Study on the Effect of Moisture Content on the Spectral Detection of Soluble Solids in Apricot (Prunus armeniaca ‘Diao Gan')

lei kang
Tarim University
Huaping Luo
luohuaping739@163.com

Tarim University
Xueting Ma
Tarim University
Jinlong Yu
Tarim University
Hongyang Liu
Tarim University
Huaiyu Liu
Tarim University
Yuesen Tong
Tarim University

Article

Keywords: Hyperspectral, Moisture Content, Morphological Parameters, Soluble Solids Content, Quantitative Prediction Model, Apricot

Posted Date: December 10th, 2025

DOI: https://doi.org/10.21203/rs.3.rs-8030114/v1

Additional Declarations: No competing interests reported.

Version of Record: A version of this preprint was published at Scientific Reports on February 20th, 2026.
See the published version at https://doi.org/10.1038/s41598-026-39890-w.

Study on the Effect of Moisture Content on the Spectral Detection of Soluble Solids in Apricot (Prunus armeniaca 'Diao Gan')

Lei Kang[1,2,3]; Huaping Luo[1,2,3,*]; Xueting Ma[1,2,3,*]; Jinlong Yu[1,2,3]; Hongyang Liu[4]; Huaiyu Liu[1,2,3]; Yuesen Tong[1,2,3];

1 College of Mechanical and Electrical Engineering, Tarim University, Alar 843300, China; 18203138832@163.com

2 Modern Agricultural Engineering Key Laboratory at Universities of Education Department of Xinjiang Uygur Autonomous Region, Tarim University, Alar 843300, China

3 Xinjiang Production and Construction Corps Key Laboratory of Utilization and Equipment of Special Agricultural and Forestry Products in Southern Xinjiang, Alar 843300, China

4 College of Horticulture and Forestry, Tarim University, Alar 843300, China

* Correspondence:luohuaping739@163.com;120160004@taru.edu.cn

Abstract

To reduce the influence of moisture content variation on the spectral detection of soluble solid content (SSC) and achieve rapid, non-destructive detection of SSC, as well as optimize the processing parameters of apricot products, improve detection efficiency and quality control, this study, based on spectral detection technology, combined with the multiple scatter correction (MSC) preprocessing method, concentration residual method for outlier removal, competitive adaptive reweighted sampling method for feature band selection and partial least squares (PLS) method, constructed SSC detection models for apricots at different moisture contents, and explored the impact of moisture content on the detection model effect of SSC in apricot. This study showed that as moisture content decreased, both the absolute values of the valley depth and valley area in the first-derivative spectrum near 970 nm, as well as the peak height and peak area of the reflection peak, gradually diminished, indicating a weakening of moisture characteristics. Furthermore, within the 450 nm-1450 nm wavelength range, SSC prediction accuracy significantly improved with decreasing moisture content. Under 8-hour apricot drying conditions, the model achieved optimal prediction accuracy with an R_p of 0.9844, RMSEP of 0.5712, and RPD of 5.7989, meeting high-precision quantitative requirements. This study discovered the influence of different moisture intervals on the hyperspectral SSC prediction model of apricot fruits, laying a foundation for the subsequent research on moisture content correction spectra to eliminate the influence of moisture content on spectral detection of SSC content.

Keywords: Hyperspectral; Moisture Content; Morphological Parameters; Soluble Solids Content; Quantitative Prediction Model; Apricot

1 Introduction

Apricots are beloved by consumers for their dense flesh, rich flavor, and high soluble solids content[1, 2]. Soluble solids content (SSC) serves as a crucial physicochemical indicator reflecting fruit sugar content and flavor. It not only directly influences the edible quality of dried fruits but also functions as a key parameter for evaluating processing maturity and final product quality. However, traditional SSC detection methods rely on chemical analysis or refractometer measurements. While these methods offer high precision, they suffer from limitations such as cumbersome operation, sample destruction, and inability to enable large-scale prediction[3]. In recent years, visible-near infrared hyperspectral imaging technology has emerged as a key research direction for non-destructive fruit inspection. This technique simultaneously captures both spatial and spectral information of samples, reflecting chemical composition and physical characteristics across multiple contiguous spectral bands.

Previous studies have demonstrated that environmental factors and intrinsic sample properties significantly influence the stability of physicochemical value prediction models. Research by Jiang Xiaogang et al. indicates that temperature is a significant factor affecting apple spectral characteristics. By comparing multiple temperature correction methods—including EPO, GLSW, OSC, and global calibration—the EPO method was found to deliver the most optimal results[4]. The study by Sun Xudong et al. found that changes in temperature and illumination can interfere with the spectrum during field measurements. They employed chemometric algorithms of global model, External Parameter Orthogonalization (EPO), and Generalized Least Square Weighting (GLSW) to correct for the effects of temperature and illumination, thereby enhancing the accuracy of outdoor detection[5]. Suo Yuting et al. addressed the spectral variations caused by different lighting conditions by fitting the parameters of the Roujean and Ros-Li models through the least square method, effectively reducing the spectral differences resulting from outdoor lighting changes[6]. Depin Ou et al. investigated soil moisture removal correction models to enhance the spectral sensitivity of soil organic matter, addressing the significant influence of soil moisture content on the spectral signature of organic matter[7].

