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**Application of near-infrared spectroscopy
for rapid detection of moisture content of ginger
(*Zingiber officinale* Rosc.)**

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Abstract

Background. Ginger is a horticultural commodity and a biopharmaceutical crop with many benefits and high economic value. Ginger is widely used as a raw material in the functional food, cosmetics, and herbal pharmaceutical industries. Water content is a critical parameter affecting the quality, storage stability, and activity of bioactive compounds in ginger rhizomes.

Purpose. This study aims to develop a calibration model to predict ginger rhizome moisture content using near-infrared spectroscopy and chemometric modeling for fresh, dried, and fresh-dried ginger.

Materials and methods. This study used three varieties of ginger, i.e., merah ginger, emprit ginger, and gajah ginger, obtained from the Beringharjo market in Yogyakarta, Indonesia. Two moisture-content conditions were applied: fresh ginger obtained directly from the market and dried ginger after two weeks of storage at room temperature (28°C) with a relative humidity of 76.1%. The spectroscopic instrument used in this study was a NIR spectrometer (Flame-NIR-Ocean Optics, USA) operating over the wavelength range of 950–1700 nm. The reflectance spectra of three varieties of ginger rhizomes, i.e., emprit, gajah, and merah, were measured at wavelengths of 950–1700 nm, with reference

water content values measured using the thermogravimetric method. The partial least squares regression (PLSR) model was used to predict the moisture content of dried and fresh ginger, as well as a combination of fresh and dried ginger.

Results. The dried ginger model showed the highest prediction accuracy ($R^2P = 0.75$; RPD = 2.00). The key wavelength contributing to water content prediction was identified in the 1400–1500 nm region, corresponding to the first overtone of O–H stretching vibrations. These results indicate that near-infrared spectroscopy can be used for fast and non-destructive prediction of water content in ginger rhizomes.

Keywords: NIRS; ginger rhizome; moisture content; PLSR; chemometrics

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Introduction

Ginger (*Zingiber officinale* Rosc.) is an important spice widely used in culinary, aromatic, and traditional medicine, as well as in the herbal and pharmaceutical industries. Ginger rhizome is rich in sugars, organic acids, fatty acids, tocopherols, and antioxidants (phenolics and flavonoids) [1], and has a unique characteristic, spicy taste, and aroma [2; 3] and health benefits [4; 5]. Freshly harvested ginger is high in water content (85–90% on a wet basis), which increases the likelihood of fungal and microbial growth, the primary causes of ginger spoilage globally, making it difficult to store for long periods [6]. High water content can accelerate the growth of spoilage microorganisms and metabolic activity [7]. Water content also affects physical [8], essential oil, and oleoresin content [9], and bioactive compounds [10]. Therefore, accurate and rapid measurement of moisture content is essential for quality control and for optimizing ginger drying and storage processes.

The most commonly used method for water content determination is the thermogravimetric method, recognized as a reference method for its accuracy. It includes placing the sample in a fan-assisted electric oven and drying the sample at 70–110 °C [11]. However, this method is destructive to samples and requires waiting time, making it less effective for large-scale quality assurance applications and real-time quality monitoring, especially in routine industrial analysis.

Near-infrared spectroscopy (NIRS) has emerged as a promising technique for rapid, non-destructive quality evaluation and is widely applied in the agriculture and food sectors [12]. NIR spectra primarily reflect absorption by overtones and combination bands of molecular vibrations, such as CH, OH, SH, and NH

bonds [13]. Due to the broad and highly overlapped NIR absorption bands, the spectral information is often complex and cannot be directly interpreted [14]. In addition, spectral measurements are influenced by light scattering, baseline shifts, and instrumental noise [15], thus affecting the relationship between spectral responses and sample composition. Therefore, multivariate techniques are required to extract meaningful quantitative information from NIR spectra.

Among these chemometric techniques, Partial Least Squares Regression (PLSR) has become the most widely used calibration method due to its effective approach to modeling the relationship between high-dimensional spectral data and reference measurements, as well as its ability to handle multicollinearity and noisy data [16]. PLSR is useful for predicting quality parameters when there are many variables and few samples, owing to its ability to combine Principal Component Analysis (PCA) and multiple regression [17].

