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RESEARCH ARTICLE

Rapid and cost-effective assessment of nutrients in pistachio (*Pistacia vera* L.) leaves through Fourier transform near-infrared spectroscopy (FT-NIRS)

Yunus Emre Sekerli[1] | Gokhan Buyuk[2] | Muharrem Keskin[1] | Nafiz Celiktas[3]

[1]Department of Biosystems Engineering, Faculty of Agriculture, Hatay Mustafa Kemal University, Antakya, Hatay, Turkey

[2]Department of Soil Science and Plant Nutrition, Faculty of Agriculture, Adiyaman University, Adiyaman, Adiyaman, Turkey

[3]Department of Field Crops, Faculty of Agriculture, Hatay Mustafa Kemal University, Antakya, Hatay, Turkey

Correspondence
Yunus Emre Sekerli, Department of Biosystems Engineering, Faculty of Agriculture, Hatay Mustafa Kemal University, 31040 Antakya, Hatay, Turkey.
Email: ysekerli@gmail.com

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Abstract

Background: Pistachio nuts provide many health benefits in human diet. Nutrient levels in plant leaves and fertilizer schedules are determined based on traditional soil and leaf chemical analyses. However, these methods require additional labor, time, and cost, which is why most farmers do not prefer them and cannot detect nutrient deficiencies in time. Fast, easy-to-use and low-cost nutrient level assessment techniques are needed.

Aim: This study aims to explore the viability of near-infrared reflectance spectroscopy (NIRS) as a fast, user friendly, and cost effective technique for evluating the major macro- and micronutrient contents of dried and ground pistachio leaf sample.

Methods: The feasibility of NIRS for estimating nutrient contents was investigated by analyzing samples from 200 pistachio trees. Dried and ground pistachio leaves were subjected to NIRS analysis. PLSR (Partial least square regression) analyses were performed to develop nutrient content prediction models using spectral information of samples.

Results: It was found that the NIRS system had a very good potential to estimate the K, Ca, Cu, and Mg contents of the leaf samples ($R^2 > 0.80$). It was also found that Fe and Mn concentrations could also be estimated with good accuracy ($R^2 = 0.70$–0.80). However, the NIRS system did not give good results for the prediction of N, P, and Zn ($R^2 < 0.40$).

Conclusion: In conclusion, the NIRS system can be used to quickly, easily, and economically assess the K, Ca, Cu, Mg, Fe, and Mn contents of dried and ground pistachio leaves. This technique has the potential to improve nutrient management practices in pistachio farming within a sustainable and environmentally conscious framework. Fourier transform NIRS (FT-NIRS) can provide valuable insights by complementing rather than replacing traditional chemical analysis. Laboratory analysis is still required for definitive nutrient content information, but FT-NIRS can significantly reduce the reliance on such analysis, thereby mitigating the environmental impact caused by the excessive use of chemical fertilizers and minimizing the health risks to laboratory staff. In addition, the rapid information-gathering capabilities of the FT-NIRS can be emphasized.

KEYWORDS
leaf, near-infrared spectroscopy, nondestructive analysis, nutrient elements, pistachio

1 | INTRODUCTION

The pistachio tree (*Pistacia vera* L.) belongs to the genus *Pistacia* of the family Anacardiaceae. The fruits (nuts) of these trees have significant contents of fiber, protein, minerals, and vitamins. These nuts also possess valuable bioactive compounds, which include carotenoids, flavonoids, phenolic acids, anthocyanins, and so forth, and provide anti-inflammatory, antiviral, and antimicrobial health effects (Ghaffari et al., 2014; Nobari et al., 2022; Roxas et al., 2020; Saludes-Zanfano et al., 2022). They are also effective in mitigating drug resistance and type 2 diabetes while improving cognitive function, human gut microbiota, skin health, and glucose regulation (Mandalari et al., 2022). Pistachios originated in western Asia and were distributed by traders to the Middle East, Mediterranean and European countries, and then to the USA (Hosseini et al., 2022; Karacan & Ceylan, 2020).

