

Article

Effects of Harvest Timing on Navel Orange Quality During Storage Using Hand-Held NIRS

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Abstract

This study investigated the influence of harvest timing on the quality of navel oranges by the use of hand-held near-infrared spectroscopy (NIRS) device. ‘Newhall’ navel oranges were harvested in seven batches from 200 to 249 days after full bloom (DAFB). The samples were stored under cold storage (5 °C) and at room temperature (25 °C), respectively. Harvest-stage SSC and weight loss during storage were analyzed, and SSC-related trends in stored fruit were further evaluated at the 49-day endpoint. The results indicated that cold storage helped reduce weight loss in navel oranges. SSC exhibited a trend of increasing first and then decreasing with harvest date, reaching a peak at DAFB of 228. The NIRS model corrected by external parameter orthogonalization (EPO) achieved the best prediction performance for SSC, with $R^2_p = 0.60$, RMSEP = 1.38%, and RPD = 1.58 under room temperature, and $R^2_p = 0.49$, RMSEP = 1.46%, and RPD = 1.40 under cold storage. The EPO method reduced temperature-related interference and improved the robustness of SSC prediction under different storage conditions. Separately, based on measured postharvest weight loss and SSC changes, navel oranges harvested at 214–228 DAFB showed relatively better storage behavior under 5 °C conditions, with an estimated storage duration of approximately 62 days. Early-harvested fruit exhibited stronger storability but lower flavor quality, whereas late-harvested fruit had better eating quality but shorter storage life. It should be noted that these results correspond to different optimization objectives, including storability-oriented and quality-balanced criteria. This study provides preliminary evidence for the potential application of handheld NIRS in navel orange quality monitoring during storage, and offers an exploratory framework rather than a decision-making system for investigating the relationship between harvest timing and storage conditions. However, its predictive performance is moderate and further validation is required before practical application in production or decision-making systems.



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1. Introduction

Harvest timing is one of the key factors affecting the postharvest quality and storage performance of navel orange. The timing of harvest directly influences respiratory metabolism, water loss rate, and disease resistance of the fruit [1], thereby determining its stability during storage and distribution. In China, navel oranges are mainly harvested from November to March of the following year [2]. Fruit harvested too early generally exhibits better physiological storability; however, insufficient accumulation of sugars and flavor compounds often results in poor eating quality. In contrast, fruit harvested too late tends to have higher sweetness, but the onset of senescence leads to enhanced respiration, a significantly shortened storage life, and an increased risk of decay [1]. Therefore, identifying the optimal harvest date and exploring the matching strategy between harvest timing and storage conditions are of great importance for balancing flavor quality and storage longevity of navel oranges.

Hand-held near-infrared spectroscopy (NIRS) instruments offer rapid, non-destructive, and in situ measurement capabilities, making them highly suitable for evaluating the quality of both on-tree and stored fruit [3]. However, NIRS is an indirect analytical technique that relies on calibration models. During model development, variations in sample distribution and measurement conditions often limit the robustness and transferability of laboratory-based models, particularly when applied to samples stored under different temperature conditions [4]. Temperature differences between cold storage and laboratory environments can induce spectral shifts, leading to reduced prediction accuracy of models established using room-temperature samples. Previous studies have demonstrated that temperature significantly affected the performance of NIRS models. Cozzolino et al. (2024) reported that a portable NIRS system achieved significantly better prediction of egg storage time under cold storage compared to room temperature [5]. Similarly, Rahmia et al. (2022) observed distinct spectral differences between cold-stored and room-temperature pepino fruit, and even after equilibration to room temperature, the model performance of cold-stored samples remained inferior [6]. Zhang et al. (2025) further confirmed that storage temperature markedly influenced model performance, with significant differences observed between models developed at 0 °C and 4 °C for peach fruit quality prediction [7]. In addition, Ramadan et al. (2025) indicated that temperature variations during spectral acquisition could lead to the formation of different spectral subsets, and combining these subsets into a single model may reduce prediction accuracy [8]. To minimize temperature-induced variability, Torres et al. (2017) equilibrated cold-stored citrus samples to room temperature prior to spectral acquisition, ensuring consistent measurement conditions [9]. This experimental design highlights the recognized influence of temperature on spectral measurements. However, the specific effects of temperature variation (e.g., cold storage versus room temperature) on model prediction performance have not been systematically investigated.

Fruit quality undergoes dynamic and irreversible changes during storage, which are mainly reflected in weight loss, variations in soluble solids content (SSC), and firmness decline. These changes are also key factors contributing to the failure of prediction models developed from harvest-stage spectra when applied to cold-stored fruit. Zhao et al. (2023) [10] analyzed the variations in diffuse reflectance spectra and quality attributes of apples during storage, and found that spectral reflectance gradually decreased with storage time. Meanwhile, SSC, firmness, and weight loss exhibited regular changes, and strong correlations were observed between spectral characteristics and storage duration [10]. Pérez-Marín et al. (2019) reported that, during cold storage of oranges, the spectral profiles of samples progressively deviated from the reference population as storage time increased, reflecting quality deterioration-induced spectral variations [11]. Although previous studies have separately investigated the effects of temperature variation and quality changes on NIRS model performance, their

combined influence on the prediction of navel orange quality during storage had not been systematically explored. In particular, harvest timing, as a key factor determining the initial quality and storability of fruit, may interact with storage temperature, jointly influencing the dynamic evolution of fruit quality during storage.

Therefore, this study used ‘Newhall’ navel orange, the main cultivated cultivar in southern Jiangxi, as the experimental target. Seven harvest batches were collected from 200 to 249 days after full bloom (DAFB), and fruits were stored under cold storage (5 °C) and room temperature (25 °C) conditions. Based on NIRS, the effects of harvest timing on harvest-stage SSC, storage-related weight loss dynamics, and endpoint SSC-related trends after storage were investigated. In addition, a temperature-compensation model was introduced to improve the prediction accuracy of SSC. The aim of this study is to provide a scientific basis for optimizing harvest and storage practices, as well as theoretical support for cold-chain management and the development of dynamic harvest standards for Gannan navel oranges.

