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# Predicting Quality Properties of Pears during Storage Using Hyper Spectral Imaging System

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**Abstract:** This paper presents a comprehensive analysis of the application of visible–near-infrared (Vis/NIR) spectroscopy for the estimation of various chemical attributes of pear fruit. Specifically, the paper investigates how pH, titratable acidity (TA), soluble solids content (SSC), and Vitamin C change as the pear undergoes different storage durations and temperatures. To obtain the most accurate prediction models, we applied a variety of pre-processing techniques to the acquired spectra. Notably, the combination of Savitzky-Golay (S.G.), Multiplicative Scatter Correction (MSC), and second derivatives (D2) emerged as the most effective method for predicting the fruit's pH, with an impressive rp = 0.95 and SDR = 4.9. In contrast, combining S.G., MSC, and first derivatives (D1) yielded the most accurate predictions for TA, with a robust rp = 0.98 and SDR = 9.6. The research further delved into understanding how the storage period and temperature can significantly influence the pear fruit's chemical properties. Our findings established that as the storage duration and temperature rise, the pH of the fruit also escalates, while TA sees a decline. The research further elucidates that prolonged storage periods and elevated temperatures lead to the pear fruit shedding its intrinsic qualities, resulting in a reduction in soluble solids and Vitamin C content. To summarize, this paper underscores the immense potential of Vis/NIR spectroscopy as a non-destructive and expedient tool for monitoring the chemical attributes of pear fruit during storage, especially when subjected to diverse temperature and time conditions. These insights not only add to the existing body of knowledge but also align with earlier research on how storage conditions can affect fruit quality.

**Keywords:** spectral; fruits; quality; prediction; spectral

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## 1. Introduction

The pear stands out as a fruit of choice for many due to its rich nutritional profile. It boasts a plethora of essential nutrients, including amino acids, a diverse range of vitamins, vital minerals, and compounds known for their anticancer properties. Additionally, its delightful taste further enhances its appeal [1]. However, once harvested, pears undergo metabolic activities like respiration and water evaporation, which can adversely impact their quality over time [2]. Given this, it becomes imperative to closely monitor the chemical properties of pears during their storage phase to ensure optimal storage conditions [3].

Having a deep understanding of these chemical properties not only ensures prolonged freshness but also plays a pivotal role when pears are processed into various consumer products. For instance, the fruit's acidity level can influence the final taste and consistency

of products like jams or canned goods. Similarly, the sugar content plays a decisive role in determining the sweetness and color of the end product.

In the present scenario, the techniques deployed to ascertain the chemical and mechanical attributes of pear fruit in laboratory settings, such as measuring soluble solids content (SSC), titratable acid (TA), and hardness, are largely destructive. They also tend to be expensive and time intensive [4]. This calls for the exploration of methods that are both efficient and non-destructive [5]. One promising solution is the use of electromagnetic radiation, more specifically, visible/near-infrared spectroscopy (Vis-NIR). This innovative technology has garnered attention for its precision and reproducibility, showing great promise for enhancing post harvest processes in the fruit industry [6].

Past research in this domain has showcased the potential of Vis/NIR transmission spectroscopy, especially in the 600–904 nm wavelength range, for predicting the SSC in healthy pears and those with specific defects [7]. There has also been considerable interest in understanding how different factors, such as the speed of pear movement, can impact the accuracy of online measurements of SSC using Vis/NIR spectroscopy [8]. Moreover, the versatility of Vis/NIR is evident in studies that employed this technique to predict the hardness of both unripe and ripe pears [9]. The latest advances in the field have seen the integration of portable sensors, which can predict pear SSC with an even higher accuracy [10]. Furthermore, a recent study by Song et al. (2022) delved deep into the qualitative properties of pear fruit, achieving prediction accuracy rates nearing 96% [11].

While numerous studies have championed the use of Vis/NIR spectroscopy for non-destructively assessing fruit quality, most of these studies have operated under similar conditions. This often leads to models that might not be versatile enough to predict minor variations in quality attributes. Hence, our research seeks to fill this void by focusing on how Vis/NIR spectroscopy can be employed to predict fruit quality across varied storage temperatures (0, 5, and 10 °C) and timeframes (15, 30, 45 days). This comprehensive approach allows for observing a broader spectrum of changes in fruit quality attributes. Our literature review indicates that our study is pioneering in its approach to this intriguing area of research.

## 2. Materials and Methods

### *2.1. Sample Preparation*

For this study, we utilized pear fruit of the Duchess variety, sourced meticulously from an orchard located in Ardabil province, Iran. To ensure the utmost consistency in our research, we handpicked pears that exhibited no signs of damage, shock, or disease. These selected pears were then systematically segregated into nine distinct sets, with each set comprising 15 pears. The storage conditions for these pears were meticulously designed, with three distinct temperature settings: 0, 5, and 10 °C, and three separate storage durations: 15, 30, and 45 days.

It is worth noting that the ideal storage temperature for pears to retain their freshness and quality is 0 °C (as supported by Wang et al., 2014 [12]). However, considering the prevalent environmental conditions of Ardabil during the typical pear storage season, we also included temperatures of 5 and 10 °C in our study. After each predefined storage duration, the samples were retrieved from cold storage. Before initiating any spectroscopy, experiments, or conducting reference chemical tests, we ensured that all pear samples were acclimated to the ambient temperature for 8 h. This step was crucial to ensure uniformity in sample conditions. To visually demonstrate how pears change over different storage periods and temperatures, Figure 1 provides illustrative images of the fruit at various stages.