Water, as one of the main chemical components inside fruits, exhibits strong absorption characteristics in the spectral band, which can interfere with sugar-related spectral signals and affect the accuracy of SSC prediction models[8]. How to effectively weaken the interference of moisture during the process of apricot to highlight the spectral characteristic signals of SSC is the key to improving the prediction performance and stability of the model. Based on this, this study focused on apricots as the research subject. This study utilized visible-near infrared hyperspectral imaging technology on apricots. By integrating hyperspectral data, moisture content, and soluble solids content (SSC) measurements across different drying durations, characteristic wavelengths were screened within the 450–1450 nm band. Based on this, quantitative SSC prediction models were developed for apricots across different moisture content ranges. Spectral characteristics were analyzed for each moisture interval, and the impact of moisture variation on the accuracy of hyperspectral-SSC modeling was investigated. Results confirmed that moisture content is a critical factor influencing the accuracy of hyperspectral-SSC detection models for apricots.

2 Materials and Methods

2.1 Materials

On July 4, 2025, 400 apricots were randomly collected from orchards in Alar City, Division 1 of the Xinjiang Production and Construction Corps. The apricots were uniformly sized, uniformly ripe, and free of visible mechanical damage. Samples were individually wiped with clean towels to minimize dust interference with spectral reflectance measurements, then labeled and weighed.

2.2 Methods

2.2.1 Data Collection

The experiment employed an FS-64C pushbroom hyperspectral camera to acquire hyperspectral image data. This device utilizes transmission grating spectroscopy technology, featuring a spectral range of 400–1700 nm, an imaging rate of 100 frames per second, and a spectral resolution of 2 nm. The hyperspectral camera was positioned vertically to the sample at a distance of 2 meters. Two Godox-QL-1000 halogen lamps were placed symmetrically on either side of the sample stage at a 45°angle to the camera's optical axis plane, maintaining a distance of approximately 2 meters from the sample to ensure stable illumination intensity. Connect the hyperspectral camera to a Windows-based computer host and an external display via a data cable, as shown in Figure 1, to enable real-time image acquisition of apricot fruits. Before each acquisition, perform white calibration using the reflectance calibration plate provided with the spectral camera. Subsequently, cover the camera lens with the lens cap to perform black calibration. Finally, adjust the camera parameters to ensure image quality. This study analyzed samples at different stages of the drying process (specifically after 2 h, 4 h, 6 h, and 8 h of drying) to simulate the dynamic changes in apricots as they transition from fresh fruit to dried fruit. At the end of each drying stage, 100 apricots were randomly selected from the sample batch, and hyperspectral reflectance images were captured.

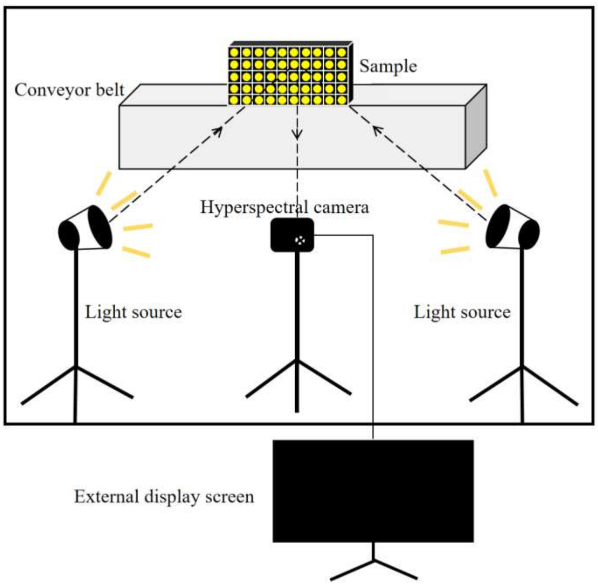

Figure 1. Indoor sample placement.

After completing the spectral acquisition, use the side with the acquired spectrum for physicochemical parameter determination. Determine the moisture content of the sample according to the national standard GB/T 5009.3-2016. Set the temperature of the JC-9070A horizontal forced-air drying oven to 80°C. and the apricot samples were placed inside for drying. At 2h, 4h, 6h, and 8h intervals, 100 samples were removed to measure net weight at each stage. All samples were dried to constant weight to determine final dry mass, and moisture content at each stage was calculated accordingly. The calculation of moisture content is shown in Formula 1.

$$X = \frac{m_1 - m_2}{m_1} \times 100\% \qquad (1)$$

In the formula: X represents the moisture content of the sample; m_1 denotes the mass of the sample at different drying stages, in grams; m_2 indicates the mass of the sample after drying to constant weight, in grams.

The SSC content of apricot samples was measured using the SMART-SENSOR-ST355A handheld refractometer. First, the refractometer was calibrated prior to measuring the SSC of apricots. Second, juice from each sample was sequentially dripped into the solution test area of the refractometer. The protective cover was closed, and the SSC was measured three times for each sample. The average value was recorded as the SSC for that sample.