2. Materials and Methods

2.1. Samples and Treatment

The experimental navel orange orchard was located in Tandong Town, Rongjiang New Area, Ganzhou City, Jiangxi Province (114°51'38" E, 25°46'46" N). Climatic conditions in Ganzhou were characterized based on daily meteorological statistics. The cumulative temperature above 10 °C (≥ 10 °C active accumulated temperature) was approximately 6960 °C·d, corresponding to an effective accumulated temperature of about 4020 °C·d. The annual precipitation was 1819.2 mm. The annual sunshine duration was estimated to be approximately 1650–1900 h based on long-term climatic records. Harvesting was conducted in seven batches after the full bloom period in 2024, with the harvest dates corresponding to DAFB of 200, 207, 214, 221, 228, 242, and 249, covering the initial physiological maturity stage to the fully ripe stage. All citrus trees in the experiment were of the Newhall navel orange variety, selected for uniform tree vigor and similar fruit load (Figure 1). The planting density was 2 × 4 m, with a total of 170 trees. For each sampling, two fruits were collected from the east and west sides of the canopy of each tree, totaling 100 fruits (Table 1). Of these, 20 fruits were used for storage experiments, while the remaining 80 fruits were immediately subjected to spectral analysis and then juiced to measure their soluble solids content (SSC) after sampling. The fruits designated for the storage experiments were immediately transported back to the laboratory. Each batch of 20 fruits was randomly divided into two groups of 10 fruits each, and the two groups were placed in the following two storage environments:



Figure 1. Field orchard of navel orange trees used in this study.

Table 1. Summary list of fruit sampling.

Batch	DAFB	Tree Number	Fruit Number			
			Total	Destructive Analysis	Storage (25 °C)	Storage (5 °C)
1	200	50	100	80	10	10
2	207	50	100	80	10	10
3	214	50	100	80	10	10
4	221	50	100	80	10	10
5	228	50	100	80	10	10
6	242	50	100	80	10	10
7	249	50	100	80	10	10

Cold storage group: Fruit was stored at 5 °C with a relative humidity of 80–85% using a refrigerated chamber.

Room temperature group: Fruit was stored at 25 °C with a relative humidity of 80–85%. Temperature was controlled using an air-conditioning system to simulate ambient conditions.

All storage treatments were conducted under controlled temperature and humidity conditions, with samples maintained in the dark to simulate practical cold-chain and ambient distribution environments. The two storage temperatures (5 °C and 25 °C) were selected to represent typical cold-chain and ambient storage scenarios under practical commercial conditions. The relatively small sample size was mainly due to constraints in experimental resources, including budget and experimental facility limitations.

2.2. Portable Nir Spectrometer and Spectral Acquisition

Spectral data were collected using a portable near-infrared spectrometer (H100F, Sunforest, Incheon, Republic of Korea), which was applied in previous studies [12]. The instrument was equipped with a miniature spectrometer (C111708MA, Hamamatsu Photonics, Hamamatsu, Japan) with a spectral range of 650–950 nm and a wavelength interval of 2 nm, and two 10 W tungsten–halogen lamps positioned at an angle of 100°. The emitted light was diffusely reflected by the fruit tissue and collected by the probe, and spectral data were recorded using Laboratory Program V1.5 (Sunforest, Incheon, Republic of Korea). A polytetrafluoroethylene (PTFE) white reference was integrated into the inner cover of the device, and both white reference and dark spectra were recorded prior to measurement with an integration time of 150 ms. During sample acquisition, the cover was removed, and the fruit was placed in close contact with the probe. Spectra were collected with an integration time of 150 ms and automatically converted into absorbance spectra, and each fruit was rotated 180° along the equatorial axis for repeated measurement. Before measurement, cold-stored fruits were equilibrated to room temperature and gently wiped to remove surface condensation, minimizing moisture interference. To avoid temperature-induced spectral variation, the instrument was restarted and recalibrated when its temperature exceeded the initial temperature at startup by 10 °C.

2.3. Determination of Weight and Soluble Solids Content (SSC)

Fruit weight was measured every 7 days during storage using an electronic balance with a precision of 0.01 g, and the weight loss rate was calculated according to Equation (1). Meanwhile, near-infrared spectral data were collected at each sampling point, after which the fruit samples were returned to storage for continued monitoring.

To obtain reliable reference values of soluble solids content (SSC), 80 fruits were sampled at each harvest time for physicochemical analysis on the day of harvest. The sampled fruits were cut along the equatorial plane, and the pulp was extracted and juiced.

SSC was measured using a digital handheld refractometer (PAL-1, Atago Co., Ltd., Tokyo, Japan), with a measurement range of 0–53% and an accuracy of $\pm 0.2\%$. A small amount of freshly extracted juice was placed onto the optical detection window of the refractometer, and each sample was measured in triplicate, with the average value used for analysis. After each measurement, the detection window was rinsed with distilled water and dried, and the refractometer was recalibrated to zero before the next measurement. Soluble solids content (SSC) was selected as the representative quality indicator due to its strong correlation with fruit maturity and its widespread use in NIRS-based citrus quality prediction studies. No destructive SSC measurements were performed during the storage period; SSC reference values for stored fruit samples were obtained only at the storage endpoint (day 49).

$$R = \frac{(G_0 - G_i)}{G_0} \times 100\% \quad (1)$$

where R is the weight loss rate, G_0 is the initial fruit weight at harvest, and G_i is the fruit weight after storage for i days ($i = 7, 14, 21, \dots, 49$).