Pistachio nuts (in shell) were produced with a total amount of 915.7 thousand tons on an area of 817.0 thousand hectares with an average yield of 1121 kg/ha in the world in 2021 (Food and Agriculture Organization of the United Nations [FAOSTAT], 2021). The USA, Iran, Türkiye, China, and Syria were the top five countries with the productions of 523.9, 135.0, 119.4, 78.8, and 43.1 t, respectively (FAOSTAT, 2021). Based on the 2016 FAO data, global pistachio trade was about 3.0 billion US dollars, and the US had about one third of this trade volume (Karacan & Ceylan, 2020). Pistachio is an important nut in Türkiye and is produced mainly in the southeast region of the country, mainly in the provinces of Gaziantep, Sanliurfa, Siirt, and Adiyaman (Şimşek, 2018).

Pistachio tree yield and quality hinge predominantly on mineral nutrient uptake from soil (Shool et al., 2023). Nitrogen (N), phosphorus (P), and potassium (K) are key plant nutrients. Although these macronutrients shape fertilizer strategies, additional nutrients impact growth and quality. Adequate levels are established at 2.2%–2.5% N, 0.1%–0.2% P, and 1.8%–2.0% K in pistachio leaves (dry basis) (Beede et al., 2005). Soil N and P variabilities, coupled with heightened leaching risk due to excessive irrigation or rainfall, escalate water resource contamination risks.

Traditionally, soil, plant leaf, or tissue ionomic analyses are essential, especially at early stages, for determining the type and quantity of fertilizers needed for optimal plant growth, yield, and quality (Acosta, Quiñones, et al., 2023). However, these analyses involve multiple laboratory processes that demand significant time, energy, labor, chemicals, and expenses (Keskin et al., 2022). Moreover, they expose laboratory staff to chemicals posing potential health risks. Often, farmers resort to fertilizer application without proper analysis, leading to either insufficient or excessive doses resulting in plant toxicity, increased costs, reduced profitability, and adverse environmental effects (Council for Agricultural Science and Technology [CAST], 2019; Sekerli et al., 2021a). The overuse of fertilizers can have harmful effects on surface and groundwater systems, resulting in problems, such as the growth of excessive algae, unpleasant changes in odor and taste in drinking water, and incidents of fish poisoning (CAST, 2019; Environmental Protection Agency [EPA], 2012). For instance, over 20% of the shallow household wells for drinking water were reported to have nitrate levels above standard limits in farming areas in the USA (EPA, 2012). The demand for cost-effective, quick, and practical leaf nutrient assessment methods is intensified due to drawbacks associated with chemical analyses and excessive fertilizer use. Nondestructive leaf nutrient analysis is pivotal for plant research and agriculture, facilitating frequent monitoring and timely detection of nutrient imbalances without harming plants. This technique helps optimize fertilizer application, aids in boosting crop productivity, and contributes to fostering sustainable agriculture through efficient nutrient management. Plant leaves with nutritional deficiency exhibit alterations in their color and reflectance attributes (Keskin et al., 2021). Consequently, these leaf characteristics could be employed for appraising the inadequate nutrient levels in crops. Various tools like machine vision with digital cameras, chlorophyll meters, normalized difference vegetation index (NDVI) meters, fluorescence meters, chromameters, spectroradiometers, and near-infrared reflectance spectroscopy (NIRS) have been investigated for the assessment of leaf visual quality, water content, and nutrient concentrations (Acosta, Quiñones, et al., 2023; Keskin et al., 2021; Padilla et al., 2018; Sekerli et al., 2021b).

Near-infrared (NIR) falls within a spectrum that is well-suited for assessing organic compounds, as it enables the absorption of energy by chemical bonds like carbon–hydrogen (C–H), oxygen–hydrogen (O–H), and nitrogen–hydrogen (N–H) (Kinhal, 2022). The differences in samples arise from their unique proportions and combinations of absorbed energy, primarily associated with the stretching and vibrations of various bonds like C–H, N–H, S–H, C C, C C, C–N, and O–H within the NIR spectral range (700–2500 nm) (Prananto et al., 2020).