Previous studies have demonstrated the successful application of NIRS for predicting moisture content in various agricultural commodities, including cocoa [18], fruits [19], tubers [20], and vegetables [21]. NIRS has also been applied to ginger to determine moisture content [22] and other quality parameters [23]. However, previous studies employed benchtop spectrometers, which are comparatively expensive and unsuitable for field use. Moreover, the previous studies developed a single calibration model without accounting for the substantial differences in moisture levels between fresh and dried ginger. Nonetheless, moisture variations alter the optical scattering properties and the chemical composition of ginger tissues, resulting in spectral changes that affect the calibration model [24].

Furthermore, the application of portable fiber-optic NIR spectroscopy for moisture prediction in ginger has received little attention. Compared with conventional benchtop instruments, portable fiber-optic NIR spectrometers offer advantages in portability, rapid on-site measurement, and lower operational costs, making them well-suited for field applications and quality control in small- and medium-scale processing industries [25]. The instrument has been applied to predict quality parameters of fruits [26] and grains [27], and to detect healthy or unhealthy potatoes [28]. To the best of our knowledge, no previous study has evaluated the performance of a portable fiber-optic NIR spectrometer for moisture prediction across fresh and dried ginger. Studies employing NIR spectroscopy for ginger have compared benchtop and micro NIR spectrometers for dried ginger [29] or used a portable NIR spectrometer for ginger powder [30]. Therefore, further investigation is needed to determine whether moisture-characterized ginger provides more accurate and robust predictions than a single unified model.

Therefore, this study aims to develop PLSR models for predicting moisture content in three ginger varieties (merah ginger, emprit ginger, and gajah ginger) under fresh and dried conditions using a portable fiber-optic NIR spectrometer. The study compares calibration models developed using dried and wet ginger individually, as well as a unified calibration model. The study will demonstrate the feasibility of portable NIR spectroscopy as a practical tool for rapid quality assessment in the ginger industry.

Materials and methods

Sample Preparation

The materials used in this study were three varieties of ginger: merah ginger, emprit ginger, and gajah ginger, obtained from the Beringharjo market in Yogyakarta, Indonesia. Merah ginger is dark red-brown, with a relatively small, branched rhizome and a rough surface. Emprit ginger has lighter brown skin and an intermediate rhizome size, with grouped and moderately thick branches. In contrast, gajah ginger is the largest rhizome, characterized by a light-brown skin, a fleshy structure with few thick branches, and a comparatively smooth surface. Ginger samples were collected in the morning and cleaned of any remaining soil and dirt. Analysis was performed on two moisture-content conditions: fresh wet ginger and dried ginger. Dried ginger was obtained after two weeks of storage at room temperature (28°C) with a relative humidity of 76.1%.



Fig. 1. Three varieties of ginger used in this study, i.e., merah, emprit, and gajah (left to right)

NIR Data Acquisition

The spectroscopic instrument used in this study was a NIR spectrometer (Flame-NIR-Ocean Optics, USA) operating over the wavelength range of 950–1700 nm. The light source was a tungsten–halogen lamp (HL-2000-HP- FHSA, Ocean Optics, USA) equipped with a reflectance probe (QR400-7-VIS-NIR, Ocean Optics, USA). The sample was placed on the static platform, and the reflectance spectra were scanned from above as shown in Figure 2.