2.4. Data Processing and Model Evaluation

The collected spectral data were preprocessed using the Savitzky–Golay (SG) second derivative with 11 smoothing points and a second-order polynomial. Partial least squares regression (PLSR) was used for model development and validation. To reduce temperature interference, second-derivative spectra corrected by external parameter orthogonalization (EPO), generalized least squares weighting (GLSW), and a global modeling approach were evaluated. The global modeling approach involved incorporating corrected samples into the original calibration set, followed by recalibration of the model [12]. EPO was used to remove external interferences by projecting the original spectra onto a subspace orthogonal to the principal components of interfering variables (e.g., temperature and illumination) [13]. GLSW was used to construct a filtering matrix based on covariance structure analysis to suppress the effects of external factors such as temperature and ambient light [14]. The key parameters, g (1–20) for EPO and α (10^{-4} –1) for GLSW, were optimized using a grid search algorithm [13,14]. The number of latent variables was determined using five-fold cross-validation [15]. Model performance was evaluated using the coefficient of determination for cross-validation (R^2_{cv}) and the root mean square error of cross-validation (RMSECV), as well as the coefficient of determination for prediction (R^2_p) and the root mean square error of prediction (RMSEP). In addition, the residual predictive deviation (RPD), defined as the ratio of the standard deviation (SD) to RMSECV or RMSEP, was used to assess model performance [16]. Generally, an RPD value greater than 1 indicates basic predictive ability, while a value greater than 3 indicates good predictive performance [17]. During the experiment, for each harvest batch, individual fruit weight and spectral data were recorded over time under both storage conditions; additionally, SSC values were measured destructively at the end of storage (day 49). Although weight and spectral data were collected repeatedly during storage, SSC reference values were not measured dynamically. Changes in external quality, including decay and dehydration-induced shriveling, were also monitored. All data were organized in Microsoft Excel to establish a longitudinal dataset, providing a basis for developing NIRS-based models for predicting the combined effects of harvest time and storage duration, as well as for optimizing dynamic harvest strategies and postharvest handling practices. Because weight loss was repeatedly measured on the same fruit during storage, the storage data were interpreted using a longitudinal framework. Harvest batch, storage temperature, storage duration, and their interactions were considered as the main explanatory factors, while repeated observations from the same fruit were accounted for when interpreting weight-loss trends. Given the limited

number of fruits in each harvest-by-temperature combination, these analyses were used to support biological trend interpretation rather than definitive population-level inference.

For SSC-related outcomes, destructive reference measurements were not obtained at each storage time point. Therefore, SSC-related storage results were interpreted mainly at the endpoint and as trend-level evidence from NIRS prediction, rather than as repeated destructive SSC measurements during storage.

3. Results

3.1. Effects of Harvest Timing on Weight Loss of Navel Orange Fruit

Figure 2 shows the weight loss of navel oranges harvested at different stages under cold storage (5 °C) and at room temperature (25 °C), respectively. Overall, weight loss tended to increase continuously with storage time under both conditions, suggesting a cumulative effect of water loss through transpiration and respiration, which contributed to a gradual decline in fruit weight during storage. Therefore, differences among harvest batches, storage temperatures, and storage durations are discussed as biologically meaningful trends under the present experimental conditions, rather than as definitive treatment rankings.

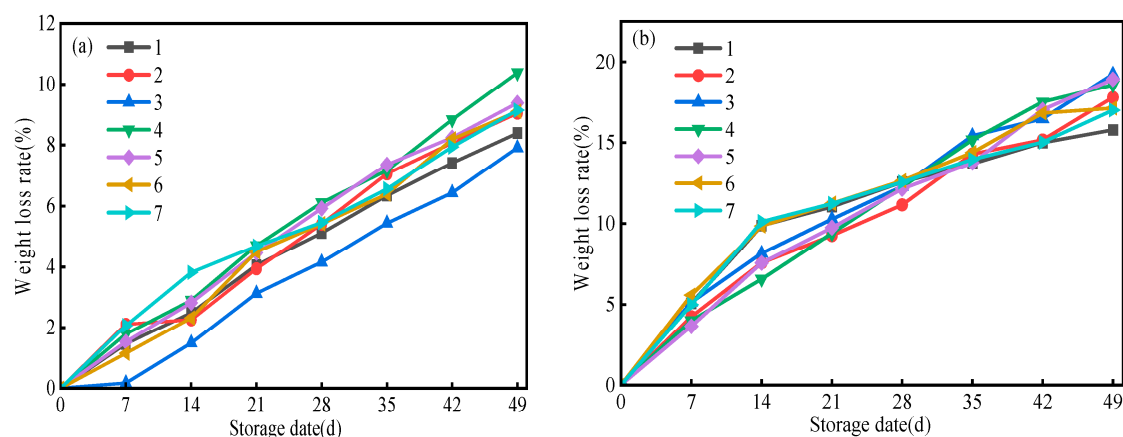


Figure 2. The variation in weight loss rate with storage time at different harvest periods, as listed in Table 1. (a): Storage at 5 °C. (b): Storage at 25 °C.

Under cold storage conditions, the weight loss of navel oranges exhibited an approximately linear increase during the 0–49 days of storage, with relatively small differences among different harvest batches. This pattern was similar to that reported in apples [18]. The rate of weight loss was relatively low at the early stage of storage (7–14 days), reaching about 1.12%, and gradually accumulated to approximately 9.06% by day 49 across most treatments. These results indicate that low temperature effectively suppressed the rate of water loss [19]. However, consistent differences in weight loss were observed among harvest batches. For instance, batches 3 and 4 maintained relatively higher weight loss rates over multiple storage periods, whereas some batches (e.g., batches 1 or 7) showed comparatively lower values. This may be attributed to differences in harvest maturity, which can affect peel permeability and storage tolerance [20]. By contrast, under room temperature conditions, weight loss followed a pattern characterized by a faster increase in the early stage and a gradual accumulation thereafter. In the early stage, the cuticular wax layer of the peel may be unstable after harvest, stomata remain open, and the vapor pressure deficit is higher at room temperature, leading to rapid water loss. Meanwhile, higher respiration rates result in increased dry matter consumption, further accelerating weight loss. In the later stage, peel shrinkage and wrinkling increase resistance to transpiration, and as citrus

fruits are non-climacteric, their respiration rate gradually declines during storage, reducing dry matter consumption. These combined effects contribute to a slower rate of weight loss.

A comparison between the two storage conditions showed that the overall weight loss under room temperature tended to be higher than that under cold storage. Noticeable weight loss began to appear as early as 14 days at room temperature. The average weight loss at 7 and 14 days reached 4.66% and 8.54%, respectively, which were relatively higher than those under cold storage (1.47% and 2.59%). Based on the approximately linear relationship observed under cold storage, the average rate of weight loss can be estimated at 0.19% per day. In contrast, under room temperature conditions, the weight loss rate was higher in the early stage (0–14 days), with an average rate of approximately 0.61%, and decreased to about 0.26% during the middle and late stages (14–49 days). It is generally considered that when weight loss exceeds 5–10%, the shelf life of fruit is terminated [21]. Using 10% as the threshold, navel oranges stored under cold conditions could be preserved for up to 42 days, depending on the harvest batch, whereas those stored at room temperature could only be maintained for up to 21 days. Therefore, appropriate storage strategies for navel oranges under cold and room temperature conditions can be established accordingly.