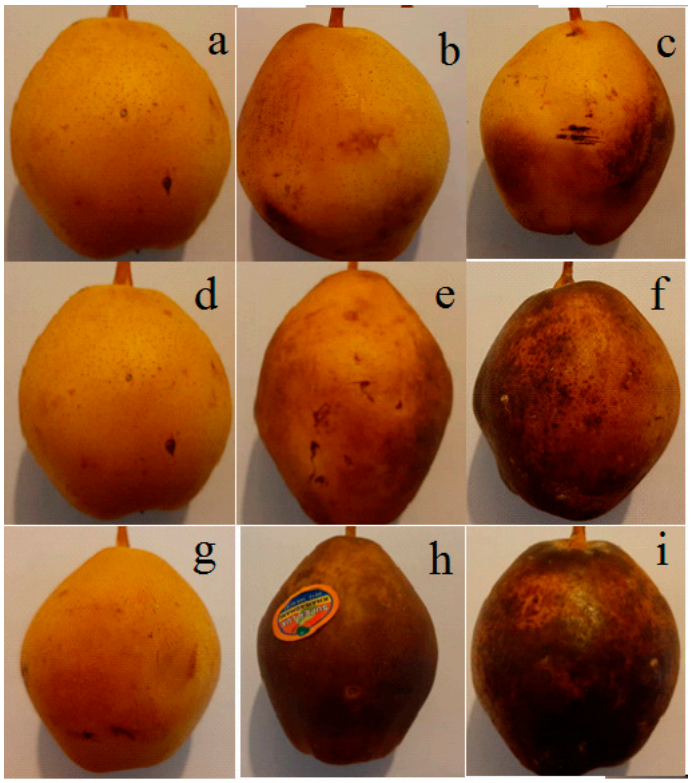



**Figure 1.** Pears stored under various temperature conditions and for different storage periods of time. The conditions include (**a**) 0 °C for 15 days, (**b**) 5 °C for 15 days, (**c**) 10 °C for 15 days, (**d**) 0 °C for 30 days, (**e**) 5 °C for 30 days, (**f**) 10 °C for 30 days, (**g**) 0 °C for 45 days, (**h**) 5 °C for 45 days, and (**i**) 10 °C for 45 days.

### *2.2. Data Acquisition*

The spectral data from the pear samples were meticulously obtained using a state-of-the-art spectroradiometer, specifically the PS-100 model from Apogee Instruments, INC., based in Logan, UT, USA. This device is renowned for its accuracy and precision, making it an excellent choice for such studies. One of the noteworthy features of the PS-100 spectroradiometer is its extensive spectral range, spanning from 250 nm to 1150 nm. This broad range conveniently encompasses both the visible (Vis) and the near-infrared (NIR) spectra, thus allowing for a comprehensive analysis of the pear's attributes that fall within these wavelengths. The Vis/NIR range is especially significant as it is known to reveal crucial information about the internal and external qualities of fruits, including pears.

The Vis/NIR spectroscopy was meticulously performed on each pear sample from four distinct sides to ensure a holistic and unbiased representation of each pear's spectral data. It is worth noting that care was taken to maintain a consistent angle for the spectroscopy around the pear's equatorial axis. This equatorial approach ensured that the spectral data captured were representative of the entire fruit and not biased towards any particular section.

Post acquisition, the spectra from each of the four sides were diligently stored, with illustrative representations provided in Figure 2. This visual aid serves to offer readers a clear view of how the spectra varied (or remained consistent) across different facets of the pear. The spectra from all four sides of a given sample were averaged to refine the data further and provide a singular, representative spectrum for each pear. This process of averaging ensures that any minor anomalies or variations in the spectra from individual sides are balanced, giving a spectrum that accurately represents the entire pear. In summary, by leveraging the capabilities of the PS-100 spectroradiometer and adopting a meticulous approach to spectroscopy from multiple angles, we have been able to capture and represent the spectral data of pears comprehensively and unbiasedly.



**Figure 2.** Vis/NIR spectrum acquisition of pear fruit.

Our comprehensive study systematically compiled and analyzed the acquired spectra from individual pear samples. The visual representation of these spectra, including the averaged spectra from various test conditions, can be viewed in Figure 3. A careful examination of this figure, particularly the segment on the right, reveals some distinct and noteworthy features.

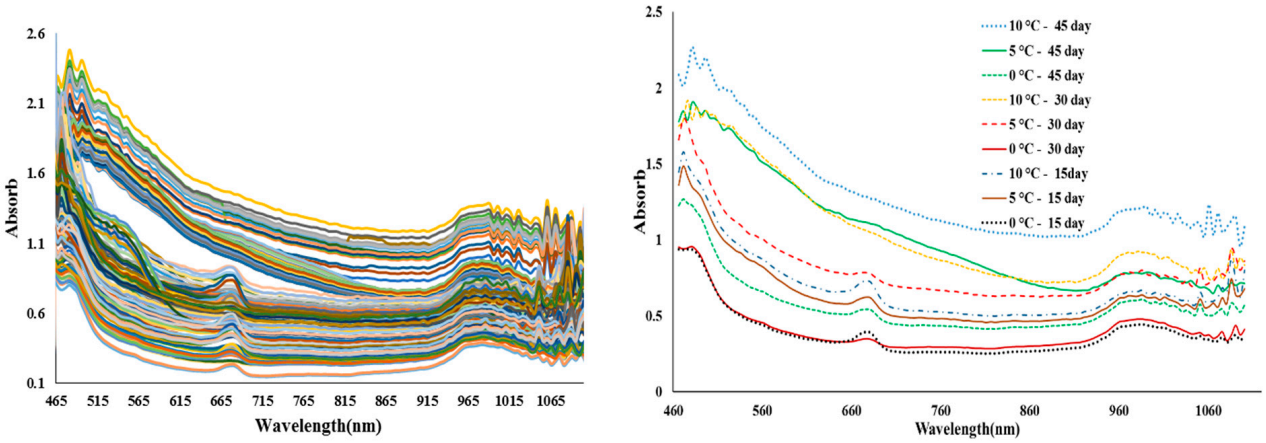



**Figure 3.** Vis/NIR absorption spectra of pear samples. Mean spectra in different test conditions.

Prominently, three specific peaks emerge in most of the spectra. These peaks, which can be pinpointed around the wavelengths of 470 nm, 670 nm, and 970 nm, are not merely arbitrary but are indicative of certain chemical compounds and processes intrinsic to the pear samples [13,14].