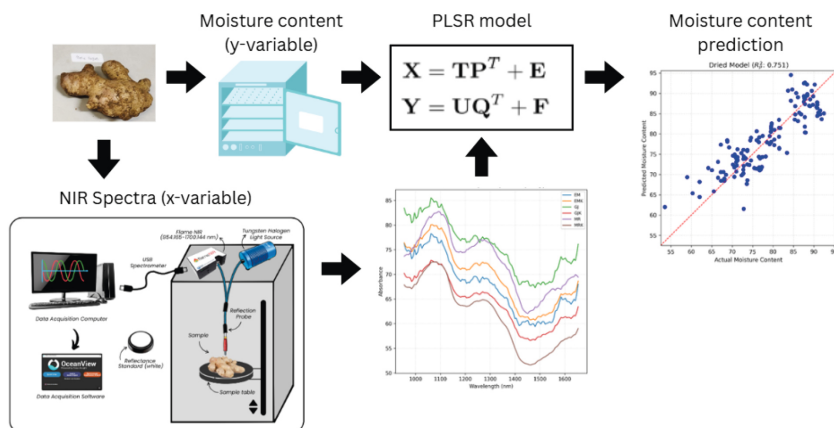


Fig. 2. Workflow of the determination of the moisture content of ginger using the NIR spectrometer

Ginger was scanned three times for replication in a reflectance mode. The spectra were measured at a distance of 2.0 cm between the sample and the sensor probe, with an integration time of 350 ms and averaging over 7 scans. Instrument calibration was performed using a ceramic diffuse reflectance standard (WS-1, Ocean Optics, USA), and calibration was repeated after every 10 sample measurements. Spectral data were collected using Ocean View Software (Ocean Insight, USA) as .txt files and exported to Excel (.csv) files, which were then used as independent variables (x-variables).

Moisture Content Measurement

Moisture content (%) of ginger samples was determined using the thermogravimetric method, in which 5 g of sample was weighed, placed in a small dish, and dried in an oven at 105 °C for 24 hours or until a constant weight was reached [11]. The measurement was done in triplicate and averaged. The moisture content value is then used as the response variable in developing the NIR calibration model as the y-variable.

Partial Least Squares Regression Model Development

The partial least squares regression (PLSR) model was used to predict the moisture content of dried and fresh ginger, as well as a combination of fresh and dried ginger. The combination was made in order to mimic the real-life scenario of unknown samples, whether fresh or dried. Essentially, PLS models y as a function of

x, i.e., $y = f(x)$. The PLSR was developed using x-variables from the NIR spectra and y-variables representing the referenced moisture content. The difference in moisture content between dried and fresh ginger affects the spectral data. Moreover, the NIR spectra themselves are inherently complex and often contain unwanted random noise, physical scatter effects, and baseline variation [31]. Therefore, various spectral preprocessing steps were applied to mitigate these drawbacks, such as scatter correction (standard normal variate, SNV and multiplicative scatter correction, MSC), baseline correction (polynomial detrending), derivatives (Savitzky Golay first (SG1) and second (SG2)), smoothing (mean), and scaling (mean centering) [32].

Three types of PLSR models were developed using the samples, i.e., fresh, dry, and a combination of fresh and dry. For each model, the dataset of x and y variables was split into 70% for calibration and 30% for prediction. Model validation was carried out using a leave-one-out full cross-validation on the calibration dataset. The performance of the PLSR model was evaluated using the coefficient of determination (R^2), with values closer to 1 indicating better predictive ability, and the Root Mean Square Error (RMSE), with lower values indicating higher accuracy. Evaluation of regression model performance was based on equations 3.1 for determining the coefficient determination (R^2C) of calibration and prediction, respectively, as well as the root mean square error (RMSE) of calibration and prediction in equation 3.3. Moreover, the model was assessed using the ratio of performance to deviation (RPD), as formulated in equation 3.3.

$$R^2 = \frac{\sqrt{\sum_{i=1}^{nc} (\hat{y}_i - y_i)^2}}{\sqrt{\sum_{i=1}^{nc} (\hat{y}_i - y_m)^2}} \quad (3.1)$$

$$RMSE = \sqrt{\frac{1}{np} \sum_{i=1}^{np} (\hat{y}_i - y_i)^2} \quad (3.2)$$

$$RPD = \frac{SD}{RMSEP} \quad (3.3)$$

Spectral data analysis and PLSR model development for moisture content prediction were performed in Google Colab. Important Python libraries used were Pandas for data handling, NumPy for numerical operations, Scikit-learn for PLSR and model validation, and SciPy for preprocessing filters.

Results and Discussion

Water Content of Ginger

The water content of fresh and dried gajah ginger, emprit ginger, and merah ginger is shown in Table 1. The standard deviation (SD) of ginger water content

was used to assess variability around the mean; a larger SD indicates greater variability. The fresh ginger presented in Table 1 has a higher moisture content than the dried ginger, with the gajah variety having the highest.