2.2.2 Data Processing

To optimize the quality of hyperspectral data acquisition and reduce data redundancy, this study preprocessed the collected data prior to establishing the hyperspectral-SSC detection model. First, flat-field calibration was performed on the raw hyperspectral images to eliminate systematic errors caused by variations in ambient illumination, ensuring the accuracy of spectral reflectance measurements. Second, a region of interest (ROI) measuring 10pi × 10pi was manually delineated to extract the effective pixel spectra from the apricot surface, thereby eliminating background noise and invalid areas. Due to the mirror effect in hyperspectral camera imaging, the selection direction of the ROI was from right to left in sequence, as shown in Figure 2. Subsequently, the extracted spectral reflectance data underwent preprocessing, outlier removal, and feature wavelength selection.

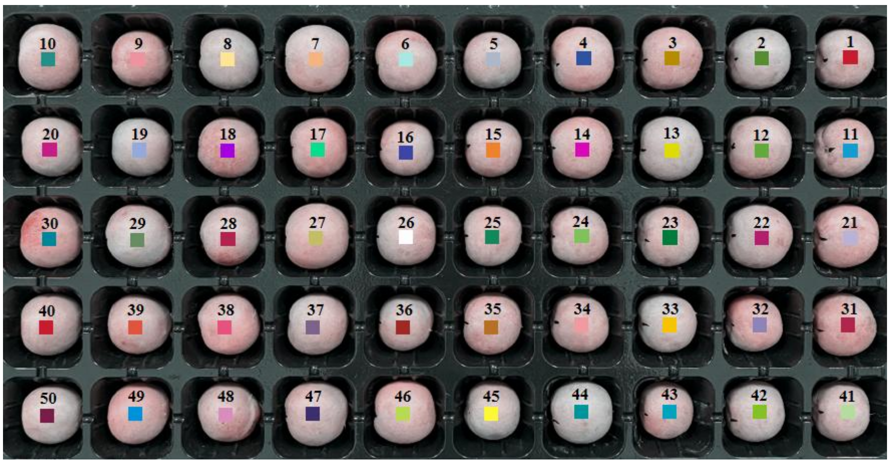

Figure 2. Sample Region of Interest Selection.

To further enhance data quality, a preprocessing method employing multiple scattering correction is adopted to mitigate light scattering effects caused by sample particle structure and surface irregularities. This approach amplifies characteristic signals in the spectrum related to chemical composition, thereby improving the accuracy of subsequent quantitative analysis and the model's generalization capability[9].

To prevent introduced noise and interference from disrupting the true correlation between spectral data and sugar content, outlier samples must be removed from the data. Using sample data dried for 2 hours as an example, the concentration residual method was applied with a threshold of h=2 to remove outliers from both spectral data and physicochemical values. The concentration residual threshold was set according to standard methods in chemometrics. As shown in Figure 3, 13 outlier samples were excluded. Additionally, 10, 9, and 13 outlier samples were excluded at drying times of 4h, 6h, and 8h, respectively.

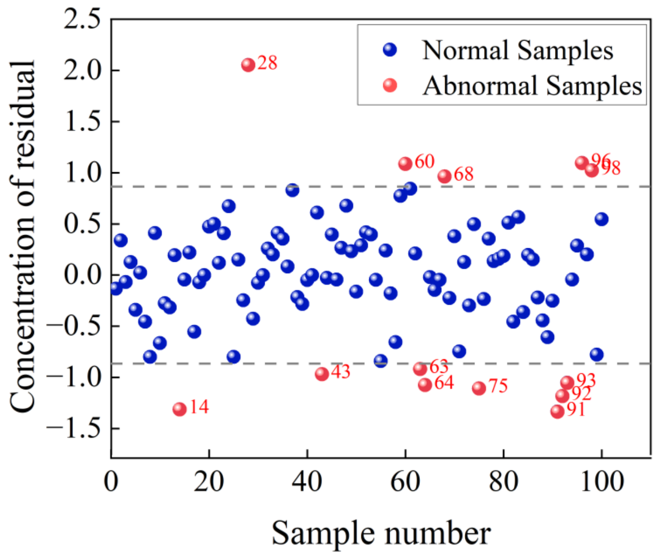

Figure 3. Elimination of apricot samples using the concentration residual method (total samples: n = 100; threshold: 2.0; eliminated samples: 13; valid samples: n = 87).

To accurately and automatically screen out the few key wavelengths most relevant to apricot SSC from the vast amount of full-spectrum data, the Competitive Adaptive Re-weighted Sampling (CARS) algorithm is employed for variable selection during the variable selection phase[10]. Set the cross-validation fold number of the CARS algorithm to 10, the iteration number to 50, and the maximum principal component to 15, and finally, output the optimal feature wavelength combination. Using sample data dried for 2 hours as an example, the results are shown in Figure 4. As the number of iterations increases, the cross-validation root mean square error gradually decreases, reaching its minimum at the 23rd iteration. Ultimately, 60 feature variables were selected. The upper part of the figure shows the variation in the retention rate of feature wavelength variables over 50 iterations; the middle section displays the RMSECV variation curve during 50 iterations; the lower section reflects the trend in coefficient values for each variable across 50 iterations. The solid red vertical line indicates that the optimal iteration count at this point is 23. This method effectively eliminated redundant variables while retaining spectral band information highly correlated with the dynamic changes in SSC, significantly enhancing the robustness and predictive accuracy of subsequent modeling. Additionally, the optimal number of iterations for drying times of 4h, 6h, and 8h was 21, 15, and 18, respectively.

