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Spectral parameter-based models for leaf potassium concentration estimation in Ping'ou hybrid hazelnut

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Abstract: Ping'ou hybrid hazelnut is produced by cross cultivation and is widely cultivated in northern China with good development prospects. Based on a field experiment of fertilizer efficiency, the leaf spectral reflectance and leaf potassium (K) concentration were measured with different quantities of K fertilizer applied at four fruit growth stages (fruit setting stage, fruit rapid growth stage, fruit fat-change stage, and fruit near-maturity stage) of Ping'ou hybrid hazelnut in 2019. Spectral parameters that were significantly correlated with leaf K concentration were selected using Pearson correlation analysis, and spectral parameter estimation models of leaf K concentration were established by employing six different modelling methods (exponential function, power function, logarithmic function, linear function, quadratic function, and cubic function). The results indicated that at the fruit setting period, leaf K concentration was significantly correlated with D_y (spectra slope of yellow edge), R_g (reflectance of the green peak position), λ_o (red valley position), SD_b (blue edge area), SD_r/SD_b (where SD_r represents red edge area), and $(SD_r–SD_b)/(SD_r+SD_b)$ (P<0.01). There were significant correlations of leaf K concentration with D_y, R_g, SD_b, R_g/R_o (where R_o is the reflectance of the red valley position), and $(R_g–R_o)/(R_g+R_o)$ at the fruit rapid growth stage (P<0.01). Further, significant correlations of leaf K concentration with R_g, R_o, RNIR/Green, and RNIR/Blue were obtained at the fruit fat-change period (P<0.01). Finally, leaf K concentration showed significant correlations with D_r, R_g, R_o, SD_y (yellow edge area), and SD_r at the fruit near-maturity stage (P<0.01). Through a cubic function analysis, regression estimation model of leaf K concentration with highest fitting degree (R^2) values at the four fruit growth stages was established. The findings in this study demonstrated that it is feasible to estimate leaf K concentration of Ping'ou hybrid hazelnut at the various phenological stages of fruit development by establishing regression models between leaf K concentration and spectral parameters.

Keywords: leaf K concentration; spectrum; cubic function; regression models; fruit growth stages; Ping'ou hybrid hazelnut

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1 Introduction

Ping'ou hybrid hazelnut is a hybrid of *Corylus* that has strong adaptability and has been widely planted in China. It is mainly produced by crossbreeding between the native *Corylus heterophylla* from China and the exotic *Corylus avellana* from Europe. This hybrid hazelnut has the characteristics of cold resistance, drought resistance, and strong adaptability from *C. heterophylla*, alongside the characteristics of a large, thin shell and high yield from *C. avellana*. These

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characteristics give it broad prospects for production, development, and utilization (Wang et al., 2020). Potassium (K) is one of the essential mineral elements in plants (Allen and David, 2007; Izhar and Frans, 2014; Nieves-Cordones et al., 2014; Lu et al., 2020); it plays an important role in the synthesis of many enzymes, proteins, starches, and cellulose. Although K does not participate in the organic composition of plants (Maathuis et al., 1999), it is an indispensable nutrient element for plant growth and development (Koch and Mengel, 1974). K exists in an ionic form in plants; it has strong mobility and plays an important role in plant metabolic processes and the structure of cells and tissues (Alex, 2006). It has many physiological functions in the growth and development of fruit trees, flowering, and fruiting (Zhao et al., 2014). K management is an important basis for increasing fruit yield and improving fruit quality (Wang et al., 2011).

In actual production practices, as a hazelnut variety widely planted in Xinjiang Uygur Autonomous Region of China, field cultivation and management technology of this crop are relatively underdeveloped and lack professional scientific and technical support (Shan et al., 2015). This directly affects the growth and fruiting of Ping'ou hybrid hazelnut, resulting in low yields and uneven quality (Hu et al., 2019). Therefore, understanding how to accurately and quickly diagnose K deficiency in hazelnut as well as the change in K concentration in real-time, to supply K elements and recognize K demand in the external soil, and to achieve on-demand and precise fertilization is of great significance for the fertilization of Ping'ou hybrid hazelnut.