Table 1.

Moisture content of ginger in fresh and dry conditions		
Varieties	Moisture content (wb, %)	
	Fresh	Dried
Emprit	81.81 ± 4.35	71.07 ± 4.01
Gajah	88.47 ± 3.21	87.86 ± 2.42
Merah	76.09 ± 3.41	75.98 ± 5.94

NIR Spectral Profiles of Ginger

Figure 3 shows the average raw spectra (Figure 3a) and the Savitzky–Golay first-derivative (SG1) preprocessed spectra (Figure 3b) of the ginger samples measured in the 950–1650 nm wavelength range. The legends represented emprit fresh (EM) and emprit dried (EMK) ginger, gajah fresh (GJ) and gajah dried (GJK) ginger, and merah fresh (MR) and merah dried (MRK) ginger. The raw spectra (Figure 3a) exhibited similar patterns across all fresh and dried samples, with absorbance peaks at around 970 nm, 1050 nm, and 1250 nm. The differences were in absorbance intensity: gajah fresh ginger (GJ) had the highest, while merah dried ginger (MRK) had the lowest, which might be attributed to variations in moisture content or other chemical composition. After SG1 preprocessing, spectral alignment among samples was achieved, and baseline variation was substantially reduced, as shown in Figure 3b. The derivative spectra transformation removes scattering effects and baseline shifts, thereby disclosing spectral features and preserving chemically relevant information [32]. Accordingly, the SG1 spectra shown in Figure 3b provide a clearer representation of the underlying chemical characteristics and are therefore more suitable for developing a PLSR calibration. Using SG1 spectra, additional absorbance peaks are present at 970–1000 nm, 1150 nm, 1250 nm, 1400 nm, 1500 nm, and 1550 nm, which were not clearly present in the raw spectral profile.

The major absorption features correspond to the vibrational overtones of molecular bonds present in ginger tissues. Absorption bands around 970 nm and 1150 nm are associated with the second overtone of O–H in water and the stretching vibrations of C–H in carbohydrates [33]. The most prominent spectral feature occurred in the 1400–1500 nm, corresponding to the first overtone of O–H stretching vibration [34]. This region reflects differences in moisture content between fresh and dried ginger samples.

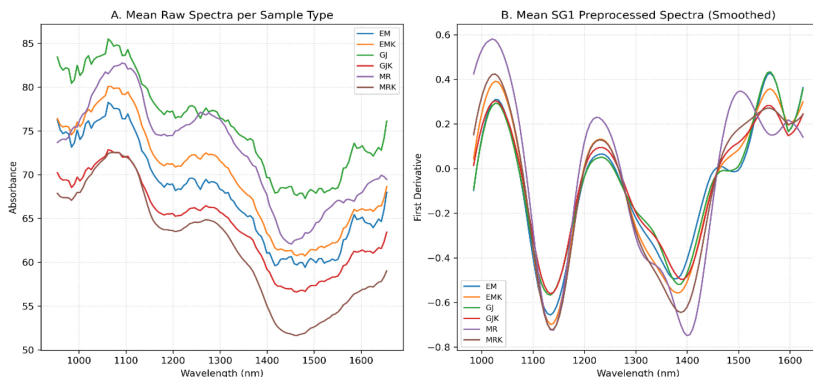


Fig. 3. Average spectra of (a) raw and (b) SG1 of fresh and dried ginger

Performance of Partial Least Squares Regression Models

The PLSR calibration model was developed to relate NIR spectral data (x-variable) to moisture content measurements (y-variable) obtained by thermogravimetry. The PLSR models were developed using raw and preprocessed data, including polynomial detrending, mean centering, first- and second-order Savitzky-Golay derivatives, standard normal variate (SNV), multiplicative scatter correction (MSC), and their combinations. The PLSR model was evaluated based on the highest coefficient of determination of calibration (R^2C) and the lowest root mean square error of calibration (RMSEC). The best model was then used to predict moisture content from the predicted datasets, and the results were evaluated based on the coefficient of determination of prediction (R^2P), the root mean square error of prediction (RMSEP), and the ratio of performance to deviation (RPD).