NIR spectroscopy has found extensive application in the evaluation of agricultural and food products, though it is more commonly employed in food research compared to agricultural applications (Keskin et al., 2019; Kinhal, 2022; Pandiselvam et al., 2022). In agriculture, NIR spectroscopy has been employed to examine the nutritional status of crops, the determination of harvest time, the detection of diseases, pests, effects of toxins and drought in crops, breeding programs, soil properties, and so forth (Kinhal, 2022; Tsuchikawa et al., 2022). Numerous studies have employed spectroscopic techniques to assess various aspects of plant health and nutrient contents. Gálvez-Sola et al. (2015) evaluated citrus leaf nutrient levels using NIRS, whereas Neto et al. (2017) determined chlorophyll and water levels in sunflower leaves using Vis–NIR spectroscopy. Sridevy et al. (2018) detected potassium and nitrogen deficiencies in maize through image processing and spectral analysis. Mani and Shanmugam (2019) assessed N, P, and K in groundnut plants using Vis–NIR spectroradiometry. Cuq et al. (2020) evaluated Ca, Cu, Mg, and Fe in grapevine blades via NIRS, whereas Mahanti et al. (2020) used the same method to rapidly assess nitrate content in spinach. Sillajoe (2020) employed EDXRF (Energy dispersive X-ray fluorescence) spectrometry and NIRS for macro- and micronutrient assessments in cucumber and garlic leaves. Johnson et al. (2021) used NIRS/MIRS (Mid-infrared spectroscopy) and chemometrics for nutrient evaluation in rice. Mishra et al. (2021) demonstrated improved N and K estimation models for bell pepper leaves using Vis–NIRS. Sekerli et al. (2021a) predicted turfgrass properties using multiple optical systems. Vasilev et al. (2022) determined chlorophyll in strawberry leaves from digital color images. Acosta, Quiñones et al. (2023) evaluated citrus leaf nutrients with Vis–NIRS with promising results. In another study, Acosta, Visconti et al. (2023) utilized Vis–NIRS to determine the macro- and micronutrient contents of persimmon leaves.

In pistachio farming, NIR spectroscopy has been applied to assess traits like adulteration, infection, and moisture content. However, its integration with precision agriculture systems remains limited (Jacygrad et al., 2022; Yaghoubi et al., 2022). In particular, no study was found on the utilization of NIRS for the assessment of nutrient levels of pistachio tree leaves. To address this research gap, the present study aimed to evaluate the feasibility of employing a Fourier transform NIRS (FT-NIRS) system for predicting macro- and micronutrient contents in pistachio tree leaves. Such studies will demonstrate the advantage of NIRS as opposed to traditional chemical methods for foliar nutrient analysis and will shed light on future studies on the feasibility of conducting leaf analysis with optical methods in a fast, high-quality, low-cost, nondestructive, and sustainable manner without the need for hazardous chemicals.

2 | MATERIALS AND METHODS

2.1 | Leaf samples

Leaf samples of pistachio trees were collected from commercial orchards located in the Adiyaman province (approximate altitude: 670 m), which is located in the mid-south Türkiye and has a Mediterranean climate with hot and dry summers and cool, wet, and often snowy winters. It is a main pistachio production area with suitable climatic conditions. A total of 200 leaf samples were obtained from 200 pistachio trees grown under dry conditions (without irrigation) in July 2021. The trees were of same age and same cultivars grafted on *Pistacia terebinthus* tree, a wild species of *Pistacia* called "menengic" in Turkish. The leaf samples included the ones from the most recently developed leaves before the flowering phase. Each sample consisted of about 50 leaves taken from the 4 sides (east, west, north, south) of one tree (50 leaves/tree).

2.2 | Chemical analysis of the leaves

Standard leaf chemical analysis methods were employed for the leaf sample analysis at the Department of Soil Science and Plant Nutrition, Faculty of Agriculture, Adiyaman University. The leaves were washed with tap water + distilled water and dried at 70°C until they reached constant weight, and then the dried leaves were ground in a hand-held electric grinder and ground to 0.2 mesh size and made ready for analysis (Kacar & Inal, 2008). Nitrogen (N) content was determined using the macro Kjeldahl method (Bremner, 1965), whereas P and K contents were assessed following the Olsen et al. (1954) and Pratt (1965) methods, respectively. Additional nutrient elements (calcium, magnesium, iron, zinc, copper, manganese) were quantified through diethylenetriaminepentaacetic acid extraction, measured by atomic absorption spectrophotometry (Lindsay & Norvel, 1978).

