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Prediction of Plant Nutrient Contents in Deciduous Orchards Fruits Using Spectroradiometer

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Abstract: There is an increasing use of HandHeld spectroradiometer data to determine nutrient contents and stress for green vegetation of hyperspectral reflectance. The objective of this study was to investigate the prediction possibility of some macro and micro nutrient contents of different deciduous orchard (pear, cherry, peach and apricot) using spectroradiometer. For this purpose, hyperspectral reflectance values obtained from blue, green, red and near-infrared bands using plant probe and fore-optic lens (10º angle) apparatus of spectroradiometer. Hyperspectral reflectance data were used to predict the N, P, K, Ca, Mg, Fe, Zn, Mn and Cu contents using multi regression analysis method. The results of study indicated that there is a relationship between spectral reflectance values and nutrient contents. The values obtained from spectroradiometer may be useful for predicting the N, P, K, Mg and Mn contents of deciduous orchards leaves in field. However, it was not adequate to predict values of Ca, Fe, Zn and Cu contents. The uses of plant probe or fore-optic to determine nutrient content were depend on nutrient type such as macro or micro.

Keywords: Hyperspectral reflectance, nutrients, deciduous orchards.

Introduction and Experimental

Multispectral and hyperspectral imaging systems (i.e.,satellites, spectroradiometers, and digital cameras) capture digital images at specific wavelengths of light reflected from plant canopies[1,2,3,4,5,6] . Hyperspectral reflectance signatures are widely used and analyzed to study different vegetations. It is a common practice in hyperspectral sensing to use HandHeld spectroradiometer to collect green vegetation information in field survey. The spectroradiometer obtained spectral reflectance measurements in 512 bands in the ultraviolet, blue, green, red and near-infrared spectral regions from 350-1050 µm. The green leaf was still photosynthesizing and yielded typical healthy green reflectance spectra with strong chlorophyll absorption bands in the blue and red regions, and peak in reflectance in the green region of visible spectrum. Approximately 76 percent of the incident near-infrared radiant flux was reflected from the leaf at 900 nm[7].

It is important to understand the physiology of the plants especially their pigmentation characteristic. Many factors can lead to decrease or increase of chlorophyll. Under stress conditions chlorophyll degradation often occurs, resulting in decreased pigmentation and increased visible reflectance. A variety of spectral measures that relate to nitrogen and chlorophyll content or other plant stresses have been developed[8] . As leaves become more chlorotic, reflectance increases and the reflectance peak normally centered at about 550 nm, broadens towards the red as absorption of incident light by chlorophyll decreases. These changes are perceived visually as a yellowing of the leaf[9]. Although the spectral changes in the visible region are readily apparent in spectra of stressed vegetation[2,9], the effects are subtle compared with the changes in the red edge: the sharp increase in reflectance between the red and near infrared[10] .

The red edge is produced by the combination of strong absorption by chlorophyll in the red region and strong reflectance in the IR (infrared) due to scattering in the leaf mesophyll and the absence of absorption by pigments[11]. The more commonly used spectral measures of vegetation, which rely on the region of the red edge, have been used to estimate vegetative biomass, productivity, leaf area index, photosynthetic activity or chlorophyll content[12]. In stressed vegetation the absorption deficiency of the chlorophyll decreases and the IR reflectance decreases due to changes in the cell structure of the plant. This leads to a reduction in reflectance in the IR simultaneous with an increase in reflectance in the red.

The traditional methods for detecting plant quality require detailed sampling and expensive laboratory analysis. Remote sensing offers potential to predict foliar biochemical concentration in plants, thereby reducing the tedious process of intensive sampling and laboratory analysis[13]. The two optimal spectral regions for sensing chlorophyll absorption characteristics of leaf are believed to be 0.45-0.52 µm and 0.63-0.69 µm. The former region is characterized by strong absorption by carotenoids and chlorophylls, whereas the latter is characterized by strong chlorophyll absorption[8].

A relationship between spectral reflectance, particularly visible absorption and macronutrients such as phosphorous, potassium, magnesium and calcium is expected due to their effect on the photosynthetic process in plants[13].

In general, nutritional stress caused first a decrease in biomass, leaf chlorophyll concentration and usually an increase in reflectance in the VI (visible infrared) and IR range. The red-edge position shifted to shorter wavelengths and had a steeper slope with N and Mg deficiencies. Among the treatments used, variations in spectral properties and red-edge position were proportional to stress levels and leaf chlorophyll concentration, and occurred around the same spectral wavelengths for several nutrients (e.g. N) in particular. Many changes in spectral properties may occur, depending on the interaction between deficiencies of a particular mineral and the level of deficiency. In wheat, for example, the same leaf chlorophyll concentration, or leaf reflectance, or the redshift position may be found with a deficiency of Fe as with an Mg deficiency. The macronutrient experiment indicates that there is justification for further research in the use of hyperspectral data to determine mineral deficiencies in crops[14] .

The objective of this study was to determine the prediction of nitrogen, phosphorus, potassium, magnesium, calcium, iron, copper, manganese and zinc content of leaves of deciduous orchards using spectral reflectance.

Field experiment and sampling

The field experiment was conducted in a completely randomized design in deciduous orchards of Eğirdir-Isparta (37° 45' N, 30° 31' E, elevation 1030 m) located on the Mediterranean region of Turkey.

Leaf samples of deciduous orchards were collected over six sampling dates (two weeks intervals) from May to July 2007. In sampling dates, 12 leaf samples representing each species were collected during the growing season in 2007. Therefore, a total of 72 leaf samples for each species were obtained.