We developed three PLSR models, i.e., dried samples, fresh samples, and a unified model incorporating both fresh and dried ginger samples. By comparing predictive performance, this study evaluates whether reducing sample heterogeneity through condition-specific calibration improves moisture content prediction compared with a single model trained on mixed sample conditions.

Table 2 presents PLSR model performances for predicting ginger moisture content for fresh ginger samples, dried ginger samples, and all data samples. The performances of the PLSR models were influenced by sample condition and spectral preprocessing. Among the three PLSR calibration scenarios, the dried ginger model yielded the highest prediction accuracy

with $R^2P = 0.67$ – 0.78 , $RMSEP = 3.97$ – 4.92% , and $RPD = 1.74$ – 2.15 . For dried ginger, the best PLSR was achieved using raw spectra with $R^2P = 0.78$, $RMSEP = 3.97$ – 3.98% , and $RPD = 2.15$. Spectral preprocessing techniques reduced accuracy, except for mean-centering, which yielded results identical to the raw spectra. The dried ginger model is superior due to the more homogeneous dried samples [6], and the low water content minimizes scattering effects, thereby better capturing chemical information associated with moisture.

The fresh ginger model performed much worse than the others, regardless of the preprocessing method used. The best result came from using a second-order detrending polynomial (Detrend P2), with $R^2P = 0.57$, $RMSEP = 4.11\%$, and $RPD = 1.53$, meaning that fresh-ginger models are acceptable for rough screening. Detrending slightly improved model accuracy due to baseline drift correction which enhances spectral response and moisture content [35]. The lower performance is probably due to fresh ginger containing mostly free and immobilized water, which do not interact much with the solid components or with each other [36].

As a result, water absorbs strongly in the NIR range and dominates the spectral response [37]. Due to high-water absorption, it is difficult to detect spectral associated with small changes in moisture and other chemicals, decreasing the PLSR performance [38]. On the other hand, in dried ginger, most of the free water is removed, creating a more uniform spectral matrix which strengthens the PLSR model between spectral features and moisture content.

The PLSR model developed using a combination of fresh and dried samples (combined model) performed better than the individual models. The best results were obtained from Detrend P2 and mean-centering preprocessing, with $R^2P = 0.69$, $RMSEP = 4.36\%$, and $RPD = 1.78$. These results were similar to those from the raw spectra ($R^2P = 0.68$, $RMSEP = 4.38\%$, $RPD = 1.78$). The combined model covered a wider calibration data range, but its prediction accuracy was lower than that of the dried ginger model due to increased spectral variation caused by the wide range of moisture levels.

In summary, as shown in Table 3, the PLSR calibration model developed using more uniform samples, for instance, dried or fresh ginger alone, could accurately predict moisture content compared to the model using a combination of fresh and dried samples. Therefore, individual calibration based on sample conditions yields NIR spectroscopy that is more robust and practical for measuring ginger moisture content.

Table 2.

PLSR results of various preprocessing methods for predicting moisture content using fresh data, dried data, and a combination of fresh and dried data