2.3 | Near-infrared (NIR) spectroscopy data

Dried and ground leaf samples were positioned onto Petri dishes made of glassware with a diameter of about 9 cm. The NIR reflectance data from each sample was collected by employing an FT-NIRS device (Büchi NIRFlex N-500). This instrument covered a spectral wavenumber range spanning from 4000 to 10,000 cm^{-1} (1000–2500 nm). The acquisition of the NIR reflectance data involved capturing and saving the average of 32 scans for each sample, and this process was repeated three times.

2.4 | Statistical data analysis

Macro- and micronutrient concentrations (N, P, K, Ca, Mg, Fe, Zn, Mn, Cu) from 200 leaf samples (from 200 pistachio trees) along with their NIR reflectance data were transferred into spreadsheet program (MS Excel 2016, Microsoft Inc.). Basic statistical analysis data (minimum, maximum, mean, standard deviation, etc.) were calculated in the spreadsheet program. The partial least squares regression (PLSR) method was utilized to develop prediction models by building linkages between spectral predictor (NIR reflectance data) and each nutrient in UnScrambler program (version 9.7, Camo Software). Two thirds of the data were used for the calibration (n = 133), and the remaining one third of the data (n = 67) was utilized for testing the prediction models (Esbensen, 2009). Root mean square error of prediction (RMSEP) and coefficient of determination (R^2) values were employed to evaluate the prediction performance of the models (Esbensen, 2009). The regression point displacement (RPD), or, in another name, the ratio of performance to deviation (RPD), was also utilized in the evaluation of the results (Çataltas & Tutuncu, 2021; Kljusurić et al., 2016). The program calculates the RMSEP values using the following equation (Esbensen, 2009):

$$RMSEP = \sqrt{\frac{\sum_{i=1}^{N} \left(y_i - y_{i,ref}\right)^2}{n}}, \qquad (1)$$

where y_i is the predicted value, $y_{i,ref}$ is the measured value, and n is the number of samples.

TABLE 1 Basic statistical data and sufficiency ranges of the macro- and micronutrient elements of the dried and ground pistachio leaf samples ($n = 200$).

Elements	Min.	Max.	Mean	SD	CV%	Skw	Krt	SR	Comment
N (%)	0.35	3.07	1.77	0.57	32.3	−0.4	−0.2	2.2–2.5	Normal
P (%)	0.01	0.09	0.03	0.01	29.2	2.5	11.7	0.1–0.2	Low
K (%)	0.03	1.53	0.63	0.30	47.4	0.4	−0.3	1.8–2.0	Low
Ca (%)	1.16	3.78	1.96	0.42	21.4	1.3	3.1	1.3–4.0	Normal
Mg (%)	0.08	2.11	0.79	0.31	38.8	1.1	2.5	0.6–1.2	Normal
Fe (ppm)	104.0	312.7	205.1	56.1	27.4	0.1	−1.2	–	
Zn (ppm)	11.2	83.7	32.4	10.1	31.2	1.2	4.7	10–15	High
Mn (ppm)	3.1	99.7	33.0	18.9	57.3	1.1	0.6	30–80	Normal
Cu (ppm)	9.7	103	50.4	21.7	43.0	0.3	−0.5	6–10	High

Note: Sufficiency ranges according to Beede et al. (2005).
Abbreviations: CV%, coefficient of variation in percentage; Krt, kurtosis; SD, standard deviation; Skw, skewness; SR, sufficiency range.

3 | RESULTS

3.1 | Leaf nutrient content analysis results

Basic statistical data and the sufficiency ranges of the nine macro- and micronutrient elements (N, P, K, Ca, Mg, Fe, Zn, Mn, Cu) obtained from the standard chemical laboratory analyses are presented in Table 1 for the dried and ground pistachio leaf samples ($n = 200$). It was observed that among the five macronutrients, N, Ca, and Mg concentrations were in normal sufficiency levels, whereas P and K contents were lower than the sufficiency ranges. Regarding the micronutrients, Zn and Cu levels of the leaves were higher than the sufficiency levels, whereas Mn was within the normal range (Table 1). The lowest variation was observed in Ca content (coefficient of variation [CV]: 21.4%), whereas Mn had the highest variation (CV: 57.3%) (Table 1).