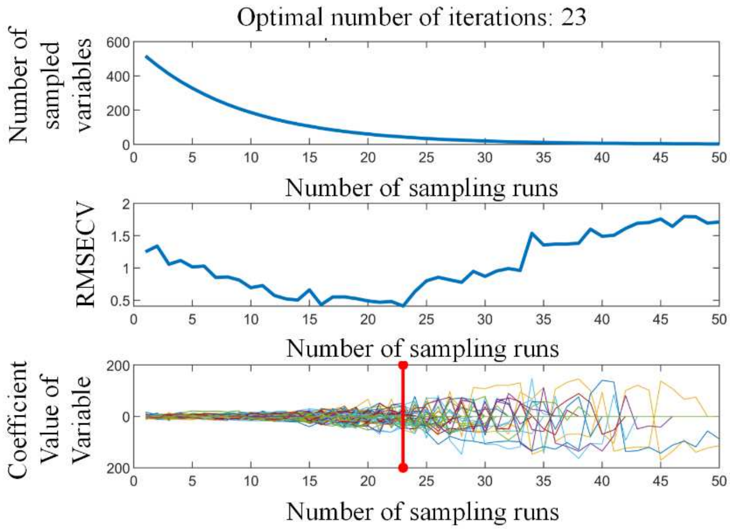

Figure 4. Characteristic wavelength selection via the CARS algorithm (total spectral bands: 561; valid samples: n = 97; iterations: 50).

2.2.3 Model Construction and Evaluation Metrics

After selecting characteristic wavelengths, this study employed partial least squares (PLS) to establish an apricot SSC prediction model. Model performance evaluation metrics include the training set correlation coefficient (R_c), prediction set correlation coefficient (R_p), root mean square error of prediction (RMSEP), and residual predictive deviation (RPD). The closer the values of R_c and R_p are to 1, the stronger the correlation between model fitting and prediction; the closer the RMSEP value is to 0, the smaller the prediction error of the model. RPD is used to measure a model's robustness and predictive capability. When RPD is less than 2.0, predictive capability is limited; when RPD is greater than or equal to 2.0 and less than or equal to 2.5, the model exhibits good predictive performance; when RPD is greater than or equal to 2.5 and less than or equal to 3.0, predictive performance is superior; when RPD is greater than or equal to 3.0, predictive capability reaches an excellent level[11]. The specific calculation methods are shown in Formulas 2, 3, and 4.

$$R = \frac{\sum_{i=1}^{N}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \overline{x})} * \sqrt{\sum_{i=1}^{N}(y_i - \overline{y})}} \qquad (2)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2} \qquad (3)$$

$$RPD = \frac{SD}{RMSE} \qquad (4)$$

In the formula, N represents the sample size; x and y denote different variables; $\overline{x}$ and $\overline{y}$ correspond to the mean values of the variables; y_i corresponds to the actual values of the variables; $\hat{y}$ corresponds to the predicted values of the variables; SD denotes the standard deviation of the variables.

3 Results

3.1 Analysis of Spectral Characteristics Across Different Moisture Ranges

To reveal the direct impact of moisture content variations on spectral morphological characteristics and the differences in spectral responses across distinct drying stages, this study first extracted the raw average reflectance spectra of apricot samples across different moisture intervals, as shown in Figure 5. Analysis was conducted within the 450–1450 nm spectral range. This range offers a high signal-to-noise ratio while simultaneously covering the visible spectrum's pigment reflection characteristics on fruit surfaces and the near-infrared spectrum's absorption information for internal components such as moisture and soluble solids. This approach effectively avoids the low signal-to-noise ratio region below 450 nm caused by stray light interference and optical component limitations, as well as the unreliable band above 1450 nm affected by detector noise. Further first-order derivative processing was performed on spectral data with different drying times (2h, 4h, 6h, 8h) to highlight subtle changes in absorption valleys and reflection peaks within the sensitive band, as shown in Figure 6.

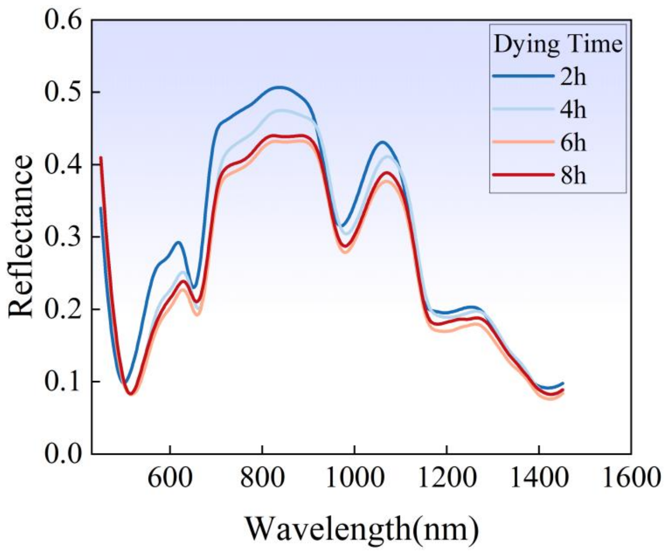

Figure 5. Hyperspectral reflectance at different drying times.