470 nm peak: This peak corresponds to the absorption by carotenoids. Carotenoids are a class of pigments that naturally occur in plants and play a pivotal role in photosynthesis. They are also responsible for the bright colors of many fruits and vegetables. In the context of pears, carotenoids influence the fruit's hue and contribute to its overall appearance and health benefits.

670 nm peak: Situated in the red region of the visible spectrum, this peak represents the absorption of chlorophyll. Chlorophyll, the green pigment found in plants and algae, is

essential for photosynthesis, allowing plants to absorb energy from light. Its presence in the pear spectra is a testament to the fruit's freshness and vitality.

970 nm peak: This peak in the near-infrared range is attributed to the absorption of protons by O-H (hydroxyl) or NH2 (amino) groups. These absorptions are particularly significant as they provide insights into the pear samples' water content, molecular interactions, and overall chemical composition. It is worth noting that these spectral peaks and the corresponding compounds they represent have been corroborated by established literature [15]. This congruence validates our findings and underscores the efficacy and accuracy of the PS-100 spectroradiometer and our methodological approach. The spectral analysis of pear samples, as depicted in Figure 3, provides a profound understanding of the fruit's chemical composition and intrinsic properties. The presence of specific peaks at defined wavelengths offers a non-destructive means to gauge the pears' quality, freshness, and nutritional content, making this technique invaluable for both research and industrial applications.

### *2.3. Chemical Properties*

To gain a deeper understanding of the chemical composition of pears, we initiated a comprehensive analysis of their chemical properties. This was achieved by extracting juice from the pears, which served as the primary medium for our various tests. Each testing methodology was chosen for its precision, accuracy, and relevance to the measured property.

pH Measurement: The pH, which indicates the acidity or alkalinity of a substance, is a crucial metric for assessing the quality and ripeness of fruits, including pears. For our analysis, we employed a sophisticated digital pH meter, specifically the PHS-4CT model from Shanghai Dapu Instrument Co., Ltd., based in Shanghai, China. This instrument, renowned for its precision, ensured that our pH readings were accurate and consistent.

Soluble Solids Content (SSC) Measurement: The soluble solids content, which primarily consists of sugars and some acids, provides insights into the sweetness and overall palatability of the fruit. For this measurement, we utilized a refractometer known for its remarkable accuracy of up to 0.1 degrees. The specific model we employed was the Pocket PAL-1 from Atago USA, Inc. This device measures the refractive index of the pear juice, which directly correlates with its SSC.

Titratable Acidity (TA) Assessment: Titratable acidity measures the total acidity present in the fruit, representing a combination of all the organic acids in the pear. The TA was determined using a standardized chemical analysis method, wherein the fruit extract was titrated with sodium hydroxide. This procedure adheres to the GB/T 12293-90 standard, ensuring that our measurements were both rigorous and consistent with established methodologies [16].

Vitamin C Content Analysis: Vitamin C, or ascorbic acid, plays a pivotal role in the overall nutritional profile of pears. It is essential for human health, acting as an antioxidant and aiding in various metabolic processes. To determine the Vitamin C content in our pear samples, we employed a titration method using potassium iodate (KIO3). This approach is based on the method proposed by Shin et al. in 2007 [17], which has been widely recognized and adopted for its accuracy and reproducibility.

In conclusion, through the use of state-of-the-art equipment and adherence to standardized methodologies, we have been able to provide a thorough and accurate analysis of the chemical properties of pears. These insights are invaluable, offering a deeper understanding of the fruit's nutritional value, taste profile, and overall quality.

### *2.4. Data Pre-Processing*

Due to the noise in the beginning and end wavelengths of the spectrum, these areas are removed and, finally, the spectral range of 465–1045 nm was used for the analysis and modeling. To accurately interpret the Vis/NIR spectrum, various factors need to be considered, such as dispersion related to wavelength, variability in tissue structure, noise, ambient temperature and humidity, and variations in the ratio of fruit chemical components. To address these factors, several pre-processing methods were employed, including

Savitzky-Golay, Multiplicative Scatter Correction (MSC), Standard Normal Variate (SNV), Spectral baseline correction, and the first and second derivatives (FD and SD). A sample of the pre-processed spectral data is presented in Figure 4 [18]. The software used in this research for pre-processing the spectra and making estimator models is The Unscrambler X 10.4 (CAMO Software AS, Oslo, Norway).