In addition, Figures 2 and 3 indicate that harvest timing not only affects the overall level of weight loss but also influences the rate of weight loss accumulation at different storage stages. Notably, under room temperature conditions, the total weight loss at 49 days exhibited a unimodal pattern across harvest batches, characterized by an initial increase followed by a decrease with delayed harvest time. Specifically, fruit harvested at intermediate stages showed the highest weight loss, whereas earlier or later harvests exhibited relatively lower values. A similar trend was observed under cold storage, although with smaller differences among treatments. This unimodal pattern may be associated with changes in peel properties during fruit maturation, including variations in cuticular wax composition, lenticel (or stomatal) structure, and water potential gradients. At intermediate maturity stages, the peel barrier function may be relatively more susceptible to water loss, whereas fruit harvested at earlier or later stages may exhibit enhanced resistance due to differences in tissue structure and epidermal characteristics [22]. Therefore, for cold storage of the fruit, according to the group standard “Code of High Quality Gannan Navel Orange Production [23]” (T/SZNB 005-2025), fruit should be harvested at 200 days after full bloom, when 85–90% of the peel is colored, and the soluble solids content (SSC) is no less than 10%.

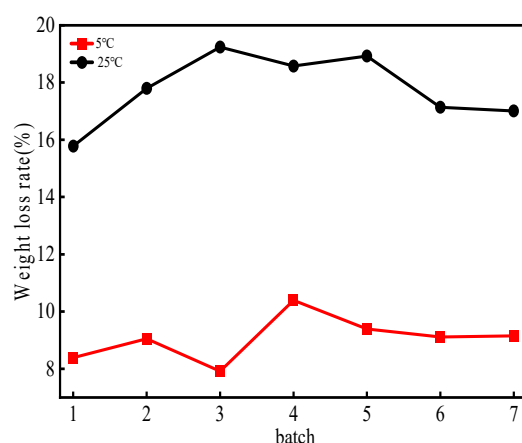


Figure 3. The weight loss rate of navel orange fruits after seven weeks of storage at different harvest periods.

At the end of storage (49 days), weight loss under room temperature was approximately 1.7–2.0 times higher than that under cold storage, indicating the noticeable effect of cold storage in reducing fruit weight loss. Therefore, cold storage appeared to be more effective

for minimizing weight loss and maintaining marketable quality during storage. In addition, selecting appropriate harvest stages and avoiding those associated with peak weight loss in the unimodal pattern may further improve storage performance and fruit preservation.

3.2. Effects of Harvest Timing on Soluble Solids Content

Figure 4 shows the effect of harvest timing on the soluble solids content (SSC) of navel oranges. As shown in the figure, SSC tended to increase gradually from 200 to 228 DAFB, reached a relatively high level at around 228 DAFB, and then tended to decline at 242–249 DAFB, showing a pattern of first increasing and then decreasing. This trend suggests that the fruit had approached full maturity. A similar pattern has been reported in citrus fruit, in which SSC generally increases during maturation and then tends to stabilize as ripening progresses [24–26].

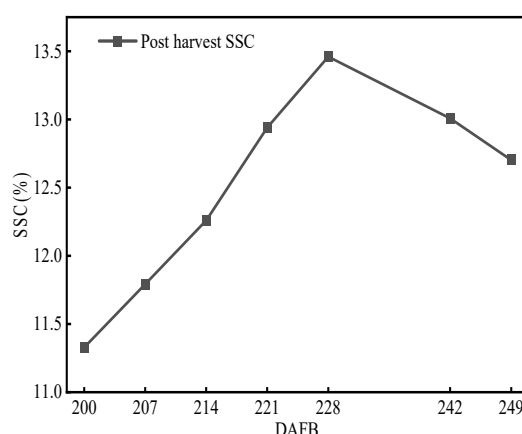


Figure 4. Effect of harvesting period on soluble solid content (SSC) changes in navel orange fruits.

In addition, the SSC values in the present study showed a trend of increasing initially and then gradually reaching a stable level, which is consistent with previous reports by Dong et al. (2024) and Yang et al. (2024) [24,27]. Dong et al. (2024) reported that the SSC of two citrus groups increased continuously from 120 to 225 days after flowering, with similar rates of increase between 120 and 195 days, whereas group B showed a faster increase after 195 days [27]. Similarly, Yang Yanfeng et al. (2024) found that the SSC of four citrus cultivars, namely ‘Wogan’, ‘Bingtangcheng’, ‘Maogugan’, and ‘W. Murcott’, exhibited a pattern of initial increase followed by stabilization over a two-year period [24].

Harvest timing should be determined scientifically according to the intended use of the fruit, i.e., for immediate sale or for storage. For fruit intended for immediate marketing, full ripeness is recommended at harvest. According to the national standard Navel Orange (GB/T 21488-2025), fruit with an SSC of at least 13% are classified as premium grade and may serve as a reference for harvest maturity. As shown in Figure 4, SSC reached 12.9% at 221 days after full bloom (DAFB), indicating that fruit could be harvested at this stage for direct sale. For fruit intended for storage, the group standard Technical Regulation for High-Quality Gannan Navel Orange Production (T/SZNB 005-2025) recommends a minimum SSC of 10% at harvest. In particular, for cold storage, fruit should be harvested at approximately 200 DAFB, when peel coloration reaches 85–90%. According to Figure 4, the SSC of navel oranges at 200 DAFB was 11.3%, suggesting that fruit harvested at this stage generally meets the minimum storage suitability for cold storage as indicated by the group standard.