Hyperspectral reflectance measurements

A portable HandHeld spectroradiometer was used to collect the spectral reflectance data from orchard canopy level and leaves. A 512-channel spectroradiometer by Analytical Spectral Devices (ASD)™ (FieldSpec® FR) was used to acquire spectral data. In HandHeld spectroradiometer, the Visible/Near Infrared (VNIR) spectrum, the 325 - 1075 nanometer wavelength domain, is measured with a 512 channel silicon photodiode array overlaid with an order separation filter. Each channel, an individual detector itself, is geometrically positioned to receive light within a narrow (1.6 nm) nominal bandwidth. The VNIR spectrometer has a spectral resolution (FWHM of a single emission line) of approximately 3 nm at around 700 nm. The optical sensor of the spectroradiometer was mounted at a 1.5 m above canopy level. The radiometer had 10° field of view, producing a view area of a 0.35 m diameter. A spectralon reference panel (white reference) was used to optimize the ASD instruments to take canopy reflectance measurements at each sampling plot. Reflectances were measured between May the 10th and July the 21st, 2007. The canopy reflectance data were expressed as relative values by dividing them by the white reference panel reflectance readings[13]. The average of the five readings obtained from spectroradiometer was considered.

In addition, plant probe was also used to collect the spectral reflectance data in orchard leaves. Plant Probe is a device used for contact reflectance measurement of vegetation and other heat sensitive targets using the Spectroradiometer. The plant probe has an innovative design and less intensive light source mimic solar illumination for safer analysis of plant tissue. The combination of instrument and probe provides superior signal to noise ratio that can discriminate even subtle spectral features. Some features of the plant probe are 24.5 cm length, 0.7 kg weight, 12-18 VDC power requirements, 6.5 W, lightsource type/Life (approx.) Halogen bulb/1500 hours, 10 mm spot size and specular reflectance 5 % max off flat first surface mirror[15]. Leaf Clip Assembly is used to clamp the leaves to the objective of plant probe to determine the standard measurements for samples.

The reflectance values measured by spectroradiometer and plant probe were recorded *via* ASD ViewSpect® software. Canopy reflectance data in the two-wavelength ranges from 325 to 399 and 900 to 1075 nm were first omitted from the reflectance data sets because of instrument noise or location of these bands within regions of atmospheric moisture absorption. The remaining reflectance data were combined into four broad wavebands; blue (400–500 nm), green (500–600 nm), red (600–700 nm) and NIR (700–900 nm) bands. Reflectance values at these wavelengths obtained from fore optic and plant probe were separately recorded for each sample.

Biochemical analyses methods

Leaf samples were analyszed to determine N, P, K, Mg, Ca, Fe, Cu, Mn and Zn content according to standard laboratory producers. Firstly, samples were washed in

water. Then samples were washed up with diluted acid (0.2 N HCl) and distilled water. After that, samples were oven-dried at 65±5º C until stable weight was obtained. Dried samples were ground, and then 500 mg of samples were wet-digested in 10 ml nitric acid (65 %) using closed-vessel microwave digestion system for 15 minutes at 180º C. The digested material was then dissolved and filled up to 100 ml with distilled water. Phosphorus concentrations of samples were determined using molybdo-vanado phosphoric acid method with spectrophotometer (Shimadzu UV-1208 model) [16]. K, Mg, Ca, Fe, Cu, Mn and Zn element concentrations were determined using atomic absorption spectrophotometer (AAS, Warian AA240FS model). The N analysis was carried out according to Kjehldal method[17].

Data treatment

Experimental data were analyzed using statistical analysis (stepwise regression analysis method, SAS software). The stepwise regression analysis applied to leaf N, P, K, Mg, Ca, Fe, Cu, Mn and Zn content among reflectance values and biochemical analysis values. Predicted values for N, P, K, Mg, Ca, Fe, Cu, Mn and Zn contents were obtained using stepwise regression models.

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Finally, R^2 values were calculated using the stepwise regression analysis between measured and predicted values. The measured nutritive value and corresponding reflectance data were pooled sampling dates (n = 72). Coefficients of determination (R^2) between the measures of nutritive value and reflectance in each broad waveband and reflectance ratios were calculated. For each measure of nutritive value of leaf, the reflectance ratio having the greatest (R^2) was selected. Regression analysis of the reflectance ratio with the nutritive value of leaf was also performed.

Results and Discussion

Biochemical analysis

Descriptive statistics of macro and micro nutrient of leaves were given table 1. As it can be seen from table 1, all nutrient contents of samples were found in normal ranges indicating non-deficiencies. Visual symptoms of nutrient deficiency can be a very powerful diagnostic tool for evaluating the nutrient status of plants. In our study, nutrients deficiency symptoms were not observed in any

of the samples.[18]

Table 1. Descriptive statistics of macro and micro nutr ient contents of leaves

		N (%)	P (%)	K (%)	Mg (%)	Ca (%)	Fe (mg/kg)	Cu (mg/kg)	Mn (mg/kg)	Zn (mg/kg)
Pear	Max.	2.23	0.07	2.85	0.29	1.99	205.80	14.45	99.90	13.00
	Min.	1.61	0.03	1.50	0.19	0.19	180.40	4.80	50.80	0.90
	Mean	1.88	0.05	2.14	0.24	1.06	197.75	8.94	84.52	9.19
Cherry	Max.	2.89	0.11	2.53	0.88	1.40	217.20	13.42	37.87	9,90
	Min.	2,43	0.01	1.67	0.17	0.39	174.90	4.20	15.40	2.10
	Mean	2.56	0.05	2.18	0.60	0.85	190.28	9.39	27.13	7.57
Peach	Max.	4.03	0.17	2.95	1.06	1.51	242.50	16.61	30.47	18.70
	Min.	3.25	0.02	1.24	0.16	0.21	179.20	4.80	24.70	2.10
	Mean	3.61	0.08	2.18	0.62	0.72	197.55	10.51	27.51	10.99
Apricot	Max.	3.93	0.09	10.61	0.89	1.98	251.20	13.05	32.80	12.30
	Min.	2.86	0.01	4.09	0.49	0.36	173.20	5.60	19.80	2.30
	Mean	3.35	0.04	8.65	0.74	1.09	210.47	9.22	28.67	9.78