Preprocessing	LV	R ² C	RMSEC	R ² CV	RMSECV	R ² P	RMSEP	RPD	
Dried	Mean_Center	19	0.85	3.09	0.77	3.87	0.78	3.97	2.15
	Raw	19	0.85	3.09	0.77	3.87	0.78	3.98	2.15
	Detrend_P2	15	0.83	3.3	0.76	3.98	0.75	4.27	2
	SG2	18	0.81	3.55	0.73	4.18	0.73	4.45	1.92
	SG2+MSC	18	0.79	3.74	0.71	4.36	0.72	4.55	1.88
	SG2+SNV	18	0.78	3.81	0.7	4.43	0.71	4.63	1.85
	SG1	19	0.76	3.92	0.67	4.63	0.69	4.75	1.8
	SNV	17	0.8	3.63	0.69	4.48	0.67	4.92	1.74
	MSC	16	0.8	3.62	0.7	4.44	0.67	4.92	1.74
	SG1+MSC	20	0.74	4.15	0.65	4.81	0.66	5	1.71
	SG1+SNV	20	0.73	4.18	0.64	4.82	0.64	5.11	1.67
Fresh	Detrend_P2	13	0.69	3.43	0.59	3.96	0.57	4.11	1.53
	Raw	20	0.73	3.22	0.6	3.93	0.57	4.15	1.52
	Mean_Center	20	0.73	3.22	0.6	3.93	0.56	4.16	1.52
	SG2	15	0.67	3.55	0.57	4.05	0.55	4.23	1.49
	SG2+SNV	14	0.62	3.8	0.49	4.41	0.51	4.4	1.43
	SNV	15	0.62	3.81	0.46	4.54	0.49	4.5	1.4
	MSC	13	0.6	3.94	0.44	4.63	0.46	4.63	1.36
	SG1	17	0.61	3.87	0.53	4.27	0.4	4.89	1.29
	SG1+SNV	16	0.57	4.07	0.48	4.48	0.34	5.12	1.23
	SG1+MSC	15	0.54	4.18	0.45	4.59	0.32	5.2	1.21
	SG2+MSC	16	0.58	4.01	0.42	4.7	0.3	5.27	1.2
Fresh and dried	Detrend_P2	18	0.75	3.69	0.7	4.06	0.69	4.36	1.78
	Mean_Center	20	0.76	3.66	0.7	4.05	0.69	4.36	1.78
	Raw	20	0.76	3.66	0.7	4.05	0.68	4.38	1.78
	SG2	20	0.72	3.94	0.67	4.26	0.65	4.61	1.69
	SG2+SNV	19	0.69	4.14	0.64	4.47	0.61	4.87	1.6
	SNV	17	0.68	4.22	0.6	4.71	0.56	5.16	1.51
	MSC	16	0.67	4.27	0.59	4.77	0.55	5.2	1.5
	SG1	18	0.62	4.57	0.56	4.92	0.54	5.3	1.47
	SG2+MSC	20	0.66	4.33	0.59	4.74	0.53	5.32	1.46
	SG1+SNV	19	0.6	4.73	0.52	5.16	0.5	5.52	1.41
	SG1+MSC	19	0.59	4.78	0.51	5.19	0.48	5.59	1.39

Table 3.

PLSR model comparison of fresh, dried, and all ginger						
Scenario	Model	LVs	R ² P	RMSEP	RPD	Analytical capability
Dried Only		15	0.75	4.27	2.00	Acceptable for Quality Control (Approaches RPD ≥ 2.0)
All (fresh+dried)		15	0.67	4.46	1.74	Acceptable for screening (RPD < 2.0)
Fresh Only		14	0.57	4.13	1.53	Unacceptable predictive analysis

Coefficient regression from the PLSR model

Figure 4 shows the regression coefficients of the PLSR models of fresh, dried, and combined fresh-dried ginger samples. All three models exhibited similar coefficient patterns across the NIR regions from 950 to 1650 nm, indicating that similar spectral information was used to predict moisture content. However, there were differences in the coefficient values. The dried ginger model had the largest positive and negative coefficients, particularly around 980–1000 nm, 1050 nm, 1150 nm, 1200–1240 nm, and 1530–1580 nm. These wavelengths are important variables for predicting moisture content in dried ginger. Unlike the dried ginger model, the fresh ginger model showed smaller regression coefficients. The combined fresh-dried model showed the same trends as the individual fresh and dried models; nonetheless, the regression coefficients were less pronounced than dried model.

The regression coefficients at approximately 980–1000, 1050, 1150, 1200–1240, and 1530–1580 nm were major contributors to the moisture content prediction model. High regression coefficients were observed around 980–1000 nm, corresponding to the second overtone of O–H stretching vibrations [39], which reflects changes in moisture and hydroxyl-containing compounds. The bands around 1050 and 1150 nm were attributed to higher overtones of C–H stretching [40] and were related to essential oils, lipids, and phenolic compounds such as gingerols and shogaols. The 1200 to 1240 nm region is mostly due to the second overtone of C–H stretching [41] connected to lipids, carbohydrates, and other compounds rich in hydrocarbons. Another feature was observed at 1530 to 1580 nm, correlated with the first overtones of N–H and O–H vibrations (Gao & Chu, 2026), representing water and hydrogen-bond interactions in ginger.