3.3. Spectral Characteristics Analysis

Figure 5 shows the average spectral curves of the last harvest batch during storage. In terms of spectral shape, the curves exhibited typical stage-dependent features across the visible

and near-infrared regions. A distinct shoulder peak was observed around 650–680 nm, where the spectra at different storage times showed relatively clear separation. This wavelength range is commonly associated with pigment-related optical responses in citrus peel tissues, and the observed differences may reflect storage-related changes in peel color characteristics. As a result, spectral intensity differed noticeably within this wavelength range. A pronounced trough appeared at approximately 700–720 nm, and the spectra from different storage stages remained distinguishable in this region. This interval is close to the red-edge region and may be sensitive to changes in peel pigments and tissue structure, suggesting that storage-induced ripening progression and pigment degradation could modify the optical response in this band. In the range of approximately 780–830 nm, the spectra showed secondary fluctuations and formed a relatively stable trough near 810–820 nm. This region may be influenced by both the scattering properties of internal fruit tissues and the second overtone absorption of O–H bonds associated with internal constituents such as carbohydrates, minerals, and water content, with possible contributions from both C–H and O–H bonds. During storage, relaxation of cellular structure, loss of membrane integrity, and changes in the ratio of free to bound water may contribute to the spectral differences observed in this region. From 830 nm onward, the spectra increased overall and showed a steeper upward trend in the 900–950 nm region. The separation among spectra at different storage stages became more pronounced in this near-infrared range, suggesting that storage duration affected the near-infrared response. This phenomenon may be associated with the combined effects of changes in water status, particularly O–H-related absorption, and enhanced tissue scattering.

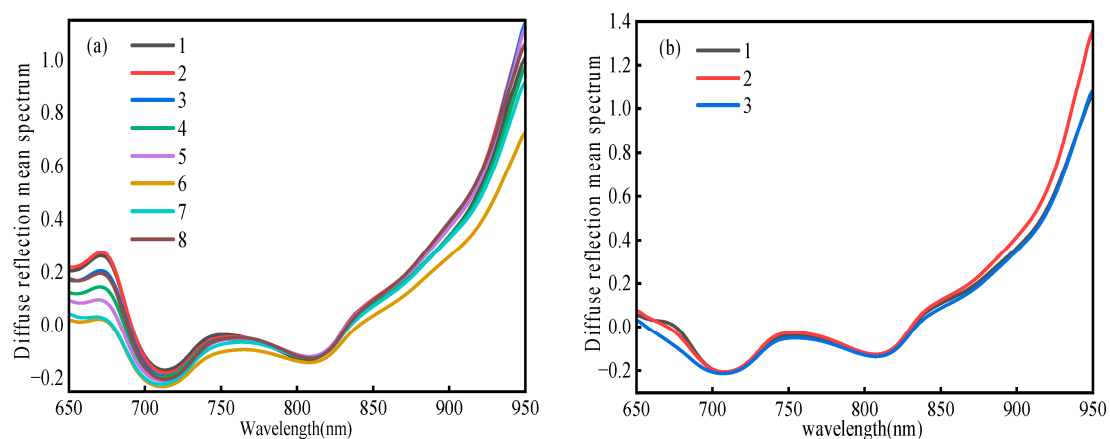


Figure 5. Average spectra of navel oranges in different storage periods. (a): Storage at 5 °C. (b): Storage at 25 °C.

In addition, comparison of the samples stored at 5 °C and 25 °C (Figure 5a,b) showed that the degree of spectral separation observed after only 3 weeks at 25 °C was comparable to that observed after 7 weeks at 5 °C. This suggests that temperature may indirectly affect spectral characteristics by influencing physiological metabolism, including respiration, enzymatic degradation, and water evaporation. These results suggest that elevated temperature (25 °C) accelerated spectral change during storage, providing support for the application of near-infrared spectroscopy in the nondestructive discrimination of navel orange freshness under different storage temperatures.

Overall, the representative spectra shown in Figure 5 suggested that storage-related spectral variation in the last harvest batch was wavelength-dependent under the present experimental conditions. The visible region, particularly 650–720 nm, appeared to be more sensitive to pigment-related changes [28], whereas the near-infrared region (830–950 nm) appeared to be more responsive to changes in water status and internal tissue structure, with these differences becoming increasingly pronounced as storage duration increased.

3.4. Spectral Prediction Models for Navel Oranges During Storage

Continuous spectral acquisition was performed to develop NIRS models for predicting the internal quality parameters of navel oranges. By incorporating temperature information, the study aimed to achieve a scientific and nondestructive evaluation of fruit quality and to analyze the effects of harvest timing on the cold-storage performance of navel oranges. Specifically, full-spectrum data collected under different temperature conditions were used to calibrate PLSR models, in order to evaluate the relationship between soluble solids content (SSC) and spectral data in stored fruit, as well as the influence of temperature on model performance [29]. Subsequently, PLSR models were developed using spectra preprocessed by external parameter orthogonalization (EPO) to minimize the effect of temperature on prediction accuracy [30]. Finally, variable selection methods were applied to identify informative variables and further improve the performance of the PLSR models.

SSC Prediction Using Temperature-Compensation Models Under Different Temperature Conditions

To evaluate the feasibility of near-infrared spectroscopy for assessing the storage quality of navel oranges, partial least squares regression (PLSR) was employed to develop predictive models for soluble solids content under two storage conditions, and the prediction accuracy was compared between these conditions. The number of latent variables (LVs) was optimized within the range of 1–20 to ensure that the models avoided both overfitting and underfitting [31]. Based on the predefined calibration and prediction sets, models were established using raw spectra and temperature-compensated spectra, including EPO and GLSW treatments. The spectral differences between samples stored at the two temperatures were used to construct a difference matrix, which was incorporated into the calibration set. The results of all models are presented in Table 2.

Table 2. Calibration Set Prediction Validation.