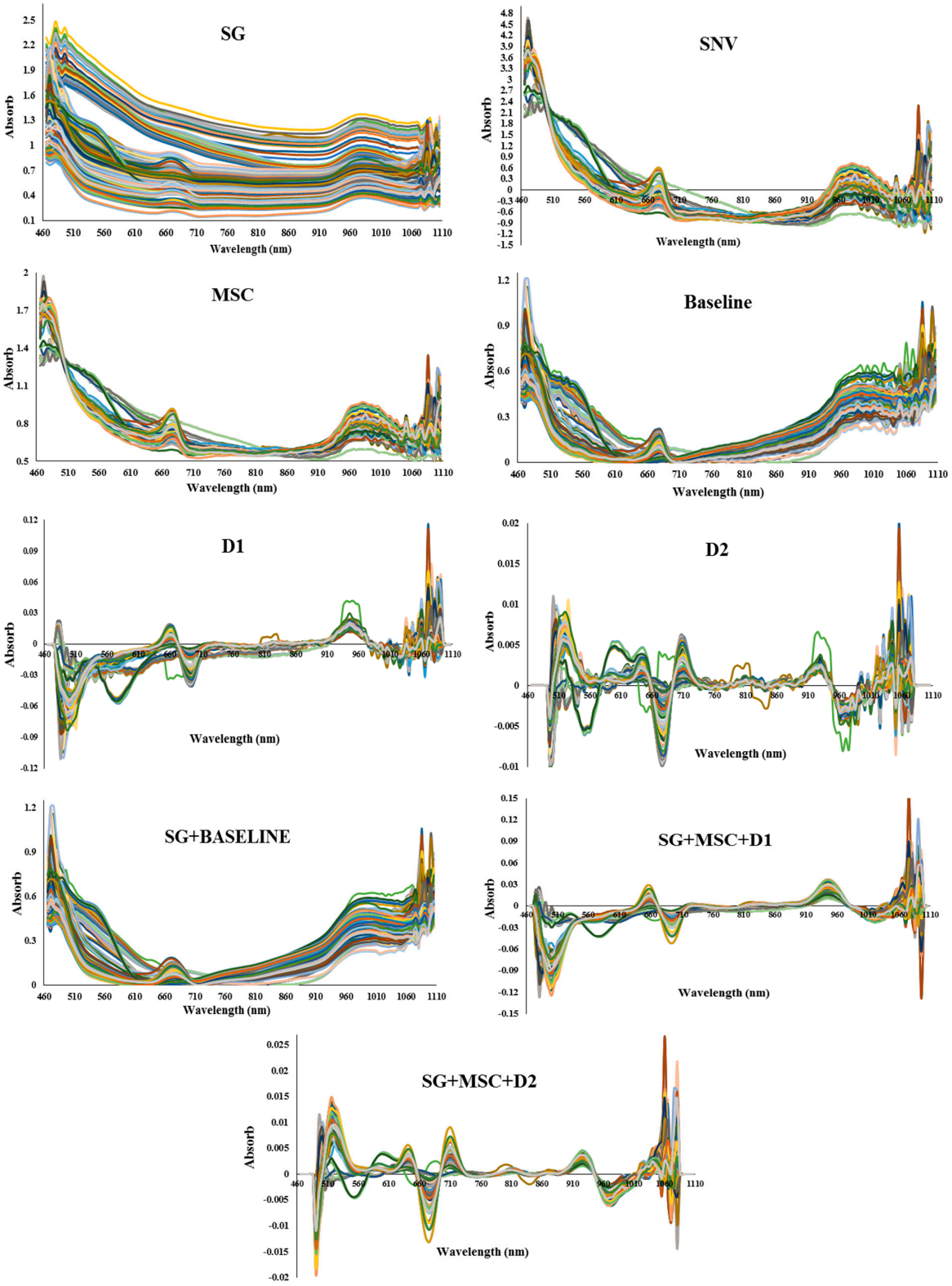



**Figure 4.** Comparison of different pre-processing methods for Vis/NIR spectra of pears.

Analysis of Outliers in PLSR Models Based on Different Pre-Processing Methods

In the application of the PLSR method, specific data points may be classified as outliers. Such data, either inadequately represented by the model or exerting excessive influence, necessitate removal to ensure model accuracy [19,20]. Analysis has indicated that samples with elevated residuals, despite their poor representation by the model, might not pose issues unless they have a significant influence, as characterized by Hotelling's $T^2$ (Rafajłowicz et al., 2019 [21]). Critically, data exhibiting both high residual and Hotelling's $T^2$ values emerge as particularly problematic as they can dominate several model components and warrant their exclusion. The SNV pre-processing method yielded no outliers, while D1 and D2 recorded the highest. Notably, the amalgamation of specific pre-processing methods, such as SG and MSC with D1 and D2, resulted in a substantial reduction in outlier incidence, likely due to the elimination of non-essential spectral regions. This intricate relationship is elucidated in Figure 5, which presents the residuals and influence of samples across varied pre-processing methods.