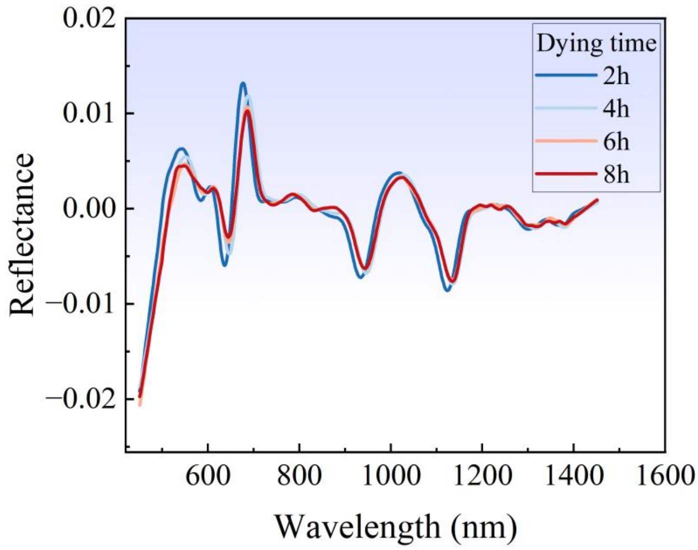

Figure 6. Hyperspectral reflectance at different drying times after first derivative preprocessing.

Overall, the spectral curve shapes of each stage remain consistent, exhibiting common reflection characteristics of fruits in all bands. However, spectral curves across different moisture ranges exhibit distinct differences in reflectance peak height and absorption trough depth, with these variations closely linked to moisture changes. Figure 7 illustrates the trend of SSC content and moisture content during the drying process. As drying time increases, the moisture content of the apricots continuously decreases while the SSC content steadily rises, reaching a plateau after 8 hours. The statistical results for moisture and SSC content of samples across different moisture ranges are shown in Table 1. During the drying process, the soluble solids content (SSC) of apricots increased significantly from 15.89°Brix at 2 hours of drying to a peak of 23.17°Brix at 6 hours. This increase is primarily attributed to substantial water loss during drying, which leads to a relative concentration increase of soluble solids in the fruit. However, in the later stages, thermal degradation of sugars may occur, resulting in a partial decrease in SSC content[12]. The drying process causes rapid evaporation of moisture, with a significant decrease in moisture content observed between 2 and 6 hours. The moisture content at 8 hours shows little difference from that at 6 hours, indicating that moisture content approaches equilibrium by the 6-hour mark.

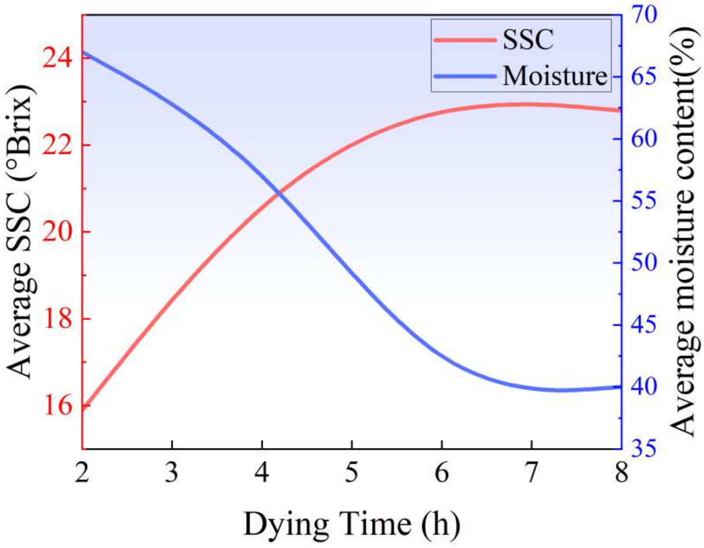

Figure 7. Variation Trends of SSC and Moisture Content at Different Drying Times.

Index	Stage	Data Range	Average Value	Standard Deviation	Coefficient of Variation
SSC（°Brix）	2h	11.20–22.70	15.89	2.26	14.24
	4h	14.20–31.00	21.07	3.39	16.10
	6h	14.40–36.30	23.17	4.02	17.35
	8h	16.40–33.40	22.79	3.43	15.05
Moisture(%)	2h	58–74	67	4	5.25
	4h	47–68	59	5	7.92
	6h	27–52	39	5	12.34
	8h	30–48	40	4	8.86

Table 1. Statistical Summary of Physicochemical Properties of Samples.