No	Preprocessing Method	Km(g)	Lv(f)	R2cv	RMSECV	Bias_C	RPD	Condition	R2p	RMSEP	Bias_P	RPD
1	Origin		9	0.59	1.41	-2.22×10^{-14}	1.56	25 °C	0.18	1.97	−0.76	1.11
2			9	0.59	1.41	-2.22×10^{-14}	1.56	5 °C	−0.74	2.70	0.83	0.76
3	2D		8	0.70	1.21	-3.01×10^{-15}	1.81	25 °C	0.51	1.52	−0.34	1.43
4			8	0.70	1.21	-3.01×10^{-15}	1.81	5 °C	0.05	1.99	0.67	1.03
5	EPO		8	0.69	1.21	1.06×10^{-15}	1.80	25 °C	0.60	1.38	0.16	1.58
6			5	0.70	1.20	4.74×10^{-16}	1.82	5 °C	0.49	1.46	0.29	1.40
7	GLSW		5	0.67	1.26	-7.66×10^{-16}	1.74	25 °C	0.57	1.42	−0.16	1.53
8			5	0.65	1.29	1.51×10^{-15}	1.69	5 °C	0.30	1.71	0.42	1.19

Note: Km(g) indicates the optimized correction parameter used in the temperature-compensation method, and Lv(f) indicates the number of latent variables used in the PLSR model. The second-derivative spectra preprocessed using the global model, External Parameter Orthogonalization (EPO), and Generalized Least Squares Weighting (GLSW) were applied to evaluate temperature interference. The difference matrix was incorporated into the calibration set. R²cv represents the coefficient of determination for the calibration set, RMSECV denotes the root mean square error of cross-validation, R²p is the coefficient of determination for the prediction set, and RMSEP indicates the root mean square error of prediction. RPD is defined as the ratio of the standard deviation (SD) to RMSECV or RMSEP. Bias_C: calibration bias. Bias_P: prediction bias.

Model performance was evaluated using cross-validation and external prediction metrics, including R²cv, RMSECV, R²p, RMSEP, bias, and RPD, to characterize model accuracy, robustness, and applicability [32].

Analysis of Table 2 indicates that the overall performance of the spectral models improved after preprocessing compared with the raw spectra. Among the preprocessing methods, EPO achieved the highest prediction accuracy. Specifically, R²cv increased from 0.59 to 0.70, while RMSECV decreased from 1.41% to 1.20%, and RPD improved from 1.56 to 1.82. These results suggest that EPO can more effectively extract SSC-related spectral information within the calibration set, while reducing non-target variations induced by temperature.

Under room temperature conditions, EPO also achieved the best predictive performance ($R^2_p = 0.60$, RMSEP = 1.38%, RPD = 1.58). In contrast, the overall prediction accuracy decreased under cold storage conditions, and the model based on raw spectra showed severe misfitting ($R^2_p = -0.74$), indicating that models without temperature compensation are unable to perform reliable cross-temperature predictions. After introducing temperature compensation, EPO exhibited relatively superior performance under cold storage ($R^2_p = 0.49$, RMSEP = 1.46%, RPD = 1.40). Moreover, both EPO and GLSW showed relatively low bias values (EPO: 0.16 at room temperature and 0.29 under cold storage), suggesting that temperature compensation not only reduces random errors but also partially corrects systematic drift.

Figure 6 presents the model predictions under room temperature and cold storage conditions, providing a visual representation of error distribution and bias trends. Overall, the analysis indicated that temperature variation is a major interfering factor affecting the stability of near-infrared prediction of SSC [33]. The comparison among raw spectra, EPO, and GLSW further confirmed that temperature compensation improved cross-temperature prediction performance. In particular, EPO exhibited more stable generalization ability across both temperature scenarios, with relatively higher R^2_p , lower RMSEP, and narrower bias values, indicating its effectiveness in reducing temperature-induced spectral interference.

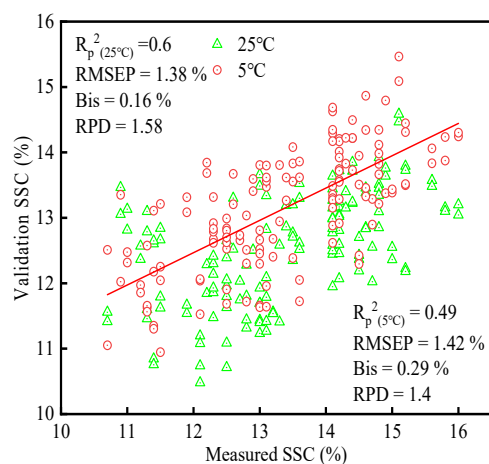


Figure 6. Prediction chart of navel orange spectral model under room temperature and refrigerated conditions.

As shown in Table 2, the RPD values of the EPO model were 1.58 under room temperature and 1.40 under cold storage, indicating an overall moderate performance level and suggesting that prediction errors remain relatively evident. From a practical application perspective, the model can be used for rapid estimation or grading of SSC, whereas precise quantification still requires expanded sample coverage, enhanced calibration across a wider temperature range, and the integration of variable selection or more robust temperature transfer strategies. Temperature variation was found to significantly weaken the cross-condition generalization ability of SSC near-infrared models, and uncorrected raw spectral models may fail under cold storage conditions. Among the preprocessing methods, EPO demonstrated the best overall performance, followed by GLSW. The second-derivative preprocessing improved prediction accuracy to some extent; however, its effectiveness under cold storage conditions was limited. At present, the best predictive performance was achieved by the EPO model under room temperature ($R^2_p = 0.60$, RMSEP = 1.38%, RPD = 1.58), while under cold storage, the optimal model was also EPO ($R^2_p = 0.49$, RMSEP = 1.46%, RPD = 1.40). Overall, these models were more suitable for rapid estimation and grading purposes. The results supported the application of handheld NIRS devices for

SSC estimation of navel oranges under storage conditions, providing a scientific basis for practical production.

During storage, the SSC of navel orange fruit was influenced by both sugar metabolism and water loss. Previous postharvest studies have shown that water loss during storage can affect fruit quality attributes and may lead to apparent changes in soluble solids content due to dehydration-induced concentration effects [34,35]. Therefore, Equation (2) was introduced in this study as a mass-balance-based, weight-loss-normalized auxiliary index to correct the measured SSC values, thereby reducing the interference caused by water loss on SSC interpretation rather than replacing direct SSC determination.

$$\text{SSCv} = \text{SSC} \times (1 - R) \quad (2)$$

where SSCv represents the corrected SSC value, SSC is the measured value, and R is the weight loss rate. These corrected SSC values were used solely for trend description and preliminary analysis to support the potential application of handheld NIRS for non-destructive SSC monitoring. Therefore, SSCv should be interpreted as a concentration-adjusted auxiliary indicator, rather than an independently validated substitute for direct destructive SSC measurement.