Table 2. Four wave bands (±5) selected from stepwise regression to determinethe relationships among reflectance and macro and micro nutrient's on thebasis of calibration data set in leaves (10° angle)

Pear	**Equations**	**SE**	**R^2**
N	1.90-34.93(R410)+75.27(R530)-83.54(640)-2.45(740)	0.08	0.98
P	0.03-4.33(R470)-0.65(R550)+3.13(R670)+0.22(R760)	0.01	0.99
K	2.68-263.96(R490)+734.71(R510)-472.73(R650)-3.6(R780)	0.05	0.99
Mg	0.25+0.38(R440)-7.66(R520)+11.03(R680)+0.05(R750)	0.04	0.78
Ca	2.39-114.78(R450)+233.76(R540)-248.7(R630)-12.1(R790)	0.20	0.99
Fe	189-4373.1(R430)+6049.9(R500)-1420.4(R610)-16.4(R770)	2.76	0.98
Cu	8.97+62.26(R400)+541.78(R570)-138.2(R620)-200.7(R710)	5.71	0.48
Mn	80.7+2972.4(R420)+1939(R580)-1166.7(R690)-346(R730)	25.32	0.60
Zn	22.2-595.5(R460)+236.76(R560)+256.9(R600)-124.7(R720)	1.88	0.97
Cherry	**Equations**	**SE**	**R^2**
N	2.58-57.63(R400)-21.49(R560)+27.43(R600)+1.61(R790)	0.14	0.86
P	0.07+9.91(R430)-18.07(R510)+6.87(R620)+0.11(R780)	0.04	0.79
K	1.17+219.66(R490)-41.50(R550)-65.55(R690)+7.40(R720)	0.43	0.63
Mg	-0.73+168.94(R450)-19.77(R580)-55.21(R640)+7.08(R710)	0.09	0.99
Ca	4.11-184.90(R420)-331.17(R520)+260.85(R610)+1.78(R770)	0.17	0.96
Fe	282.87-5189.76(R440)+1621.42(R540)+113.30(R680)-207.64(R760)	27.64	0.37
Cu	22.09-1138.58(R470)+13.58(R570)+518.69(R670)-10.30(R740)	7.19	0.22
Mn	8.24+4389.43(R480)+641.93(R530)-2428.58(R630)-24.77(R750)	1.52	0.99
Zn	31.61-2296.11(R410)+124.11(R500)+291.68(R660)-20.00(R730)	1.87	0.92
Peach	**Equations**	**SE**	**R^2**
N	3.54-34.60(R400)+61.46(R570)-43.95(R610)-5.15(R730)	0.05	0.99
P	0.34-46.83(R430)+7.08(R540)+13.39(R640)-1.31(R750)	0.05	0.88
K	2.98+304.74(R410)+118.68(R550)-174.13(R600)-29.00(R710)	0.49	0.92
Mg	0.87+156.89(R470)-40.47(R520)-58.47(R650)+0.94(R760)	0.42	0.74
Ca	0.60+32.44(R490)-3.52(R560)+18.05(R620)-2.29(R780)	0.63	0.78
Fe	182.16+659.30(R450)+539.63(R530)+825.31(R680)-133.08(R740)	9.63	0.97
Cu	3.47+735.71(R440)-123.91(R500)-207.58(R630)+12.14(R790)	7.99	0.37
Mn	31.03+2717.03(R460)-919.49(R580)-1009.94(R690)+452.75(R700)	0.76	0.98
Zn	4.31+2319.85(R420)-789.34(R590)+378.98(R660)+23.92(R720)	3.74	0.92
Apricot	**Equations**	**SE**	**R^2**
N	-0.93+2712.10(R490)-2636.68(R500)-37.45(R640)+55.09(R710)	0.05	0.99
P	0.16-12.61(R440)+3.01(R590)+0.95(R650)-0.12(R700)	0.01	0.96
K	12.26+853.87(R450)-683.41(R510)+46.21(R630)-5.27(R770)	3.33	0.70
Mg	0.81-27.95(R480)+8.67(R560)+10.22(R620)-0.95(R780)	0.08	0.92
Ca	0.29-246.21(R430)-101.95(R520)+99.98(R680)+30.71(R720)	0.42	0.91
Fe	240.06-3322.6(R470)+12872.71(R580)-10543.7(R610)-501.37(R730)	27.83	0.82
Cu	19.05-1283.09(R410)+237.36(R550)+16.26(R670)-10.14(R760)	3.87	0.65
Mn	26.08+1817.75(R460)-260.70(R530)-426.09(R660)-40.69(R740)	1.81	0.97
Zn	-7.29+269.61(R420)-416.85(R540)+268.11(R690)+61.25(R750)	1.10	0.98

Spectral prediction of nutrients

Macro and micro nutrient contents were predicted by the models obtained from the blue (400-500 nm), green (500-600 nm), red (600-700 nm) and NIR (700-900 nm) wavelengths reflectance using both fore-optic and plant probe. Prediction model are shown table 2 and 3. These Comparison of the laboratory measured values of macro and micro nutrient contents in the test data set with their predicted values based on the equations developed for spectral reflectance in pear, cherry, peach and apricot leaves according to sample dates were shown in figures 1, 2, 3 and 4. In pear leaf, it was estimated that the macro and micro nutrient contents variables were also predicted by the models of the stepwise regression (Table 2 and 3) on the basis of the reflectance data. Stepwise regression models developed from the test data set were applied to the test data set for all spectral reflectance.

highest R^2 values for N, P, K, Ca, Mg, Fe and Zn contents in degree of 10 angles fore-optic were 0.98, 0.99, 0.99, 0.99, 0.78, 0.98 and 0.97, respectively. In contrary, N, P, K, Ca, Mg, Fe, Zn and Mn had higher R^2 values in plant probe (0.99, 0.87, 0.89, 0.96, 0.87, 0.80, 0.99 and 0.71, respectively) (Figures 1).