Table 2 shows the valley depth and valley area of the absorption valley near 970 nm, extracted from the first-order derivative reflectance curve, along with the peak height and peak area of the reflection peak near 1000 nm. As drying time increased, the spectral characteristics of the apricot samples underwent a series of consistent changes, clearly reflecting the process of moisture loss within them. The absorption trough at approximately 970 nm in the fruit spectrum is considered a characteristic feature of the O–H vibrational overtone frequency of water molecules. This absorption shifts with changes in fruit moisture content[13]. This study investigates the effect of moisture on spectral characteristics using this wavelength band as an example. Table 2 shows that during the drying period from 2 hours to 8 hours, the valley depth near 970nm decreased by 13.0% and the valley area decreased by 13.4%. The monotonic decrease in valley depth and valley area indicates that the sample's ability to absorb photons near the 970 nm wavelength band continues to decline, indicating a significant decrease in the sample's moisture content. When drying time was extended to 6–8 hours, both the valley and valley area of the apricot spectra stabilized, indicating that the moisture evaporation rate of the samples had significantly slowed during this phase. The rapid dehydration stage had concluded, and the fruit gradually entered a relatively stable low-moisture state. Similarly, the characteristic peaks adjacent to the valley also reflect the characteristic response of water molecules. As shown in Table 2, with the increase of drying time, the peak height of the reflection peak decreased by 13.8% and the peak area decreased by 14.4%. The slight fluctuation of the data after 6 hours further confirms that the moisture content has reached dynamic equilibrium.

Dying time（h）	Valley Depth	Valley Area	Peak Height	Peak Area
2	**0.006455**	**-0.286529**	**0.003729**	**0.196605**
4	**0.006007**	**-0.257352**	**0.003463**	**0.182442**
6	**0.005666**	**-0.249175**	**0.003216**	**0.168229**
8	**0.005618**	**-0.248069**	**0.003219**	**0.173848**

Table 2. Variation of Characteristic Spectral Peak and Valley Parameters of Apricots at Different Drying Times.

In summary, as drying time increases, the moisture content of apricots shows a decreasing trend, and correspondingly, spectral morphological parameters near the sensitive wavelength band exhibit a regular diminishing trend. These changes suggest that moisture-related spectral features may gradually diminish, thereby allowing SSC-related information to become more prominent. This enables the partial least squares (PLS) algorithm to more clearly capture the linear relationship between spectral data and SSC concentration, ultimately establishing a robust model with exceptional predictive capability. Consequently, this study conducted hyperspectral-SSC modeling analyses across different moisture intervals, playing a crucial role in enhancing model accuracy.

3.2 Construction and Results of SSC Prediction Models for Different Moisture Intervals

To enhance the detection accuracy of the hyperspectral-SSC model, the impact of moisture variation on the SSC prediction model was analyzed. This study modeled the data separately across four drying stages: 2 hours, 4 hours, 6 hours, and 8 hours. For each stage, 100 samples were used to divide the dataset into a training set and a prediction set at a 3:1 ratio using the SPXY method. After outlier removal and feature band selection, PLS quantitative prediction models were established for different moisture intervals based on the selected feature bands. The modeling correlations are shown in Figure 8. Each subfigure presents the scatter plots of actual measured values versus predicted values, along with the prediction set-training set fitting lines. Figures (a), (b), (c), and (d) correspond to different drying time stages, respectively. The models for all four drying stages demonstrated excellent fitting performance. Both the training set and prediction set data points clustered near the fitted lines of the prediction and training sets, indicating that the established models accurately reflect the relationship between actual measurements and predicted values.

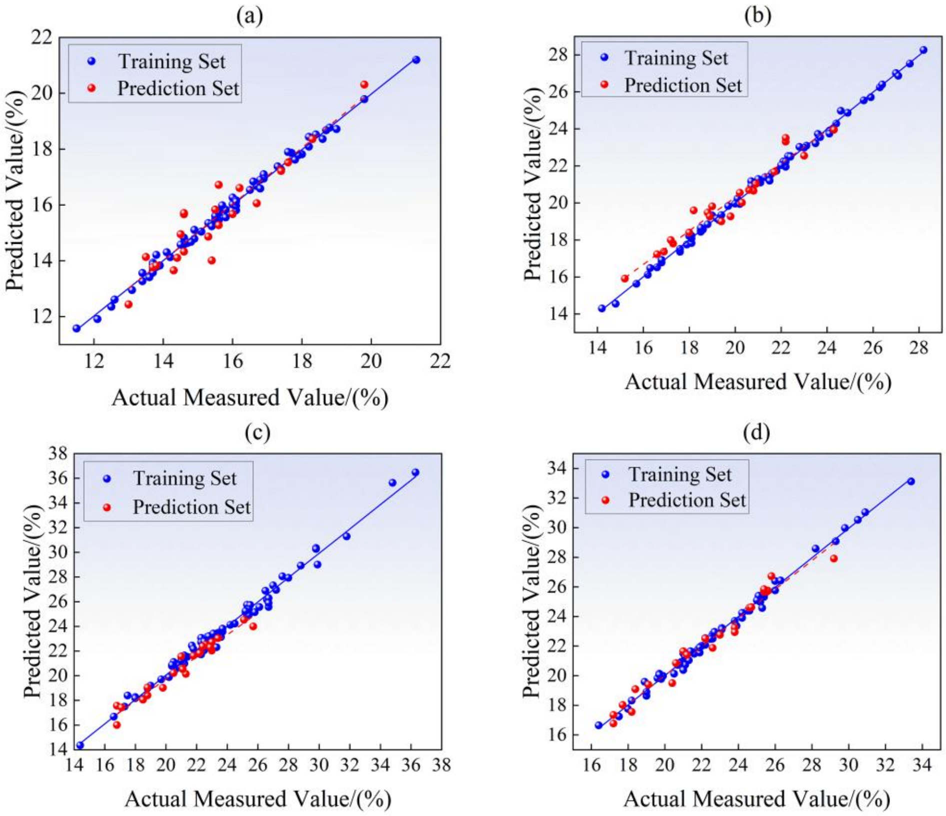

Figure 8. Regression fitting plots under different drying times: (a) 2 h regression fitting plot; (b) 4 h regression fitting plot; (c) 6 h regression fitting plot; (d) 8 h regression fitting plot.