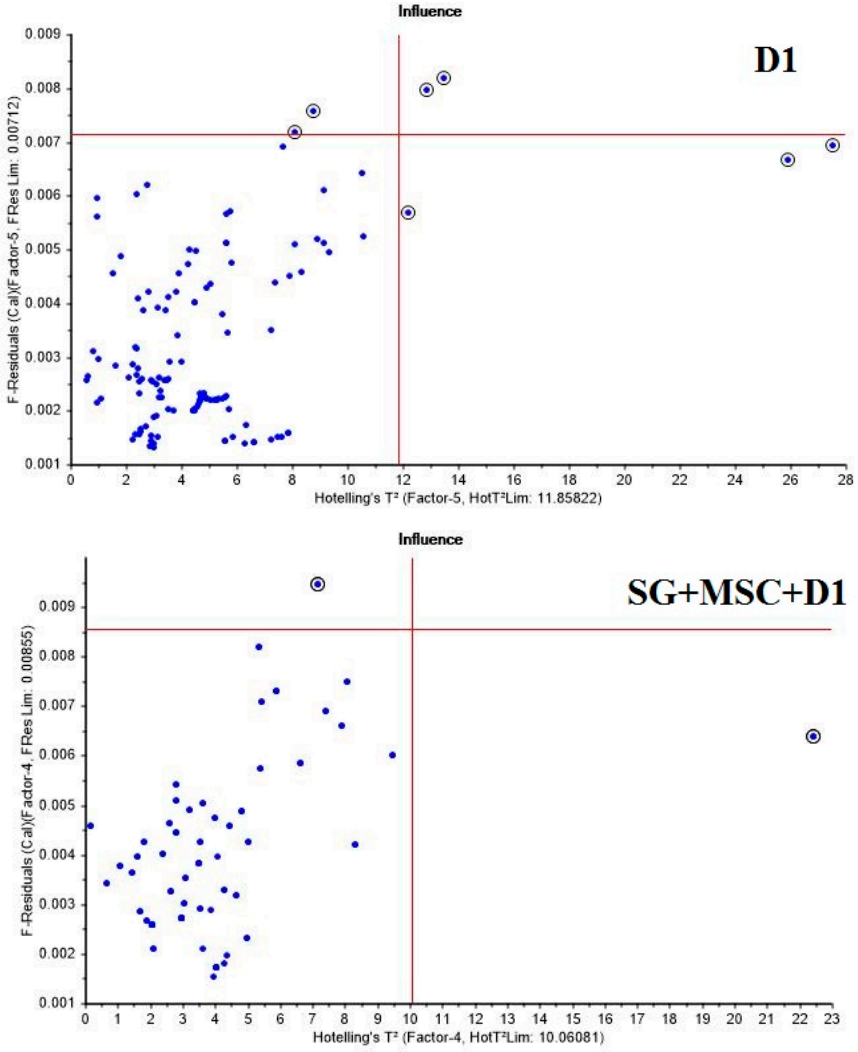



**Figure 5.** Comparison of residuals and influence across different pre-processing techniques.

In Table 1, the number of identified outlier data in models built based on various pre-processing methods is presented.

**Table 1.** Outliers detected based on pre-processing method. (F-Residuals represents the distance of the sample from the model. Hotelling's $T^2$ measures how accurately the sample is described by the mode, and both denotes samples that fall into both critical areas.

| Statistical Criteria | Pre-Processing Method | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Raw | SG | SNV | Baseline | MSC | D1 | D2 | SG + Baseline | SG + MSC + D1 | SG + MSC + D2 |
| F-Residuals | 0 | 0 | 0 | 4 | 1 | 4 | 4 | 4 | 1 | 1 |
| Hotelling's $T^2$ | 2 | 2 | 0 | 6 | 0 | 5 | 8 | 8 | 1 | 3 |
| both | 0 | 0 | 0 | 0 | 0 | 2 | 1 | 0 | 0 | 0 |

### *2.5. Partial Least Squares Regression (PLSR)*

In this study, the PLSR (partial least squares regression) method in the software Unscrambler X 10.4 was employed to establish a correlation between the wavelengths acquired from the Vis-NIR spectroscopy of pear fruit and the data obtained from the measurement of SSC, TA, pH, and vitamin C in the laboratory, following the approach presented by Nicolai et al. (2007) [22]. In this method, in the first step, the correlation matrix between the wavelengths is formed and the wavelengths that have the highest correlation are summarized in the form of a latent variable (LV). In this way, LVs are independent of each other, unlike the initial wavelengths, and the problem of collinearity between variables is solved. Then, an orthogonal base of latent variables is created in turn, in such a way that they are arranged from the highest to the lowest covariance between the spectral matrix X and the response vector y. The number of LVs is chosen in such a way that they can cover the maximum variance of the data [22]. The optimal number of LVs is determined using the leave-one-out cross-validation technique in order to avoid underfitting or overfitting [23].

### *2.6. Model Accuracy Assessment*

Two methods of cross-validation and independent validation were used to validate the estimator models. In the independent validation, 15% of the samples were considered for the validation stage. Also, full cross-validation was performed in such a way that leaves out only one sample at a time. The accuracy of the estimator models was evaluated using several statistical criteria, including the root mean square error of calibration (RMSEC), root mean square error of prediction (RMSEP), root mean square error of Leave-one-out cross-validation (RMSECV), calibration correlation coefficient (rc) and predictive correlation coefficient (rp), and cross-correlation coefficient (rcv). The standard deviation ratio (SDR) value is also used to determine the accuracy of the model, with values between 1.5 and 2 indicating average accuracy, values between 2 and 2.5 indicating good accuracy, and values above 2.5 indicating excellent accuracy. The calculation of these criteria is explained in detail in the published research [22–24].

## 3. Results and Discussion

### *3.1. SSC*

Figure 6 illustrates how storage period and temperature affect pear fruit soluble solids (SSC). It shows that as the storage period and temperature increase, the pear fruit loses its original characteristics and its SSC increases. During storage, the conversion of starch to sugar increases the amount of SSC, and higher ambient temperatures can accelerate these chemical changes. Similar findings have been reported in numerous studies, indicating an increase in SSC in fruits during storage [25,26].

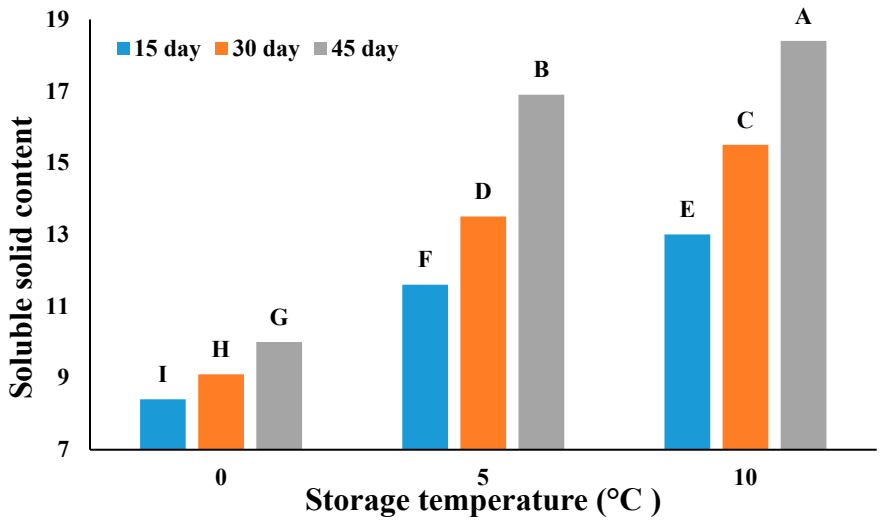



**Figure 6.** Changes in the soluble solid content (SSC) over different storage periods at different storage temperatures (0, 5, and 10 °C). Different superscript capital letters on columns indicate mean difference between groups ($p < 0.05$).