For this reason, an active spectrometer (UniSpec-SC) was used to directly determine the spectral reflectance of tree leaves and to screen the spectral parameters that are significantly related to the leaf K concentration during four growth periods of Ping'ou hybrid hazelnut. With the leaf K concentration as the dependent variable and the spectral parameters as the independent variables, a spectral estimation model was established, and independent testing of the model was carried out. It is our hope that the result of this study could provide a technical reference for rapid monitoring of leaf K concentration and for scientific guidance of field fertilization for Ping'ou hybrid hazelnut.

2 Materials and methods

2.1 Study area and experimental designing

The study was conducted in the Hybrid Hazelnut High-yield Cultivation Demonstration Garden of the Comprehensive Test Fields of Xinjiang Academy of Agricultural Sciences (43°45′32″–44°08′00″N, 86°37′33″–88°58′24″E) in Urumqi City of Xinjiang Uygur Autonomous Region, China. The orchard in which the test plots were located is approximately 2 hm^2. The altitude is 935.3 m, the annual average temperature is 6.9°C, the average annual precipitation is 208.3 mm, the evaporation is 2616.9 mm, the frost-free period is 105–168 d, and the sunlight duration is 2813.5 h.

In this study, "Xinzhen 1" hybrid hazelnuts were used as the test material, and "Xinzhen 2" hybrid hazelnuts were selected as the pollination cultivar. The spacing between the plot rows was 1.5 m×4.0 m, and the tree age was 8-year-old. The trees were planted in a north-south direction. The plant form and crown width of the selected tree species were the same. The soil in the test garden was sandy soil with a deep soil depth containing 0.914% organic matter, 38.20 mg/kg available nitrogen (N), 7.97 mg/kg available phosphorous (P), and 114.67 mg/kg available K.

A field trial examining the effects of "3414" (Zhang et al., 2011) fertilizer was conducted for artificial quantitative control over fertilization in hybrid hazelnut samples, which was carried out in the form of circular furrow application before the trees germinated in early April 2017. Three fertilizer factors, i.e., N, P, and K, were set in the experiment. There were 14 fertilizer treatments in total at four levels, including no fertilization, 0.5 times the conventional fertilization quantity, the conventional fertilization quantity, and 1.5 times the conventional fertilization quantity. Each treatment was allocated among 3 replicated plots, resulting in a total of 42 test plots with 10 trees in each test plot. The conventional fertilization quantities (scalar) of N, P, and K for each plant were

0.7, 0.3, and 0.2 kg, respectively. The N fertilizer was urea containing 46% $CO(NH_2)_2$ produced by CNPC Xinjiang Tarim Oilfield Company, China; the P fertilizer was coarse whiting containing 46% $[Ca(H_2PO_4)_2]P_2O_5$ produced by Yunnan Yuntianhua International Chemical Co., Ltd., China; and the K fertilizer was potassium sulfate-containing 51% $(K_2SO_4)K_2O$ produced by SDIC Xinjiang LuobupoHoevellite Co. Ltd., China.

2.2 Spectral data collection

2.2.1 Instrument

The UniSpec-SC (single channel) portable spectrum analyser (PP Systems Inc., USA) was used in this study. This type of spectrum analyser has a light source and can perform continuous measurements, with a measurement range of 310–1130 nm. The spectral resolution was lower than 10 nm, and the number of output bands was 821 (data were resampled at a resolution of 1 nm by the spectrometer).

2.2.2 Sampling time

Data were collected on clear and windy days during 12:00–15:00 (LST) at four fruit growth stages of Ping'ou hybrid hazelnut in 2019, including the fruit setting stage (25 May 2019), fruit rapid growth stage (25 June 2019), fruit fat-change stage (25 July 2019), and fruit near-maturity stage (30 August 2019).

2.3 Leaf collection and determination of leaf K concentration

After the standard calibration of the spectral analyser, 10 healthy leaves were collected from the current year's fresh branches of Ping'ou hybrid hazelnut in the middle and upper periphery of the canopy in the east, south, west, and north of all the sample plants in each test plot; the collection was repeated 6 times.