Soil samples were also collected from the same orchards, and the results were reported in Bayram et al. (2023). It was found from the soil sample analysis results that the majority of the soils fell within the clay loam texture class. The soils were classified as suitable for pistachio cultivation in terms of texture and characterized as non-saline, slightly alkaline, with varying levels of organic matter (ranging from very low to high) and varying levels of lime (ranging from low to very high). Based on the soil analysis results, the soils were found to be partially deficient in N but predominantly deficient in P, according to the threshold values. Moreover, a portion of the soils were described as Fe deficient, whereas 62.3% and 75.3% of the soils were deficient in Zn and Mn, respectively. Therefore, it was recommended to consider the application of fertilizers containing Fe, Zn, and Mn to the soil or leaves. In addition, high levels of lime and pH in the soils were found to be responsible for limiting the availability of certain nutrients, such as P, Zn, and Fe.

3.2 | PLSR prediction analysis results

NIR spectral reflectance data of the dried and ground pistachio leaf samples ($n = 200$) are illustrated in Figure 1. Absorption bands

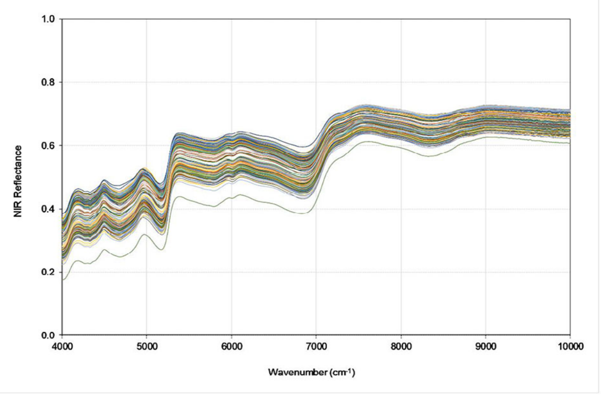

FIGURE 1 Near-infrared (NIR) reflectance data for the dried–ground pistachio leaf samples ($n = 200$).

that are visible in the spectrum near the center wavenumbers and corresponding chemical bonds and compounds are as follows: 4300–4330 cm^{-1} (CH_2, cellulose), 4650–4700 cm^{-1} (HC = CH, amino acid), 5170–5200 cm^{-1} (CONH), 5750–5850 cm^{-1} (CH_2), 6800–6900 cm^{-1} (starch, H_2O), and 8200–8500 cm^{-1} (CH_3) (Figure 1) (Büchi, 2013).

The results of the PLSR prediction analysis for the leaf macro- and micronutrient elements of the dried–ground pistachio leaf samples are presented in Table 2. In the analysis, the full spectrum (all of the wave numbers, 4000–10,000 cm^{-1}) was first used, and the related results were studied and tabulated. There are several methods to exclude the variables (wave numbers) that are not important for the prediction. One of them is the magnitude of the regression coefficients (Esbensen, 2009). In this method, the variables (wave numbers) with smaller regression coefficients (close to zero) have a minimal effect on the model compared to the variables with larger coefficients, and in most cases, some of these variables may reduce the prediction performance (Esbensen, 2009). Based on this method, the variables with higher regression coefficients were selected and used in developing new prediction models with a lower number of variables. Based on the validation results presented in Table 2, it was observed that K was the

TABLE 2 Basic statistical data for the partial least squares regression (PLSR) prediction models with full and selected spectrums for the leaf macro- and micronutrient contents of the dried–ground pistachio leaf samples ($n = 200$).