Table 2 displays the statistical parameters used for calibration and validation of PLS models to estimate the SSC of pear fruit using different pre-processing techniques on Vis/NIR spectra. The results show that the S.G. + MSC + D1 model outperforms other models, while the S.G. + MSC + D2 model has the weakest performance with an $r_p$ value of 0.91. The performance of the model by S.G. pre-processing is very similar to the model without pre-processing. The superiority of the pre-processing technique of S.G. + MSC + D2 over other pre-processing methods can be attributed to the extensive range of variations observed in the traits measured in this study. The spectral curves of various treatments do not follow a similar trajectory. Specifically, the spectral curves related to the 10-degree temperature treatment do not exhibit prominent peaks. Consequently, pre-processing methods focused on normalization and standardization can obliterate these curve peaks, resulting in the loss of valuable information. However, differentiation accentuates the latent information within the spectra, establishing a more precise correlation between radiation absorption and the targeted attributes.

**Table 2.** The validation results of Partial Least Squares (PLS) models using different pre-processing methods for Vis/NIR spectra to estimate the Soluble Solids Content (SSC) of pear fruit.

| Pre-Processing | The Number of Latent Variables (LVs) | $r_c$ | RMSEC | $r_{cv}$ | RMSECV | $r_p$ | RMSECP | SDR |
|---|---|---|---|---|---|---|---|---|
| Raw | 1 | 0.93 | 0.84 | 0.93 | 0.85 | 0.96 | 0.71 | 4.7 |
| SG | 1 | 0.93 | 0.84 | 0.93 | 0.85 | 0.96 | 0.71 | 4.7 |
| D1 | 4 | 0.90 | 1.0 | 0.88 | 1.13 | 0.92 | 0.81 | 4.12 |
| D2 | 4 | 0.90 | 1.06 | 0.88 | 1.15 | 0.92 | 0.83 | 4.02 |
| MSC | 4 | 0.93 | 0.90 | 0.91 | 0.98 | 0.93 | 0.74 | 4.5 |
| SNV | 4 | 0.93 | 0.78 | 0.91 | 0.96 | 0.94 | 0.72 | 4.6 |
| Baseline | 7 | 0.91 | 0.96 | 0.9 | 1.02 | 0.94 | 0.73 | 4.57 |
| S.G. + Baseline | 7 | 0.90 | 1.0 | 0.89 | 1.1 | 0.94 | 0.72 | 4.64 |
| S.G. + MSC + D1 | 5 | 0.96 | 0.70 | 0.94 | 0.81 | 0.95 | 0.69 | 4.83 |
| S.G. + MSC + D2 | 8 | 0.96 | 0.70 | 0.93 | 0.85 | 0.91 | 0.87 | 3.84 |

### *3.2. Vitamin C*

Figure 7 illustrates the impact of the storage period and temperature on vitamin C content in pear fruit. The figure shows that the vitamin C content of the pear fruit decreases

with an increasing storage period and temperature. Vitamin C is an unstable compound that is sensitive to storage conditions such as temperature, light, oxygen, and the presence of enzymes like ascorbate oxidase and peroxidase, which can lead to its degradation during storage [27]. Previous studies have also reported similar findings [28,29].

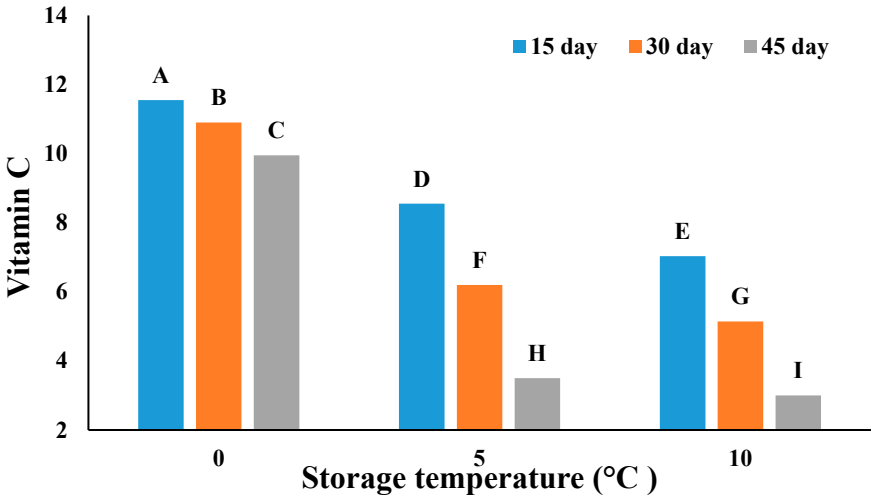



**Figure 7.** The relationship between storage temperature (°C), storage time (day), and vitamin C content of pear fruit. Different superscript capital letters on columns indicate mean difference between groups ($p < 0.05$).

Table 3 shows the statistical evaluation of the PLS models using various pre-processing methods to estimate the vitamin C of the pear fruit. Based on the independent validation, all pre-processing models demonstrated accepted accuracy. However, the S.G. + MSC + D2 pre-processing exhibited the highest accuracy, compared to the other models ($r_p$ = 0.95, SDR = 4.9). The S.G. + MSC + D2 pre-processing method demonstrated superior performance compared to other methods in predicting the vitamin C of pear fruit during storage using Vis/NIR spectroscopy. This may be due to the wide range of changes observed in the fruit's characteristics and no consistent trends in the spectral curves across different pre-processing approaches, as Grant and Bhattacharyya (1985) suggested [30].