As shown in Table 3, the accuracy of the apricot SSC prediction model steadily increases with drying time. Among the modeling results for 2h, 4h, 6h, and 8h drying periods, the 8h drying condition yielded the best modeling performance, achieving an R_p of 0.9844 and an RPD of 5.7989. Although the modeling accuracy at 2 hours was already relatively high, it remained lower compared to the 4-hour drying period. The models for 4 and 6 hours continued to improve, but the rate of increase flattened out, ultimately reaching optimal performance at 8 hours. These results indicate that during the drying process, as the moisture content decreases, the model exhibits greater robustness and accuracy.

Drying Time	R_c	R_p	RMSEC	RMSEP	RPD
2h	0.9967	0.9362	0.1590	0.6199	2.7049
4h	0.9986	0.9693	0.1725	0.6517	3.5014
6h	0.9940	0.9769	0.4410	0.6489	3.7643
8h	0.9968	0.9844	0.2633	0.5712	5.7989

Table 3. Model Performance at Different Drying Times.

In summary, as drying time increases, the R_p and RPD values of the SSC prediction model show a steady upward trend. This confirms that moisture content is one of the factors affecting the accuracy of SSC modeling. Furthermore, as the moisture content decreases, the accuracy of the SSC prediction model is effectively enhanced.

4 Discussion

Changes in apricot moisture content affect both their hyperspectral morphological parameters and the accuracy of the SSC prediction model. As the moisture content decreases, the valley depth and area of the O-H absorption valley near 970 nm, along with the peak height and area of the reflection peak near 1000 nm, exhibit a regular decreasing trend. The accuracy of the CARS-PLS-based model gradually increases, with optimal performance observed at low moisture content levels. In previous research, Wang Shifang et al. reached similar conclusions in their study analyzing the spectral characteristics of moisture's impact on soil organic matter detection[14], indicating that moisture obscures the spectral bands characterizing soil organic matter information, thereby interfering with its detection. This occurs because moisture's strong absorption effect distorts spectral signals, masking the effective characteristic information of other substances and consequently reducing modeling accuracy[15].

This study confirms that moisture content may also obscure the spectral characteristics of soluble solids content (SSC) in fruits, leading to reduced model performance in high-moisture ranges. This highlights the significant role of moisture content as an interfering factor in spectral modeling. Previous studies have indicated that temperature, light exposure, variety, and testing environments can all introduce similar interferences. Kaur et al. significantly reduced the impact of temperature on apple SSC prediction through EMSC and EPO corrections[16]. Cheng Guo et al. mitigated variety variation interference using calibration transfer[17], while Zhiming Guo et al. also found that temperature fluctuations decrease model stability[18]. This study reveals the interference effect of internal fruit moisture content on SSC and validates its importance in improving SSC prediction accuracy through modeling across different moisture intervals. This study primarily employed the PLS method, which has limited capability in fitting complex nonlinear relationships. Future research could integrate algorithms such as support vector machines, random forests, and deep learning to further enhance the model's generalization ability. Additionally, the modeling approach for different moisture intervals could be extended to other fruits like grapes and winter jujubes to validate the universality of moisture content's impact on the accuracy of SSC prediction models.

5 Conclusion

The study focused on apricot (Prunus armeniaca ‘Diao Gan') from Xinjiang, employing hyperspectral imaging technology combined with CARS feature band selection and PLS modeling methods. It analyzed the spectral morphological changes of apricots at different moisture contents and the impact of moisture content variation on the accuracy of the SSC prediction model. The valley depth and absolute valley area of the absorption valley near 970 nm in apricots exhibit a regular decreasing trend. The valley depth decreased from 0.006455 after 2 hours of drying to 0.005618 after 8 hours of drying. while the absolute value of the valley area decreased from 0.286529 after 2 hours of drying to 0.248069 after 8 hours of drying. The accuracy of hyperspectral-SSC modeling improved with extended drying time, with R_p increasing from 0.9362 after 2 hours to 0.9844 after 8 hours; RPD rose from 2.7049 after 2 hours to 5.7989 after 8 hours. The study confirmed that moisture content was a key factor affecting the accuracy of hyperspectral-SSC prediction models for apricots. Future studies can enhance the accuracy of SSC prediction models by calibrating them based on moisture content.

ACKNOWLEDGMENTS

We extend our gratitude to the expert reviewers for their constructive feedback.