Element	Spectrum	Range (cm^{-1})	RMSEC	R^2_{cal}	RMSEP	R^2_{val}	N_{pc}	N_{out}	RPD
N	Full	4000–10,000	0.51%	0.11	0.58%	0.11	3	2	0.3
	Selected	4000–8100	0.53%	0.02	0.62%	0.06	2	0	0.1
P	Full	4000–10,000	0.01%	0.26	0.01%	0.22	5	4	0.6
	Selected	4000–8340	0.01%	0.28	0.01%	0.25	7	4	0.7
K	Full	4000–10,000	0.11%	0.87	0.13%	0.78	12	3	2.2
	Selected	4000–6900	0.10%	0.87	0.10%	0.87	17	4	2.7
Ca	Full	4000–10,000	0.15%	0.85	0.18%	0.68	9	3	1.8
	Selected	4000–8340	0.18%	0.79	0.18%	0.71	8	3	1.7
Mg	Full	4000–10,000	0.12%	0.83	0.14%	0.75	12	1	1.8
	Selected	4000–7080	0.12%	0.83	0.14%	0.75	12	2	1.9
Fe	Full	4000–10,000	25.0 ppm	0.79	25.4 ppm	0.79	10	2	1.8
	Selected	4000–7880	25.8 ppm	0.78	28.3 ppm	0.77	14	3	1.8
Zn	Full	4000–10,000	9.9 ppm	0.01	10.4 ppm	0.01	2	1	0.1
	Selected	7080–10,000	7.8 ppm	0.37	9.8 ppm	0.11	6	0	0.6
Mn	Full	4000–10,000	9.8 ppm	0.73	10.3 ppm	0.65	12	4	1.5
	Selected	4000–8460	11.7 ppm	0.57	11.7 ppm	0.51	11	3	1.1
Cu	Full	4000–10,000	8.4 ppm	0.84	10.8 ppm	0.76	13	3	1.9
	Selected	7360–10,000	8.2 ppm	0.85	13.6 ppm	0.60	11	4	1.5

Abbreviations: N_{out}, number of outliers; N_{pc}, number of principal components; R^2_{cal}, coefficient of determination for the calibration data set; R^2_{val}, coefficient of determination for the validation data set; RMSEC, root mean square error of calibration; RMSEP, root mean square error of prediction; RPD, ratio of performance to deviation.

element that can be predicted by the NIR reflectance with the highest performance ($R^2 = 0.87$) followed by Fe ($R^2 = 0.79$), Cu ($R^2 = 0.76$), Mg ($R^2 = 0.75$), and Ca ($R^2 = 0.71$). In contrast, N, P, Zn, and Mn were the elements with the lower prediction performance ($R^2 < 0.70$). As recommended for obtaining more reliable prediction performance results in the PLSR analyses, the calibration models were subjected to validation using a separate test set (one third of the whole data set) that was used only for the validation process. The obtained results showed that R^2 and RMSE values were slightly lower for the validation in comparison to the models derived during calibration (Table 2). It was observed as a general trend that the calibration models obtained with all wave numbers (full model) provided slightly better results as compared to the models with selected variables except for K and Zn with an increase of about 0.10 in their R^2_{val} values (Table 2). When examining the results of the validation process, it was observed that removing noisy segments (generally between 8000 and 10,000 cm^{-1}) from the reflectance spectrum led to a slight improvement in the performance of the K and Ca prediction models, yielding higher values. However, there was no significant change in the performance of the Mg prediction model, with a slight decrease. In regards to the RPD parameter, only the prediction model for K was found to be a good prediction model as the RPD value of 2.5–3.0 is considered "good" and an RPD of greater than 3.0 is accepted as "excellent" (Kljusurić et al., 2016). The elements of Ca, Mg, Fe, and Cu can be classified into two groups as "low level" and "high level" using the corresponding PLSR models as they have lower RPD values between 1.5 and 2.0 (Kljusurić et al., 2016). The reference versus measured plots for the PLSR models to predict potassium, iron, magnesium, and copper contents are presented in Figure 2.

4 | DISCUSSIONS

This present work addresses the estimation of leaf nutrient contents of dried and ground pistachio tree leaves using the NIRS technique. It was the first study applied to pistachio tree leaves and also included the estimation of multiple macro- and microelements in contrast to studies with only one or several nutrient elements. Xiao et al. (2022) tested an NIRS system and deep learning technique to assess leaf nitrogen concentration (LNC) of fresh cotton leaves, and they found a good accuracy of up to 83% to classify the leaves into three LNC groups. Phanomsophon et al. (2022) showed that the NIRS method provided good accuracy (>80%) for the classification of N, P, and K concentration levels of durian fruit tree leaves and stated that they obtained higher accuracy with fresh leaf samples than dried–ground leaf samples. Prananto et al. (2021) used the NIRS technique (1350–2500 nm) to predict macro- and micronutrient elements in dried and ground cotton leaves and reported high prediction performance for N, P, K, Ca, Mg, and S contents ($R^2 > 0.75$). They also tested the system on fresh leaves and reported that the prediction accuracy was lower for fresh leaves by 19% and 11% for the macro- and micronutrients, respectively,