While the highest R² values were determined from N, P, Ca, Mg, Zn and Mn (0.86, 0.79, 0.96, 0.99, 0.92 and 0.99, respectively) in degree of 10 angles fore-optic, N, P, K, Cu, Mg, Fe, Zn and Mn (0.92, 0.89, 0.99, 0.87, 0.94, 0.98, 0.84 and 0.99, respectively) had highest R² values using plant probe in cherry leaf (Figures 2).

In peach leaf, the highest R² values were achieved from N, P, K, Ca, Mg, Fe, Zn and Mn (0.99, 0.88, 0.92, 0.78, 0.74, 0.97, 0.92 and 0.98, respectively) in degree of 10 angles fore-optic, P, K, Cu, Fe and Mn had highest R² values in plant probe (0.73, 0.96, 0.99, 0.93 and 0.99, respectively) (Figures 3).

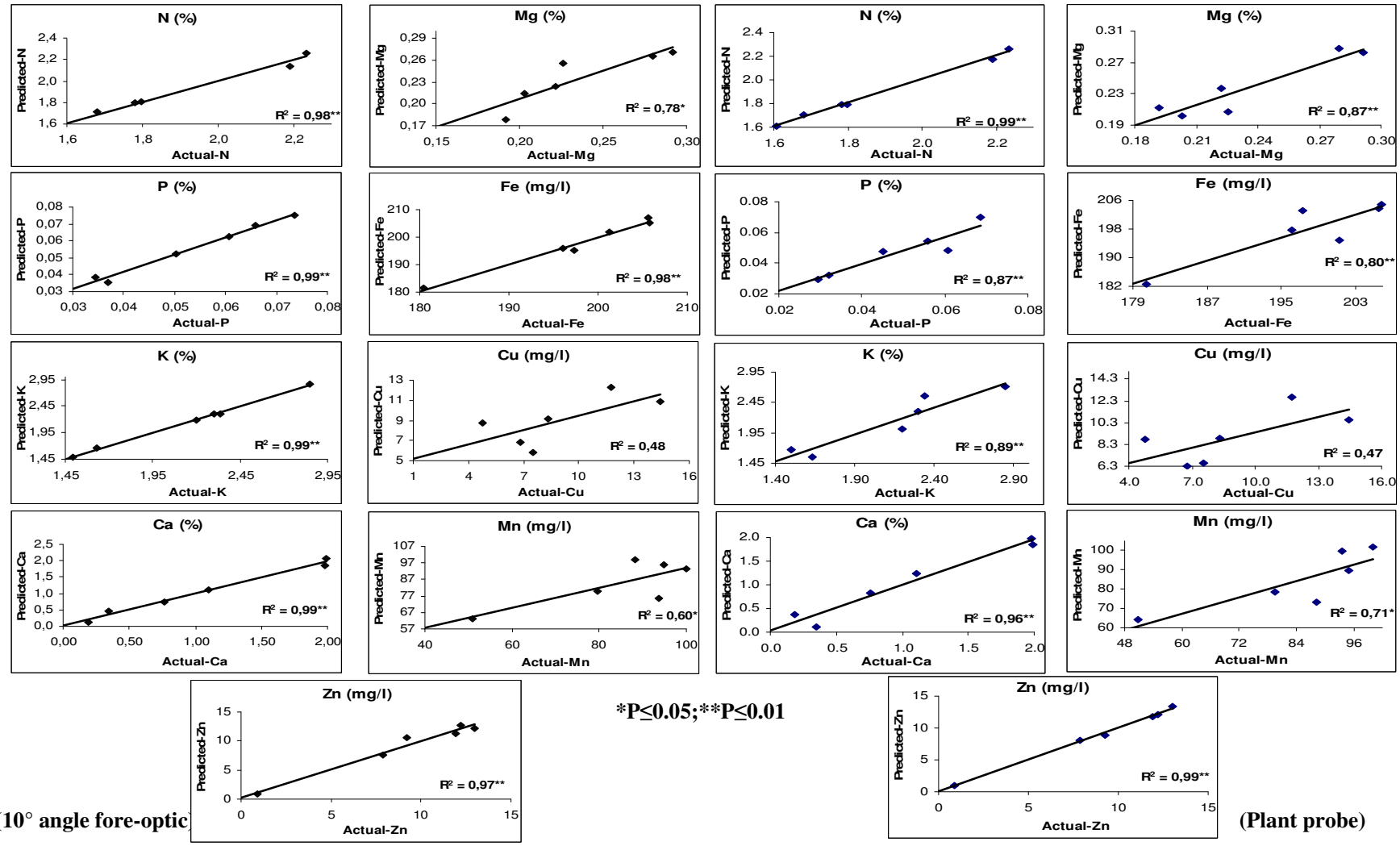
In apricot leaf, the highest R² values were N, P, K, Ca, Mg, Fe, Zn and Mn contents in degree of 10 angle fore-optic 0.99, 0.96, 0.70, 0.91, 0.92, 0.82, 0.98 and 0.97, respectively. In contrary, P, K, Ca, Cu, Mg, Fe and Mn had higher R² values in plant probe 0.74, 0.99, 0.88, 0.83, 0.86, 0.97 and 0.99, respectively (Figures 4).

The R² values for N, P, K, Mg and Mn ranged from 0.47-0.99, 0.73-0.99, 0.63-0.99, 0.58-0.99 and 0.60-0.99. The R² values for Ca, Fe, Zn and Cu ranged from 0.10-0.99, 0.37-0.98, 0.25-0.99, 0.22-0.99 (Table 4).