To ensure one-to-one correspondence between measured leaf K concentration and measured spectral parameters, we collected the leaves when the spectral parameter data values were measured at each fruit growth stage. The leaf samples collected in the same test plot were mixed into one sample, for a total of 168 samples (42 test plots×4 stages). After collection, the leaves were cleaned with absorbent cotton, dehydrated at 105°C for 30 min, dried at constant weight at 80°C, crushed, and passed through a 60-mesh nylon sieve. Leaf K concentration was determined qualitatively and quantitatively by identifying characteristic spectral lines by the flame photometry method (Payal and Bably, 2020).

2.4 Data analysis

Table 1 shows the 25 spectral parameters that can predict the leaf K concentration in this experiment. Pearson correlation analysis was used to screen out the spectral parameters that were significantly correlated with leaf K concentration at different fruit growth stages, and a two-sided test was also performed. The leaf K concentration of Ping'ou hybrid hazelnut was considered as the dependent variable (y), and the spectral parameters that were significantly correlated with leaf K concentration at fruit different growth stages were considered as the independent variables (x). Six different modelling methods, namely, exponential function (y=ae^{bx}), power function (y=ax^b), logarithmic function (y=aln$x$+b), linear function (y=ax+b), quadratic function (y=ax^2–bx+c), and cubic function (y=ax^3+bx^2+cx+d), were used to build the regression models.

We determined the optimal model based on fitting degree (R^2), and calculated the residuals of the regression model with the largest R^2 at different fruit growth stages tested by normal, independent, and equal variance tests to judge the validity and reliability of the regression relationship. The normal distribution of the regression model residuals was tested by normal distribution chi-square test of the residuals, the independence was tested by Durbin-Watson (DW) method, and the homogeneity of variance was determined by Levene's test (W). Using independent samples, the model's accuracy was estimated using the root mean square error (RMSE) and relative error (RE).

Data calculations were conducted using Microsoft Excel 2007 software, and statistical analyses were performed using SPSS 21.0 software.

Table 1 Types of spectral parameters

Parameter based on spectral index	Parameter based on spectral position	Parameter based on spectral area
RNIR/Green	D_b (spectra slope of blue edge)	SD_b (blue edge area)
RNIR/Red	λ_b (blue edge position)	SD_y (yellow edge area)
RNIR/Blue	D_r (spectra slope of red edge)	SD_r (red edge area)
SD_r/SD_b	λ_r (red edge position)	
SD_r/SD_y	D_y (spectra slope of yellow edge)	
R_g/R_o	λ_y (yellow edge position)	
(NIR–Green)/(NIR+Green)	R_g (reflectance of the green peak position)	
(NIR–Red)/(NIR+Red)	λ_g (green peak position)	
(NIR–Blue)/(NIR+Blue)	R_o (reflectance of the red valley position)	
$(SD_r–SD_b)/(SD_r+SD_b)$	λ_o (red valley position)	
$(R_g–R_o)/(R_g+R_o)$		
$(SD_r–SD_y)/(SD_r+SD_y)$		

Note: D_b, the maximum first-order differential at 490–530 nm; λ_b, the wavelength position for D_b; SD_b, the sum of the first-order differential values at 490–530 nm; D_y, the maximum first-order differential at 550–580 nm; λ_y, the wavelength position for D_y; SD_y, the sum of the first-order differential values at 550–580 nm; D_r, the maximum first-order differential at 680–750 nm; λ_r, the wavelength position for D_r; SD_r, the sum of the first-order differential values at 680–750 nm; R_g, the maximum wavelength reflectivity at 510–560 nm; λ_g, the wavelength position for R_g; R_o, the maximum wavelength reflectivity at 640–680 nm; λ_o, the wavelength position for R_o; NIR, wavelength range at 760–850 nm; Green, wavelength range at 510–560 nm; Red, wavelength range at 650–670 nm; Blue, wavelength range at 350–400 nm.

3 Results

3.1 Correlation between leaf K concentration and spectral parameters at different fruit growth stages

3.1.1 Fruit setting stage

As shown in Table 2, leaf K concentration showed significant positive correlations with D_b (spectra slope of blue edge), λ_g (green peak position), and R_o (reflectance of the red valley position) (P<0.05), and highly significant positive correlations with D_y (spectra slope of yellow edge), R_g (reflectance of the green peak position), λ_o (red valley position), and SD_b (blue edge area) (P<0.01) at the fruit setting stage. There were highly significant and negative correlations of leaf K concentration with SD_r/SD_b (where SD_r represents red edge area) and $(SD_r–SD_b)/(SD_r+SD_b)$ (P<0.01) at the fruit setting stage.