Figure 5 shows the actual and predicted moisture content values obtained using PLSR, with the predicted values aligning closely with the regression line, indicating strong agreement between actual and predicted values for all samples. However, the dried ginger data showed more clustering around the regression line (Figure 5c) than the fresh data (Figure 5b) and the overall ginger data (Fig-

ure 5a), as shown by the predictive performance (Table 3). The more scattered data observed for fresh ginger (Figure 5b) were possibly due to the relatively variable moisture content of ginger and water, which exhibited stronger and more distinct O–H absorption features.

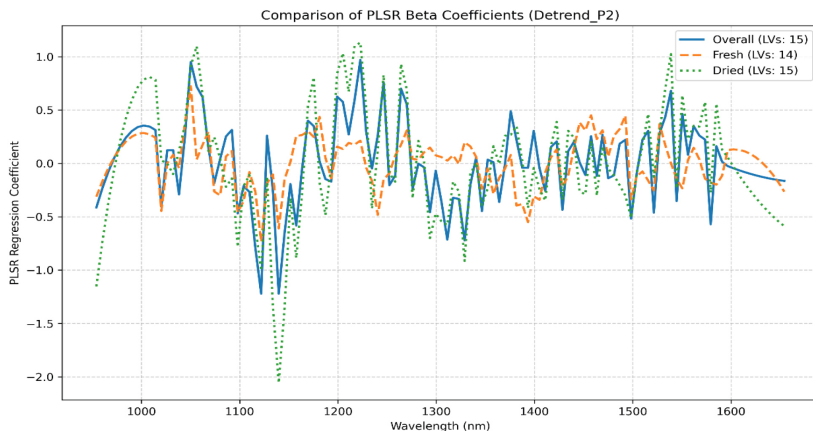


Fig. 4. Coefficient regression of the PLSR model for predicting water content in fresh, dried, and all ginger

The displayed scatter plots were the same as the PLSR results in Table 3, in which the more robust PLSR models not only had higher R^2 and lower RMSE but also showed closer agreement between predicted and actual values.

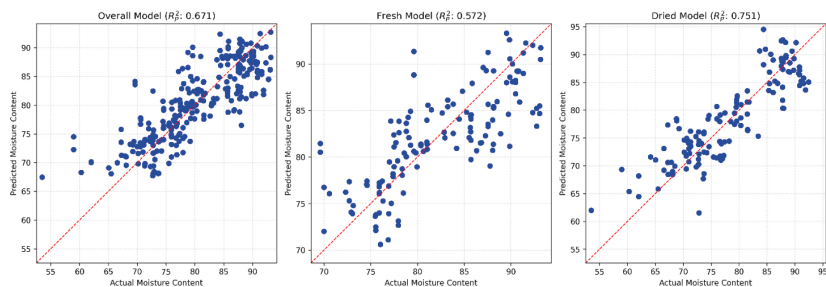


Fig. 5. Scatter plot of predicted and actual (a) all fresh and dried ginger, (b) fresh ginger, and (c) dried ginger

Conclusions

NIR spectroscopy combined with chemometrics is effective for fast and non-destructive determination of ginger moisture content. The dried ginger

model showed the highest accuracy with $R^2P = 0.75$ and $RPD = 2.00$, followed by the combination of fresh and dried ginger; the least is obtained from fresh ginger. The wavelengths at 980–1000 nm, 1050 nm, 1150 nm, 1200–1240 nm, and 1530–1580 nm are the main contributors to the prediction of moisture content in ginger.

Conflict of interest information. The authors declare no conflict of interest.

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Description of the application of the generative model. During the preparation of the article, we used Scopus AI and ChatGPT to brainstorm and improve the manuscript's organizational structure and flow. After using these services, we reviewed and edited the content as necessary and take full responsibility for the published article.

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