FUNDING

This research was supported by the National Natural Science Foundation of China (1119069), Xinjiang Production and Construction Corps Special Fund (524408001), Sponsored by Natural Scicnce Support Program of Xinjang Production and Construction Corps(2024DB040), and Tianchi Talented Young Doctoral Fund Project and Tarim University President’s Fund Project (TDZKBS202560).

AUTHOR CONTRIBUTIONS

L.K. and H.L.(Huaping Luo) conceived the study and designed the methodology; L.K. and J.Y. developed the software and performed formal analysis; H.L.(Hongyang Liu), Y.T. and X.M. conducted the investigation and validation; L.K. curated the data and prepared the original draft; X.M. and L.K. created the visualizations; H.L.(Huaping Luo) supervised the project and acquired funding; X.M., J.Y., H.L.(Huaiyu Liu) and H.L.(Hongyang Liu) reviewed and edited the manuscript. All authors reviewed and approved the final version.

COMPETING INTERESTS

The authors declare no competing interests.

DATA AVAILABILITY

The data that support the findings of this study shall be made available from the corresponding author upon reasonable request.

REFERENCES

1. Yang, Q.A., et al., *Effects of Different Natural Drying Methods on Drying Characteristics and Quality of Diaogan apricots.* Agriculture-Basel, 2024. **14**(5).
2. Zhao, C., et al., *Volatile Compounds Analysis and Biomarkers Identification of Four Native Apricot (Prunus armeniaca L.) Cultivars Grown in Xinjiang Region of China.* Foods, 2022. **11**(15).
3. Gao, F., et al., *Nondestructive Identification of Apricot Varieties Based on Visible/Near Infrared Spectroscopy and Chemometrics Methods.* Spectroscopy and Spectral Analysis, 2024. **44**(1): p. 44-51.
4. Jiang, X.G., et al., *Achieving robustness to temperature change of a NIR model for apple soluble solids content.* Food Quality and Safety, 2023. **7**.
5. Sun, X.D., et al., *First step for hand-held NIRS instrument field use: Table grape quality assessment consideration of temperature and sunlight chemometrics correction.* Postharvest Biology and Technology, 2023. **201**.
6. Suo, Y.T., et al., *A Comparative Study on Roujean and Ross Li Models of Winter Jujube in South Xinjiang Under Different Outdoor Light.* Spectroscopy and Spectral Analysis, 2021. **41**(6): p. 1737-1744.
7. Ou, D.P., et al., *Prediction of soil organic matter by Kubelka-Munk based airborne hyperspectral moisture removal model.* International Journal of Applied Earth Observation and Geoinformation, 2023. **124**.

8. Liu, D.Y., et al., *Effect of a plant growth regulator on optical properties of kiwifruit during growth in wavelength range of 950-1650 nm.* Postharvest Biology and Technology, 2019. **156**.
9. Wan, C., et al., *Prediction of Kiwifruit Sweetness with Vis/NIR Spectroscopy Based on Scatter Correction and Feature Selection Techniques.* Applied Sciences-Basel, 2024. **14**(10).
10. Di, Y.B., et al., *Study on Outdoor Spectral Inversion of Winter Jujube Based on BPDF Models.* Agriculture-Basel, 2025. **15**(13).
11. Gao, F., J.Y. Xu, and H.P. Luo, *Inversion of Spatial Characteristic Spectrum and Feasibility Study of Outdoor Spectral Correction.* Spectroscopy and Spectral Analysis, 2024. **44**(2): p. 336-346.
12. Liao, Y.X., et al., *Effects of variable-temperature drying on the qualities and sweet-substance profile of Zizyphus jujuba Mill. cv. Junzao.* Food Chemistry-X, 2024. **22**.
13. Ibrahim, A., et al., *Preliminary Study for Inspecting Moisture Content, Dry Matter Content, and Firmness Parameters of Two Date Cultivars Using an NIR Hyperspectral Imaging System.* Frontiers in Bioengineering and Biotechnology, 2021. **9**.
14. Wang, S.-f., X. Cheng, and H.-y. Song, *Analysis of the Effect of Moisture on Soil Organic Matter Determination and Anti-Moisture Interference Model Building Based on Vis-NIR Spectral Technology.* Guang pu xue yu guang pu fen xi = Guang pu, 2016. **36**(10): p. 3249-53.
15. Tang, J.Z., et al., *A novel approach to spectral moisture interference correction for nitrogen and soil organic matter inversion in native black soils: Bayesian-optimized dynamic moisture mitigation.* Ecological Informatics, 2025. **90**.
16. Kaur, H., R. Künnemeyer, and A. McGlone, *Correction of Temperature Variation with Independent Water Samples to Predict Soluble Solids Content of Kiwifruit Juice Using NIR Spectroscopy.* Molecules, 2022. **27**(2).
17. Guo, C., et al., *Enhancing Transferability of Near-Infrared Spectral Models for Soluble Solids Content Prediction across Different Fruits.* Applied Sciences-Basel, 2023. **13**(9).
18. Guo, Z.M., et al., *Nondestructive monitoring storage quality of apples at different temperatures by near-infrared transmittance spectroscopy.* Food Science & Nutrition, 2020. **8**(7): p. 3793-3805.