**Table 3.** The statistical criteria for validating and calibrating PLS models using different pre-processing methods of Vis/NIR spectra to estimate vitamin C in pear fruit.

| Pre-Processing | LVs | $r_c$ | RMSEC | $r_{cv}$ | RMSECV | $r_p$ | RMSECP | SDR |
|---|---|---|---|---|---|---|---|---|
| Raw | 2 | 0.93 | 0.77 | 0.93 | 0.94 | 0.93 | 0.71 | 4.2 |
| SG | 2 | 0.91 | 0.84 | 0.90 | 0.85 | 0.95 | 0.6 | 4.9 |
| D1 | 6 | 0.88 | 0.99 | 0.86 | 1.1 | 0.93 | 0.71 | 4.2 |
| D2 | 3 | 0.88 | 1.02 | 0.86 | 1.12 | 0.91 | 0.81 | 3.7 |
| MSC | 4 | 0.91 | 0.89 | 0.89 | 0.99 | 0.93 | 0.73 | 4.1 |
| SNV | 4 | 0.91 | 0.87 | 0.89 | 0.97 | 0.94 | 0.7 | 4.3 |
| Baseline | 7 | 0.89 | 0.96 | 0.86 | 1.08 | 0.91 | 0.83 | 3.6 |
| S.G. + Baseline | 7 | 0.88 | 0.99 | 0.86 | 1.1 | 0.90 | 0.86 | 3.5 |
| S.G. + MSC + D1 | 4 | 0.92 | 0.82 | 0.90 | 0.94 | 0.91 | 0.83 | 3.6 |
| S.G. + MSC + D2 | 12 | 0.91 | 0.89 | 0.90 | 0.87 | 0.95 | 0.6 | 4.9 |

### *3.3. pH*

Figure 8 indicates that the pH of pear fruit increases as the storage period and temperature increase. This may be attributed to the biochemical reactions occurring within the fruit that intensify with temperature and time, leading to the conversion of acid degradation compounds and their possible esterification into corresponding esters [31].

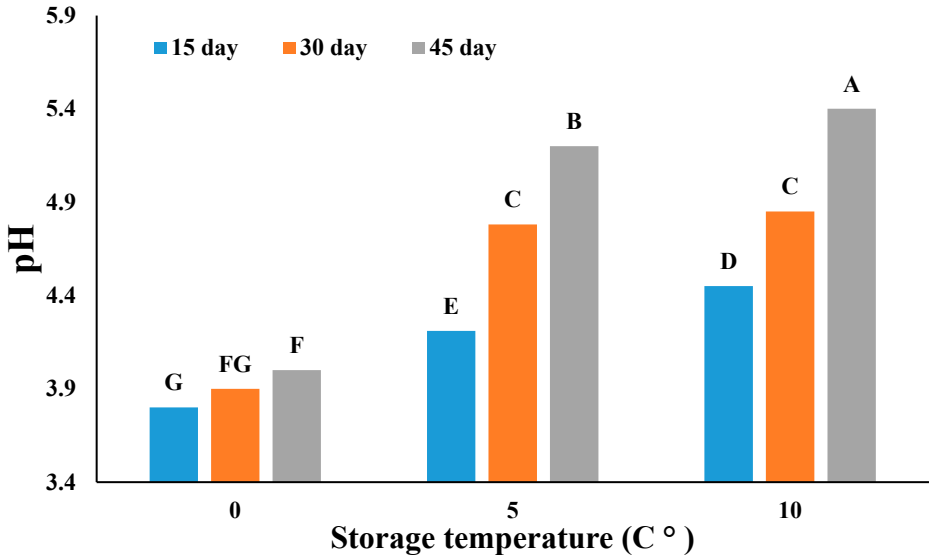



**Figure 8.** The effect of storage period and temperature on the pH value of pear fruit. Different superscript capital letters on columns indicate mean difference between groups ($p < 0.05$).

Table 4 indicates that all pre-processing models have an acceptable accuracy in independent validation. Among them, the S.G. + MSC + D1 model has the best accuracy compared to the other models ($r_p$ = 0.98, SDR = 9.6). The superiority of the combined pre-processing method over other pre-processing techniques is due to the fact that in the first step, the fluctuations caused by random noise and the instrument are eliminated by the S.G method and the curve is smoothed [32]. Then, in the next step, the noise caused by light scattering was removed by the MSC method [33], and finally, models based on spectra obtained from derivation have more independent components, increasing their ability to fit nonlinear curves. Given that the behavior of the measured variables follows a non-linear process, pre-processing methods are necessary. These methods reduce the spectral dependencies and increase the linear independence of the variables from each other. This has been previously reported by Xu et al. (2020) and Elmqvist and Fekete (2009) [18,34].

**Table 4.** The statistical results for the validating and calibrating of PLS models to estimate pH in pear fruit using various pre-processing methods of Vis/NIR spectra.

| Pre-Processing | LVs | $r_c$ | RMSEC | $r_{cv}$ | RMSECV | $r_p$ | RMSECP | SDR |
|---|---|---|---|---|---|---|---|---|
| Raw | 1 | 0.84 | 0.23 | 0.83 | 0.24 | 0.94 | 0.11 | 5.2 |
| SG | 1 | 0.84 | 0.23 | 0.83 | 0.24 | 0.94 | 0.11 | 5.2 |
| D1 | 10 | 0.82 | 0.24 | 0.77 | 0.27 | 0.88 | 0.16 | 3.6 |
| D2 | 12 | 0.83 | 0.23 | 0.77 | 0.27 | 0.91 | 0.14 | 4.1 |
| MSC | 9 | 0.85 | 0.21 | 0.80 | 0.25 | 0.95 | 0.10 | 5.7 |
| SNV | 9 | 0.86 | 0.21 | 0.81 | 0.24 | 0.97 | 0.08 | 7.2 |
| Baseline | 7 | 0.85 | 0.21 | 0.79 | 0.26 | 0.93 | 0.12 | 4.8 |
| S.G. + Baseline | 7 | 0.84 | 0.22 | 0.78 | 0.26 | 0.91 | 0.14 | 4.1 |
| S.G. + MSC + D1 | 6 | 0.88 | 0.19 | 0.82 | 0.24 | 0.98 | 0.06 | 9.6 |
| S.G. + MSC + D2 | 7 | 0.89 | 0.18 | 0.81 | 0.24 | 0.96 | 0.09 | 6.4 |

### *3.4. TA*

Figure 9 shows the impact of the storage period and temperature on the titratable acidity (TA) of the pear fruit.