Figure 7 shows the comparison between SSCv-based reference values (calculated from endpoint destructive SSC measurements at day 49 using Equation (2)) of navel oranges from different harvest batches stored at 5 °C and 25 °C, and the corresponding SSC values predicted by the handheld near-infrared spectroscopy instrument for the same samples at day 49. All SSC measurements and NIRS predictions correspond exclusively to the storage endpoint (day 49); no intermediate or time-series SSC measurements were performed during storage. Under room temperature conditions, the corrected reference SSC values remained at a relatively low level in batches 1–3 (approximately 10.40–10.63%), began to increase from batch 4, and exhibited a marked rise in batch 5 (from approximately 10.95% to 11.81%). Thereafter, the values in batches 6–7 continued to increase gradually and approached a stable level. Overall, the variation pattern could be described as relatively stable in the early stage, sharply increasing in the middle stage, and stabilizing in the later stage. At the same time, the corrected SSC values predicted under room temperature showed an overall trend consistent with the reference values, also followed a pattern of early stability, a mid-stage increase, and a slight late-stage rise, although a certain degree of systematic underestimation was observed. Because SSC variation during storage may be jointly influenced by sugar metabolism and water-loss-induced concentration effects [34,35], the corrected SSC curves should be interpreted mainly as trend-level evidence rather than as direct evidence of true sugar accumulation. These results suggest that the near-infrared spectral model is likely able to partially capture the general trend of SSC variation among different harvest batches during storage at room temperature.

Under cold storage conditions, the corrected reference SSC values decreased gradually from batches 1 to 4 (from approximately 11.85% to 11.35%), and then increased continuously after batch 4, reaching about 13.5% in batch 7. Overall, the pattern could be characterized by a slight decline in the early stage followed by a sustained increase in the later stage. Although the corrected predicted SSC values under cold storage did not completely match the variation pattern of the reference values, the two curves overlapped at several points, and the deviations between predicted and measured values for each harvest batch were relatively small. These results suggest that the prediction model established by near-infrared spectroscopy retained some ability to follow the general SSC trend of navel oranges with different maturity levels after low-temperature storage. However, the agreement between predicted and reference values was not sufficient to support precise quantitative

prediction. This also indicates that the corrected SSC values are more suitable for describing general trends than for supporting strong quantitative conclusions.

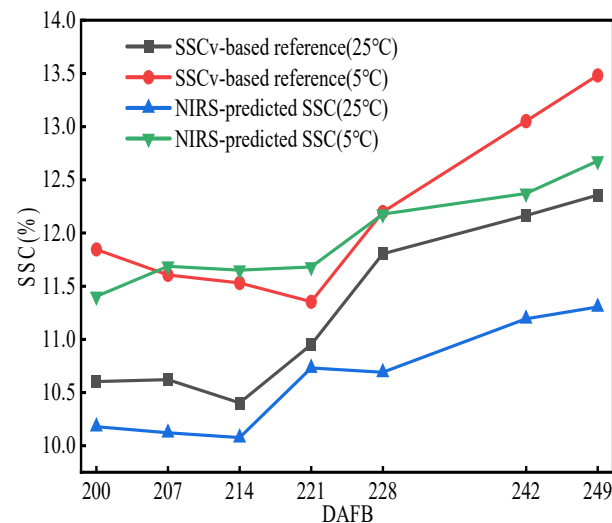


Figure 7. Comparison of SSCv-based reference and NIRS-predicted SSC values in navel oranges across harvest batches (200–249) at day 49.

Overall, these observations provide initial evidence that handheld near-infrared spectroscopy may be applied for non-destructive monitoring of SSC in navel oranges after storage. Moreover, after correction using the established equation, the interference caused by water loss can be partially reduced, which may further improve the interpretability of the observed SSC trends. However, this correction should not be interpreted as evidence that SSCv is analytically superior to direct destructive SSC measurement, because no independent validation dataset was used to verify the corrected values. These findings suggest the potential feasibility of applying near-infrared spectroscopy for postharvest SSC monitoring and provide preliminary technical support for quality assessment and grading during postharvest handling.

3.5. Comprehensive Evaluation of Harvest Stage and Storage Temperature Combinations

Based on a comprehensive consideration of weight loss control, SSC stability, and decay risk, a scenario-based analytical framework integrating harvest stage, storage temperature, and estimated storage duration was established, as summarized in Table 3. The storage duration was primarily determined based on the fruit weight loss rate. This framework was developed based on experimental data and postharvest physiological principles of citrus, and was used to support comparative analysis of storage behavior across different maturity stages and storage conditions. The proposed harvest-by-storage framework should therefore be regarded as a scenario-based exploratory framework rather than a formal optimization or decision-making model, and further validation with larger sample sizes and independent harvest seasons is needed.

Table 3. Scenario-based estimation of storage duration under different harvest windows at 5 °C.

Harvesting Period Type	Corresponding to Maturity Storage (DAFB)	R(%)	Reserve Temperature	Recommended Storage Days	Key Quality Characteristics	Recommended Use
Early harvesting period	200–207 days	0.17~0.19	5 °C	54–59 days	Low physiological activity at harvest, minimal postharvest respiration and senescence, long shelf life with stable quality maintenance, but low initial soluble solids content (SSC) and flavor at harvest	Long-term cold storage for delayed marketing, off-season supply, and cold chain logistics with extended shelf life
Mid-season harvest (optimal)	214–228 days	0.16~0.21	5 °C	52–62 days	Balanced initial SSC and flavor, moderate postharvest metabolism, controllable quality deterioration, and the widest adaptability to storage duration, achieving the optimal balance between harvest quality and storage performance	Versatile applications including medium- and long-term cold storage, cross-regional long-distance transportation, and bulk commercial storage
late harvest period	242–249 days	0.19	5 °C	53–54 days	High initial SSC and excellent eating quality at harvest, but high postharvest metabolic activity, accelerated senescence, and limited storage tolerance with rapid quality decline	Short-term refrigeration for immediate local sales, fresh market direct supply, and quick circulation

Note: The “Recommended storage days” in the table are extrapolated based on the weight-loss rate progression of individual batches, assuming that the linear trend continues beyond the observed period. Decay risk is included as a qualitative reference based on visual observations, and does not represent a quantitative measure due to limited incidence.

