, 1450, and 1650 nm) were used to assess storage quality and shelf-life of ‘Granny Smith ’apples. The SVM model showed better performance than PLSR, predicting weight loss (R^2 = 0.955, RMSEP = 0.708%, RPD = 4.852), firmness (R^2 = 0.958, RMSEP = 2.201 N, RPD = 5.088), and SSC (R^2 = 0.937, RMSEP = 0.249%, RPD = 3.932).

6. LLBI technique demonstrated the effectiveness of both line and beam laser configurations on apple quality assessment. The SVM with three LLBI parameters extracted from the modified Cauchy fitting on the LLBI profile, the system demonstrated good predictive performance for both weight loss (R^2 > 0.96) and firmness (R^2 > 0.91). Hence, line-based LLBI combined with SVM enhanced its performance in predicting weight loss (R^2 = 0.971, RMSEP = 0.608%, RPD = 6.035), while the beam laser setup yielded the best results for firmness prediction (R^2 = 0.940, RMSEP = 2.626 N, RPD = 4.100).

6. CONCLUSION AND SUGGESTIONS

This study demonstrated the effectiveness of non-destructive techniques, namely machine vision, Near-Infrared (NIR) Spectroscopy, and Laser Light Backscattering Imaging (LLBI in monitoring the post-harvest quality of green asparagus, plums, and apples. By integrating spectral and imaging data with advanced chemometric models such as PLSR, SVM, MVR, and MARS, the research successfully predicted key quality parameters, including weight loss, firmness, soluble solids content (SSC), and peel color. The optimized multispectral approach, using selected wavelengths, significantly improved model accuracy and reduced computational complexity compared to full-spectrum analysis. LLBI, particularly when combined with modified Cauchy distribution modeling, proved that it is sensitive to internal structural and surface changes in produce during storage. Together, these tools support early spoilage detection, better inventory control, and optimized cold chain management. However, Further testing on other horticultural products and quality attributes, along with improved spectral and image processing algorithms, could broaden their application

7. LIST OF PUBLICATIONS IN THE FIELD OF STUDY

Siyum, Z.H., Pham, T.T., Sao Dam, M., Friedrich, L.F., Hitka, G., Nguyen, L.L.P. and Baranyai, L., 2024. Assessment of plum quality changes during postharvest storage using multispectral NIR technique. *Journal of Agriculture and Food Research*, *18*, p.101476. http://doi.org/10.1016/j.jafr.2024.101476 **(Q1)** 2024

Siyum, Z.H., Pham, T.T., Vozáry, E., Kaszab, T., Nguyen, L.L.P. and Baranyai, L., 2023. Monitoring of banana's optical properties by laser light backscattering imaging technique during drying. *Journal of Food Measurement and Characterization*, *17*(5), pp.5268-5287. http://doi.org/10.1007/s11694-023-02019-y **(Q2)** 2023

Siyum, Z.H., Pham, T.T., Nguyen, L.L.P. and Baranyai, L., 2023. Non-destructive monitoring of asparagus (Asparagus officinalis, L) quality changes during storage using NIR spectroscopy. *International Journal of Food Science and Technology*, *58*(11), pp.5972-5981. http://doi.org/10.1111/ijfs.16704 **(Q1)** 2023

Pham, T. T., Siyum, Z. H., Ha, T. T. N., Mac, H. X., Dam, S. M., Nguyen, T. H. D., Nguyen, L. L. P., & Baranyai, L. (2023). Evaluating the quality of green asparagus treated with cassava starch-based coating using laser scattering. Progress in Agricultural Engineering Sciences, 19(S1), 59-68. https://doi.org/10.1556/446.2023.00083 **(Q3)** 2023

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