Table 3. Four wave bands (±5) selected from stepwise regression to determine the relationships among reflectance and macro and micro nutrient's on the basis of calibration data set in leaves (Plant probe)

Pear	**Equations**	**SE**	**R^2**
N	2.77+189.76(R460)-212.86(R500)+27.68(R640)-0.52(R700)	0.04	0.99
P	0.33+7.02(R440)-9.03(R520)+3.21(R600)+0.09(R720)	0.01	0.87
K	5.02-360.1(R490)-228.04(R590)+553.67(R650)+13.18(R710)	0.37	0.89
Mg	1.59-6.4(R480)-16.97(R580)+21.28(R610)-1.13(R760)	0.03	0.87
Ca	-6.93+161.43(R400)-149.43(R510)-4.82(R630)+19.09(R730)	0.36	0.96
Fe	241.04+4886.76(R410)-2702.6(R540)+420.35(R670)+261.31(R790)	9.35	0.80
Cu	-90.3-1371.67(R470)-28.55(R560)+1350.39(R680)+107.46(R750)	5.74	0.47
Mn	-564.49-2633.69(R420)-2626.5(R530)+3517.59(R620)+946.34(R780)	21.64	0.71
Zn	-176.8-419.83(R430)+395.76(R550)-268.3(R660)+177.03(R740)	0.58	0.99
Cherry	**Equations**	**SE**	**R^2**
N	1.33-17.66(R480)-17.57(R510)+52.95(R650)+0.83(R720)	0.11	0.92
P	-0.26-13.63(R460)+80.06(R500)-72.38(R660)+0.71(R730)	0.03	0.89
K	8.53-3.8(R410)-7.32(R590)+17.35(R690)-8.16(R740)	0.04	0.99
Mg	1.04+42.85(R450)+35.57(R580)-59.56(R600)-1.1(R760)	0.18	0.94
Ca	6.06-87.08(R420)+7.45(R550)+182.99(R680)-13.2(R780)	0.57	0.55
Fe	119.74-324.18(R430)-2545.56(R520)+1650.87(R670)+1393.41(R700)	5.05	0.98
Cu	-133.99+253.96(R440)+127.38(R560)-854.77(R640)+183.28(R750)	2.99	0.87
Mn	109.38-109.02(R470)-454.39(R530)+579.13(R620)-63.93(R790)	0.17	0.99
Zn	14.75-1322.63(R490)-605.27(R540)+1703.65(R630)+92.93(R710)	2.60	0.84
Peach	**Equations**	**SE**	**R^2**
N	-11.57-125.16(R470)+82.48(R520)-1.93(R640)+14.46(R790)	0.55	0.47
P	0.14-40.57(R460)-4.73(R530)+52.49(R670)-0.76(R700)	0.07	0.73
K	16.96-469.19(R420)+362(R500)-82.97(R660)-16.81(R720)	0.32	0.96
Mg	-14.19-160.45(R400)+518.61(R590)-780.77(R620)+31.09(R750)	0.54	0.58
Ca	11.04+28.46(R440)+26.04(R550)-52.97(R630)-13.34(R780)	1.19	0.10
Fe	1006.39-5741.01(R450)+1336.67(R570)+11368.37(R680)-1518.55(R760)	15.52	0.93
Cu	111.18+235.26(R410)-3554.04(R510)+1167.36(R600)+54.92(R710)	0.88	0.99
Mn	202.26+362.37(R480)-179.1(R560)+536.46(R690)-281.25(R730)	0.26	0.99
Zn	427.9+2495.24(R490)+394.3(R540)-2694.53(R650)-527.43(R740)	11.24	0.25
Appricot	**Equations**	**SE**	**R^2**
N	4.48-37.50(R400)+26.48(R540)-46.96(R620)-0.11(R760)	0.78	0.55
P	-0.03-6.91(R430)-0.74(R550)+0.42(R610)+0.55(R770)	0.03	0.74
K	1.02-220.96(R470)-66.27(R530)+773.9(R690)-197.69(R700)	0.10	0.99
Mg	1.06-60.5(R490)+5.3(R510)+43.68(R680)-0.22(R720)	0.11	0.86
Ca	3.95+5.72(R410)+27.88(R570)-122.61(R660)+0.17(R780)	0.48	0.88
Fe	325.3+5229.35(R440)+1312.03(R560)-11430(R670)+55.16(R740)	10.75	0.97
Cu	20.29-777.66(R450)+1316.55(R500)-1088.58(R650)+65.06(R710)	2.68	0.83
Mn	-38.4-2389.08(R420)-4501.7(R580)+7944.28(R630)+84.17(R790)	1.22	0.99
Zn	18.29+1036.04(R460)+734.1(R590)-1285.06(R640)-52.71(R750)	6.62	0.42