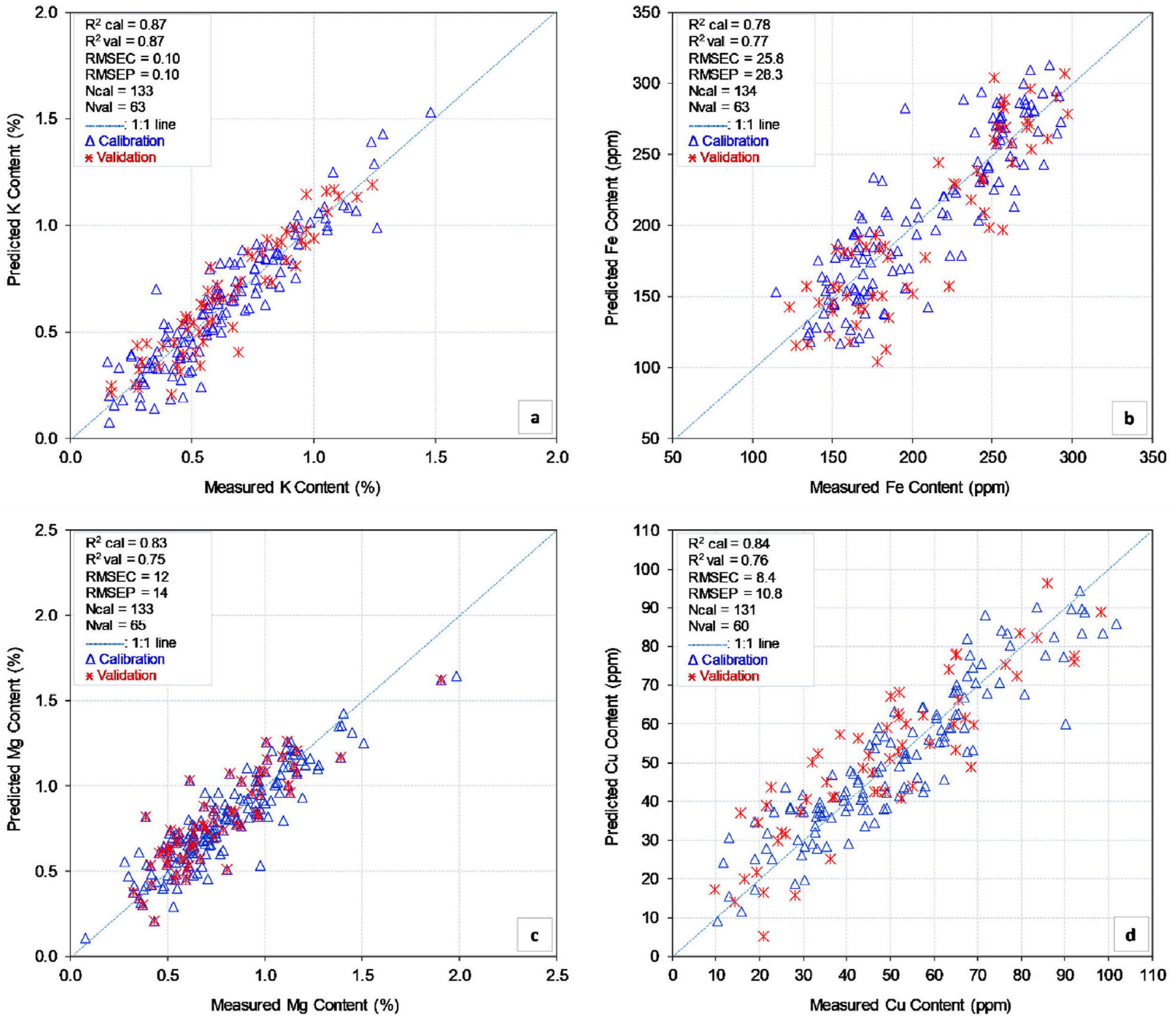

FIGURE 2 Reference versus measured plot for the partial least squares regression (PLSR) model to predict potassium (a), iron (b), magnesium (c), and copper (d) contents of the dried–ground pistachio leaf samples ($n = 200$).