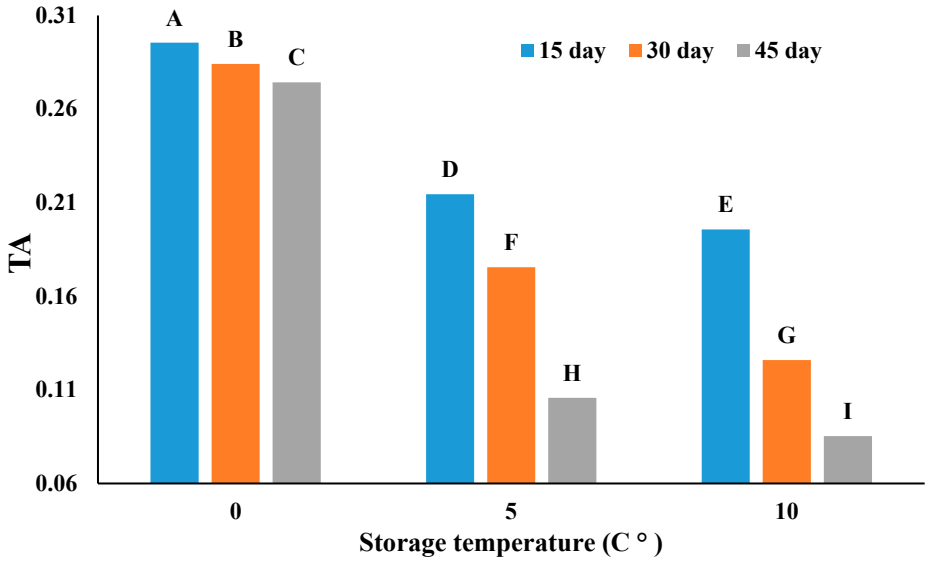



**Figure 9.** Changes in TA of pear fruit with respect to storage period and storage time. Different superscript capital letters on columns indicate mean difference between groups ($p < 0.05$).

Table 5 shows that the TA value of pear fruit decreases with an increasing storage time and temperature. This decrease in acidity during the storage period is a well-documented phenomenon in various reports [35,36]. The respiratory process in fruits during storage leads to the conversion of organic acids into sugars, causing a reduction in the percentage of measurable acidity. Acids are an energy source for fruits and they are gradually depleted during storage due to decomposition under appropriate temperature conditions [37].

**Table 5.** Validation results of PLS models based on different pre-processing methods of Vis/NIR spectra for estimating TA of pear fruit.

| Pre-Processing | LVs | $r_c$ | RMSEC | $r_{cv}$ | RMSECV | $r_p$ | RMSECP | SDR |
|---|---|---|---|---|---|---|---|---|
| Raw | 2 | 0.94 | 0.018 | 0.92 | 0.019 | 0.94 | 0.016 | 4.6 |
| SG | 2 | 0.94 | 0.018 | 0.93 | 0.019 | 0.94 | 0.016 | 4.6 |
| D1 | 3 | 0.90 | 0.022 | 0.89 | 0.024 | 0.90 | 0.021 | 3.5 |
| D2 | 12 | 0.90 | 0.022 | 0.89 | 0.024 | 0.92 | 0.019 | 3.9 |
| MSC | 5 | 0.92 | 0.021 | 0.91 | 0.021 | 0.93 | 0.017 | 4.3 |
| SNV | 4 | 0.93 | 0.019 | 0.91 | 0.021 | 0.93 | 0.017 | 4.3 |
| Baseline | 6 | 0.92 | 0.020 | 0.90 | 0.023 | 0.91 | 0.019 | 3.9 |
| S.G. + Baseline | 7 | 0.91 | 0.021 | 0.89 | 0.024 | 0.93 | 0.018 | 4.1 |
| S.G. + MSC + D1 | 3 | 0.94 | 0.017 | 0.93 | 0.019 | 0.92 | 0.019 | 3.9 |
| S.G. + MSC + D2 | 3 | 0.96 | 0.014 | 0.94 | 0.018 | 0.96 | 0.012 | 6.1 |

The models created using both independent and cross-validation methods in Table 5 have a high prediction accuracy. The SG pre-processing model performs similarly to the model without pre-processing. Additionally, the models using MSC and SNV pre-processing have similar performances, as indicated in the graphical diagram of these two methods. Finally, the S.G. + MSC + D2 pre-processing model outperforms the other models in both validation methods ($r_{cv}$ = 0.94, $r_p$ = 0.96, SDR = 6.1).

## 4. Conclusions

As the storage duration for pear fruit extends, there is a notable decline in quality. Specifically, soluble solids (SSC) and pH levels increase, while vitamin C and titratable acid (TA) decrease. However, a storage temperature of 0 °C effectively extends the pear's shelf life. In fact, pears stored at this temperature for 45 days maintain their quality attributes better than those stored at 5 and 10 °C for just 15 days.

The pre-processing of spectra using SNV, MSC, Baseline, and SG offers advantages such as aligning spectra, reducing minor noises, and emphasizing spectral peaks. The first derivative (D1) and second derivative (D2) pre-processing techniques enhance the number of peak points and spectral resolution. Among these, SNV pre-processing introduces the least outliers, whereas D1 and D2 yield the most. A combined approach, specifically using SG + MSC with derivative techniques, dramatically reduces the outlier data count.

Modeling results indicate that the spectrum preprocessed with SG + MSC + D1 has a higher accuracy for SSC and pH, likely due to an increased number of latent variables (LVs) compared to other pre-processing techniques. Conversely, the spectrum preprocessed with SG + MSC + D2 offers superior modeling precision for vitamin C and TA, again attributed to a larger number of LVs.

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