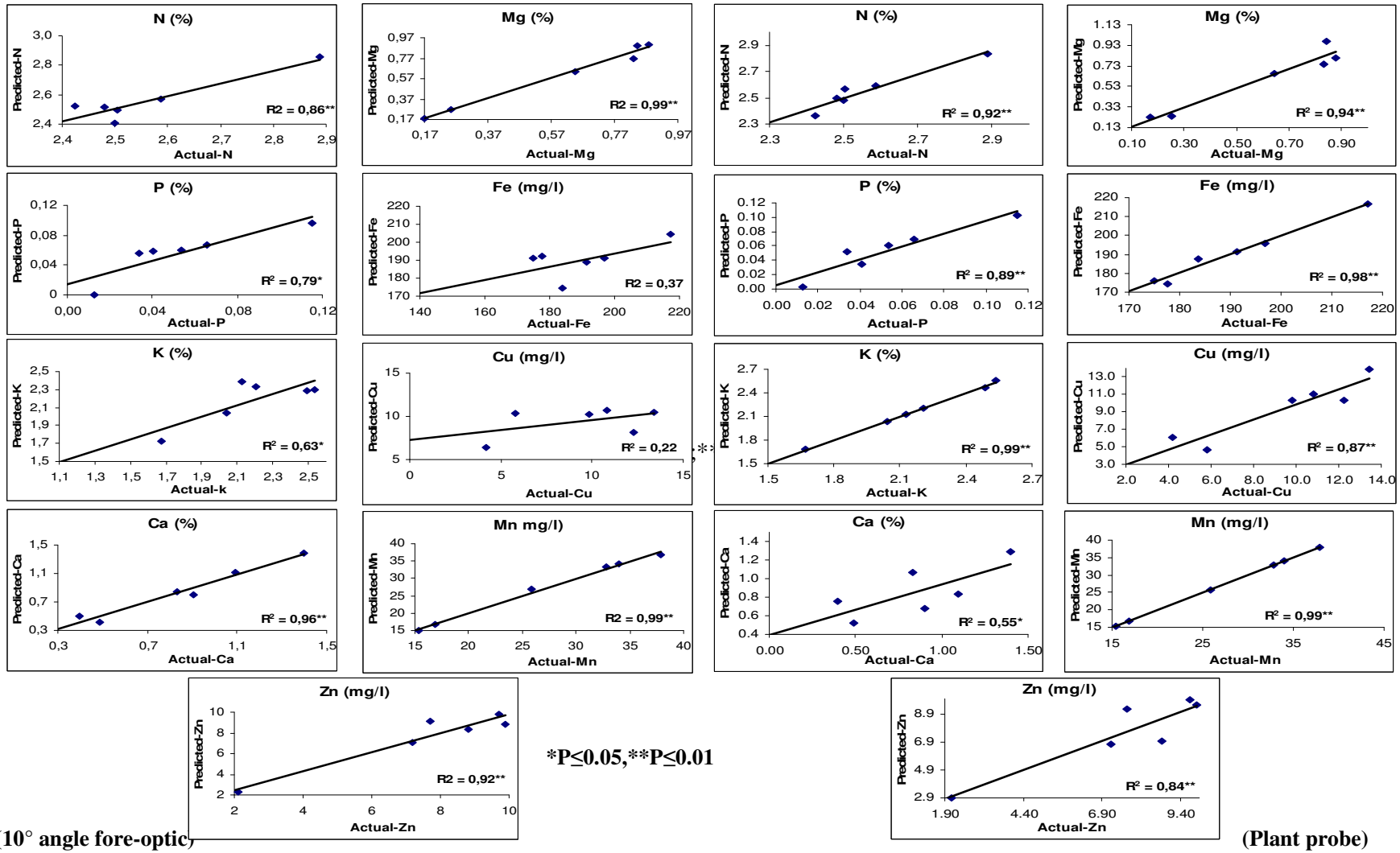
Figure 1. Comparison of laboratory measured macro and micro nutrient in the test data set with their predicted values based on the equations developed for spectral reflectance in pear leaves



*P≤0.05;**P≤0.01

(10° angle fore-optic) **(Plant probe)**

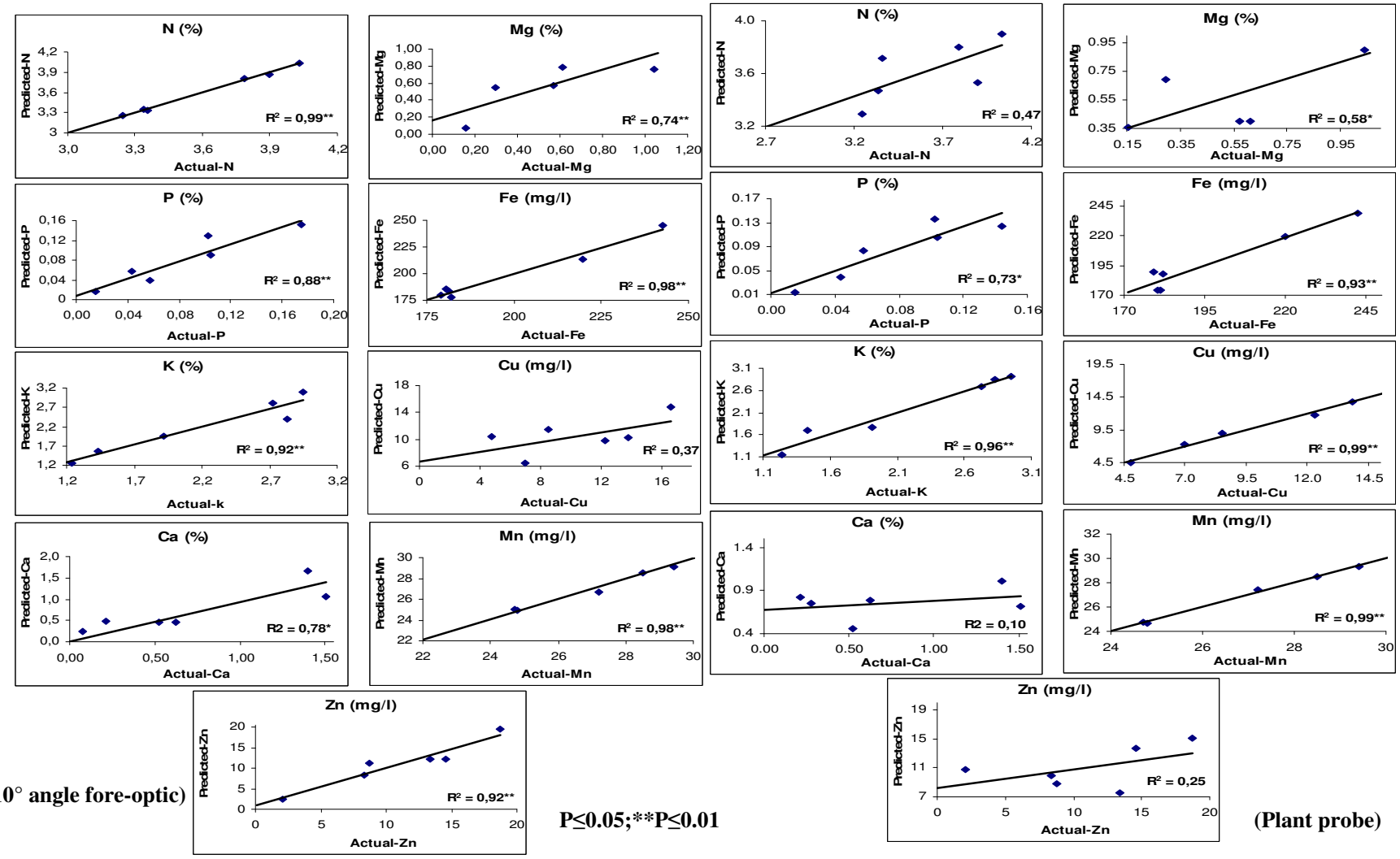
Figure 2. Comparison of laboratory measured macro and micro nutrient in the test data set with their predicted values based on the equations developed for spectral reflectance in cherry leaves