compared to the dried–ground leaves. Sekerli et al. (2021b) developed a low-cost prototype reflectance-based indoor sensor and compared it with two commercial sensors (a handheld color meter and NIRS) to appraise water and nutrient contents of turfgrass clippings (*Lolium perenne* L.) collected from a soccer field. They reported that the NIRS presented the best estimation for nutrient and water contents, except for Cu content.

In the current study, it was found that the NIRS system had a very good potential to predict the K content of the dried and ground pistachio tree leaves ($R^2 > 0.80$) from the NIR reflectance data. The performance of the model developed for the K content determination was observed to have similar success ($R^2 > 0.80$) compared to other studies conducted using NIRS on different plant leaves (Gálvez-Sola et al., 2015; Whittier et al., 2021; Yarce & Rojas, 2012). Predictions of Ca, Cu, Mg, and Fe concentrations also exhibit modest yet reasonable performance ($R^2 = 0.70$–0.80), which is comparable to or even superior to certain NIRS-utilizing studies (Cuq et al., 2020; Gálvez-Sola et al., 2015; Sekerli et al., 2021a, 2021b; Whittier et al., 2021; Yarce & Rojas, 2012). However, this technique did not offer good results for the prediction of N, P, Zn, and Mn in the present study ($R^2 < 0.70$). It should be noted that various factors, including the make and model of the NIRS system, spectral range (VIS, NIR, SIR, MIR, etc.), plant type and cultivars, preparation of the samples (drying and grinding, etc.), sample particle size, and the type of the data analysis methods should be considered when comparing the results of similar studies.

One of the important criteria to obtain good prediction performance is that the data has enough variability that could be determined with the CV. For phosphorus (P), the prediction performance was low; $R^2_{val} = 0.22$–0.25 (Table 2), and this could be due to the low variability of the P values only from 0.01% to 0.09% (CV: 29.2%) (Table 1). The NIRS system used in the present study had a spectrum range of 1000–2500 nm. Alternative fast and easy-to-use sensing systems with broader spectrums (lower than 1000 nm and higher than 2500 nm) and more advanced data analysis methods such as artificial intelligence could be investigated for better prediction performance of the nutrient contents of the leaves of plants and trees in future studies.

5 | CONCLUSIONS

It was found that the use of NIRS emerges as a valuable and efficient tool for assessing potassium, calcium, copper, magnesium, iron, and manganese levels in dried and ground pistachio tree leaves. This approach holds significant promise for optimizing fertilizer application within ecologically and economically conscious management frameworks. By reducing the need for chemical laboratory analyses, it not only curtails chemical consumption but also minimizes potential health hazards for laboratory staff.

This study, utilizing NIRS, contributes significantly to the industry and existing literature by demonstrating the feasibility of nondestructive detection of pistachio leaf nutrient levels, bypassing traditional chemical analysis methods. The results underscore the NIRS's potential as a rapid and nondestructive tool for nutrient assessment in pistachio tree leaves, with practical applications for precision agriculture. Beyond enhancing nutrient management efficiency in the pistachio industry, this novel approach opens avenues for broader applications in agriculture.

The presented findings not only advance scientific understanding of nondestructive nutrient analysis but also hold practical implications for sustainable agricultural practices and resource optimization, paving the way for future investigations and innovations in crop nutrient monitoring and management. Moreover, the implications of this research extend beyond nutrient estimation techniques, providing actionable insights for enhancing agroecosystem sustainability and preserving essential natural resources. As a pivotal step toward more responsible agricultural practices, this study contributes to reducing the ecological footprint associated with intensive chemical fertilization, fostering a harmonious coexistence between agricultural productivity and environmental conservation.

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DATA AVAILABILITY STATEMENT

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

ORCID

Yunus Emre Sekerli https://orcid.org/0000-0002-7954-8268

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