4. Discussion

The results indicated that fruits harvested at the mid-stage exhibited relatively better overall storage performance under cold storage conditions. At this stage, fruits are generally at an optimal physiological maturity, with a well-balanced sugar–acid ratio, relatively stable tissue structure, and an intact peel barrier function. Consequently, under low-temperature conditions, their respiratory metabolism can be effectively suppressed, and water loss through transpiration is significantly reduced, which may contribute to improved storage performance in medium-to long-term cold-chain distribution scenarios, such as long-distance transportation or staged market supply regulation. Fruits harvested at an early stage have not yet completed sugar accumulation, resulting in relatively low initial SSC levels. However, their metabolic activity is relatively low, tissue structure is compact, and the cuticular layer of the peel remains relatively intact, conferring comparatively good storage tolerance. Under cold storage, these fruits typically exhibit lower water loss rates and reduced decay risk. Nevertheless, due to the insufficient development of flavor compounds, they are more suitable for short- to medium-term storage, with storage management used to delay market entry and regulate supply timing. In contrast, late-harvest fruits show relatively poor storage stability. As fruit maturity increases, respiratory metabolism is significantly enhanced, while cell wall structure gradually loosens and peel barrier function declines. These physiological changes lead to increased water diffusion and accelerated senescence. Although late-harvest fruits generally possess higher SSC and better initial flavor at harvest, their quality stability during storage is relatively low. In the later stages of storage, they are prone to intensified water loss, tissue softening, and increased decay incidence. Therefore, such fruits are more suitable for rapid distribution or short-term marketing systems rather than long-term cold-chain storage.

During storage management, the quality changes in navel oranges are typically monitored or evaluated at intervals of 7–10 days. This timescale is closely related to the postharvest physiological dynamics of citrus fruits. First, both respiration rate and water loss in citrus fruit exhibit stage-dependent variation during storage. Previous studies have shown that under low-temperature conditions, noticeable shifts in respiratory metabolism and water loss generally occur at approximately weekly intervals. Therefore, using a 7–10 day evaluation period can effectively capture the dynamic changes in fruit quality [36]. In addition, microbial infection and decay development also follow a certain temporal pattern. Citrus fruits are usually in a latent infection stage during the early storage period, and it typically takes about one week for pathogens to develop from latent infection to visible decay symptoms [37]. Consequently, monitoring fruit quality at 7–10-day intervals enables a more accurate assessment of changes in decay risk.

In addition, numerous studies on citrus storage have commonly adopted 7 or 10 days as the sampling interval in experimental design to monitor dynamic changes in quality attributes. For example, similar approaches have been applied in studies on ‘Rustenburg’ navel oranges [1] and ‘Clementine’ mandarins [38]. This timescale not only captures the stage-dependent trends in quality changes but also avoids potential interference caused by overly frequent sampling. Therefore, using a 7–10-day interval for quality evaluation in navel orange storage studies is well supported by both physiological principles and methodological considerations.

Considering both storage quality and flavor retention, fruits harvested at the mid-stage (approximately 214–228 days after full bloom) combined with storage at 5 °C show relatively favorable storage behavior under the present experimental conditions, with an estimated storage duration of approximately 62 days based on extrapolated trends. This finding was consistent with the general conclusions of postharvest citrus studies, which indicated that fruits harvested at an appropriate maturity stage typically exhibit the best

storage potential [39]. Under these conditions, fruit weight loss was effectively controlled, SSC remained stable, and the progression of physiological senescence was significantly delayed. However, this result should be interpreted as a trend-based indication rather than a strict optimal recommendation. It reflects a quality-balanced optimization perspective, whereas from a storage-stability-oriented perspective, earlier harvest stages (approximately 200 DAFB) are more consistent with regional cold storage standards and provide longer physiological storage potential. Therefore, the recommended harvest stage depends on the intended application scenario rather than a single fixed optimal point. The conventional method of determining harvest timing based on ≥ 10 °C accumulated temperature relies on external climatic indicators, which may be affected by abnormal weather conditions and thus reduce its reliability; in contrast, near-infrared spectroscopy evaluates fruit quality attributes and provides a more accurate basis for harvest timing assessment. Future studies may include additional intermediate storage temperatures and different citrus varieties to further improve model robustness and generalization ability. This strategy may potentially reduce postharvest losses and extend shelf life, thereby providing economic benefits for producers and distributors.

5. Conclusions

This study systematically investigated the effects of harvest stage on the storage quality and postharvest circulation of navel oranges. From the perspectives of postharvest physiological changes, storage environment influences, and near-infrared nondestructive detection, the mechanisms underlying quality variation were analyzed, and a preliminary scenario-based framework integrating harvest stage, storage temperature, and storage duration was proposed. The results indicated that fruit weight loss increased gradually during storage, while cold storage at 5 °C helped reduce water loss. EPO-preprocessed NIRS reduced temperature interference and captured SSC trends under both room temperature and cold storage. These results support the application potential of handheld NIRS for rapid, non-destructive monitoring, but further validation is required for reliable quantitative SSC prediction under different storage conditions. By comprehensively evaluating quality changes and storage risks, it was found that fruit harvested at the mid-stage exhibited relatively better overall storage performance under cold storage conditions. Early-harvest fruit showed strong storage tolerance but relatively lower flavor quality, whereas late-harvest fruit had higher SSC but shorter storage life.

Based on measured postharvest physiological indicators, harvesting at 214–228 days after full bloom combined with storage at 5 °C represented a relatively favorable storage condition combination under the present experimental conditions, with an estimated storage duration of approximately 62 days based on extrapolated trends. Under these conditions, fruit weight loss could be effectively controlled, SSC showed relatively stable trends, and senescence was delayed. Fruit harvested at an appropriate maturity stage generally exhibited good storage potential. However, these results should be interpreted within a dual-criteria decision framework rather than a single optimal recommendation. This study provided a preliminary theoretical reference for optimizing cold-chain logistics and establishing dynamic harvest standards for Gannan navel oranges. It should be noted that these conclusions are based on limited sample sizes and preliminary observations, and further validation is needed before generalization to commercial production systems.

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