***P≤0.05,**P≤0.01**

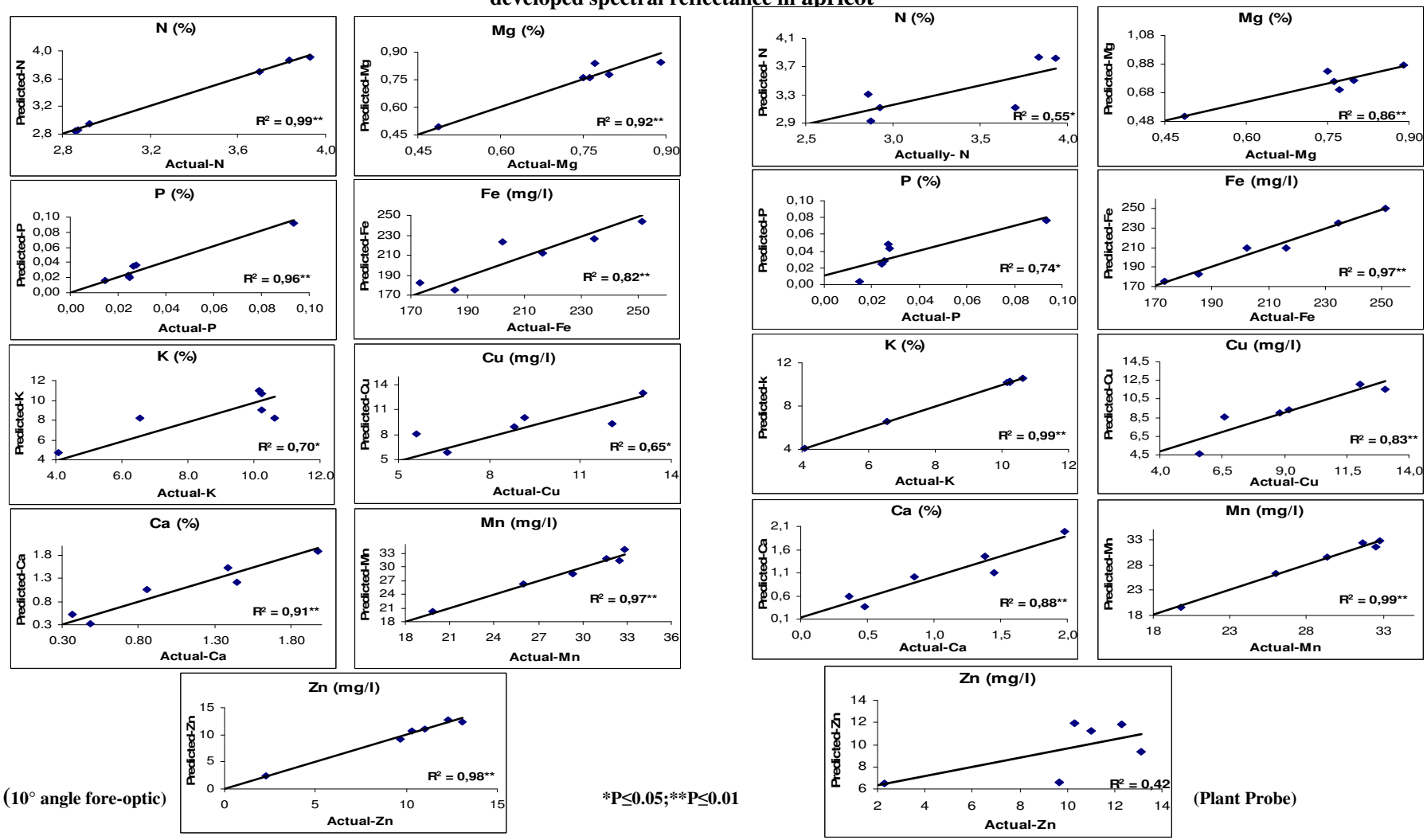
(10° angle fore-optic) **(Plant probe)**

Figure 3. Comparison of laboratory measured macro and micro nutrient in the test data set with their predicted values based on the equations developed spectral reflectance in peach



(10° angle fore-optic) **P≤0.05;**P≤0.01** **(Plant probe)**

Figure 4. Comparison of laboratory measured macro and micro nutrient in the test data set with their predicted values based on the equations developed spectral reflectance in apricot



(10° angle fore-optic) *P≤0.05;**P≤0.01 (Plant Probe)

Table 4. The R^2 values obtained from plant probe and 10º degree fore-optic in leaves

Nutrients	Pear		Cherry		Peach		Apricot	
	Probe	10 º	Probe	10 º	Probe	10 º	Probe	10 º
N	0.99	0.98	0.92	0.86	0.47	0.99	0.55	0.99
P	0.87	0.99	0.89	0.79	0.73	0.88	0.74	0.96
K	0.89	0.99	0.99	0.63	0.96	0.92	0.99	0.70
Ca	0.96	0.99	0.55	0.96	0.10	0.78	0.88	0.91
Mg	0.87	0.78	0.94	0.99	0.58	0.74	0.86	0.92
Fe	0.80	0.98	0.98	0.37	0.93	0.97	0.97	0.82
Cu	0.47	0.48	0.87	0.22	0.99	0.37	0.83	0.65
Mn	0.71	0.60	0.99	0.99	0.99	0.98	0.99	0.97
Zn	0.99	0.97	0.84	0.92	0.25	0.92	0.42	0.98

Discussion

Chemical methods used to determine plant nutrients are time consuming and costly and generate hazardous waste that must be disposed. Specroradiometric methods have great advantages compared with chemical methods, and it not requires the collection and preparation of vegetation samples like NIRS methods.

Leaf reflectance depends usually on the type of vegetation, canopy architecture and the biochemical composition of plant tissue. For nutrients variation in R^2 values in the present study was mainly because of the biochemical composition of plant tissue because different species were used this study. Having compared the of laboratory measured and predicted values in pear, cherry, peach, apricot orchard leaves, it was clear that real-time reflectance measurements at the fresh leaf in the field by plant probe or fore-optic offer an alternative for estimating the chemical composition of plants, such as N and Mg concentrations of leaves[14] and P, K, and Mn concentrations of leaves.

Mutanga et al.(2004) found that R^2 values of N, P, K, Ca and Mg were 0.70, 0.80, 0.64, 0.50 and 0.68 respectively. The high R^2 values found in this study may be associated with the close nutrient concentrations found in the samples, which did not shown any nutrient deficiencies. Several studies on different plant species have indicated that reflectance of plant leaves correlated with leaf chlorophyll and leaf N concentration[19] .

The R^2 values of Ca, Fe, Zn and Cu were found minimal. This may be associated with minimal concentration of Cu and Zn as micro nutrients. Iron can exist in trivalent or divalent forms in plant tissues or complexed within Fe-containing proteins and enzymes, thus influencing its bioavailability for metabolic reaction and biosynthesis.

The comparison of differences in species between predicted and measured values (Table 2 and 3) were probably affected the nitrogen content because leaf chlorophyll concentration is highly and negatively correlated with leaf reflectance at 400-790 nm. Nitrogen concentration of plant leaf is an important indicator of nutritive value and changes considerably with growth stage, growth environment, and plant genotype and management practices. Studies on different plant species have indicated weak relationships between the concentration of N in plant tissues and reflectance in a single narrow waveband, and that two-waveband reflectance of plant leaves correlate more closely with N concentration in leaves[13]. The results of canopy reflectance in the present study are in agreement with the previous reports of the two-band reflectance improving the relationship between N concentration of plant tissues and reflectance. More recently, leaf reflectance in red-edge range of wavelengths (690–740 nm) could be used to estimate leaf N concentration and total N content of ryegrass (*Lolium multiflorum Lam.*). We have selected two wavelengths for prediction near 600-790 nm. The best prediction of nutrients amounts was obtained between these intervals.

The absorption features seen in vegetation spectra are related to organic compounds common to the majority of plant species. Plant canopy is contained in the relative intensity of the various absorption features rather than in the presence or absence of a specific absorption features. The major spectral absorption features can be attributed to plant pigments (chlorophylls, zanthophyll, and carotenoids) and water. Other, minor absorption features are attributable to other chemical components; these include cellulose, lignin, proteins, starches, and sugars. Non-photosynthetic components of the canopy have spectra dominated by absorption features attributed to lignin and cellulose. Prediction of plant P was the best in the early growth stage using reflectance in the blue (440 and 445 nm) and NIR (730-930) regions[20]. In this study, one wavelength in blue and NIR region were used to predict plant P amount.

All mineral nutrients levels caused pronounced modifications in leaf reflectance. In this study wavelengths from 400 to 760 nm were found to be correlated with nutrient amounts. It is well known that maturity can have an effect on leaf reflectance. Generally older leaves have much higher reflectance than young leaves. Low reflectance in the blue (450 nm) and red region (675 nm) is due to chlorophyll absorption characteristics **(Ayala-Silva, T., 2005).** Reflectance dips in the IR at 700–750 nm are associated with strong chlorophyll absorption and leaf cell structure[21] . The sharp dip around 764 nm has been associated with absorption by O_2 and water[22]. **Gupta et al. (2000)** considered near-IR wavelength after 760 nm for detailed study to avoid atmospheric O_2 and H_2O absorption bands and to provide reasonably wider optional bandwidth (s) in the IR region.

The R^2 values of Cu determined by fore-optic were found minimal level in all deciduous orchards leaves. However, the R^2 values of Cu, Ca and Zn by plant probe were found minimal for all orchard leaves. The use of fore-optic for determining the N, P, Ca, Mg and Zn contents was successful plant probe was useful for determination of the K, Fe, Cu and Mn.

The NIR spectrum originates from radiation energy transferred to leaves. It seems that there is an interaction or spectral problem that R^2 values are less than 0.50 in some nutrients like cupper and zinc.

Conclusions

Overall, the primary results of the experiment indicated that further research on the use of spectroradiometer data to determine mineral nutrients with other statistical model need to be conducted. The values obtained from spectroradiometer can be used to predict the N, P, K, Mg and Mn contents of orchard leaves in field. However, predictions of Ca, Fe, Zn and Cu contents are not adequate for use.

The fore-optic may be used for determination of macro nutrients, while plant probe may be useful for micro nutrients determination. Furthermore, this technique is rapid, making it possible to analyses a large number of samples in a practical and timely manner. However, the use of hyperspectral values as a standard analyses method in determination of nutrient contents requires further understanding of relationship between spectral properties, nutrient concentration and structural changes in plant tissues. In order to transfer this method to the field, further investigations of possible interactions are necessary.

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