Table 2 Pearson correlation coefficients between leaf K concentration and spectral parameters of Ping'ou hybrid hazelnut at the fruit setting stage

Spectral parameter	r	Spectral parameter	r
D_b	0.6941*	RNIR/Green	–0.3152
λ_b	–0.3491	RNIR/Red	–0.2781
D_r	0.5121	NIR/Blue	0.4457
λ_r	–0.4801	SD_r/SD_b	–0.6628**
D_y	0.9422**	SD_r/SD_y	–0.0497
λ_y	–0.0041	R_g/R_o	0.1331
R_g	0.7891**	(NIR–Green)/(NIR+Green)	–0.3015
λ_g	0.6501*	(NIR–Red)/(NIR+Red)	–0.2914
R_o	0.6561*	(NIR–Blue)/(NIR+Blue)	0.4291
λ_o	0.6752**	$(SD_r–SD_b)/(SD_r+SD_b)$	–0.6948**
SD_b	0.7471**	$(SD_r–SD_y)/(SD_r+SD_y)$	–0.5062
SD_y	0.0901	$(R_g–R_o)/(R_g+R_o)$	0.1231
SD_r	0.4292		

Note: r, Pearson correlation coefficient. ** means that correlation is highly significant at P<0.01 level; * means that correlation is significant at P<0.05 level.

3.1.2 Fruit rapid growth stage

From Table 3 it can be seen that there were significant positive correlations of leaf K concentration with D_b and SD_r (P<0.05) and highly significant positive correlations of leaf K concentration with D_y, R_g, λ_o, SD_b, R_g/R_o, and $(R_g–R_o)/(R_g+R_o)$ (P<0.01) at the fruit rapid growth stage. However, there was a highly significant negative correlation between leaf K concentration and SD_b (P<0.01) at this stage.

Table 3 Pearson correlation coefficients between leaf K concentration and spectral parameters of Ping'ou hybrid hazelnut at the fruit rapid growth stage

Spectral parameter	r	Spectral parameter	r
D_b	0.6581*	RNIR/Green	–0.0291
λ_b	–0.0211	RNIR/Red	0.3091
D_r	0.4782	NIR/Blue	0.4352
λ_r	0.1152	SD_r/SD_b	–0.4373
D_y	0.9461**	SD_r/SD_y	0.1973
λ_y	–0.1451	R_g/R_o	0.6831**
R_g	0.7652**	(NIR–Green)/(NIR+Green)	–0.0161
λ_g	0.3031	(NIR–Red)/(NIR+Red)	0.3211
R_o	0.0672	(NIR–Blue)/(NIR+Blue)	0.4272
λ_o	0.5222	$(SD_r–SD_b)/(SD_r+SD_b)$	–0.4942
SD_b	0.7281**	$(SD_r–SD_y)/(SD_r+SD_y)$	0.1532
SD_y	–0.5441*	$(R_g–R_o)/(R_g+R_o)$	0.6821**
SD_r	0.5811*		

Note: r, Pearson correlation coefficient. ** means that correlation is highly significant at P<0.01 level; * means that correlation is significant at P<0.05 level.

3.1.3 Fruit fat-change stage

As shown in Table 4, there was a significant positive correlation between leaf K concentration and (NIR–Blue)/(NIR+Blue) (P<0.05); and there were highly significant positive correlations of leaf K concentration with R_g, R_o, and NIR/Blue (P<0.01) at the fruit fat-change stage. However, leaf K concentration showed significant negative correlations with RNIR/Red and (NIR–Red)/(NIR+Red) (P<0.05), and highly significant negative correlations with RNIR/Green and (NIR–Green)/(NIR+Green) (P<0.01) at this stage.

Table 4 Pearson correlation coefficients between leaf K concentration and spectral parameters of Ping'ou hybrid hazelnut at the fruit fat-change stage

Spectral parameter	r	Spectral parameter	r
D_b	0.3831	RNIR/Green	–0.7312**
λ_b	–0.0762	RNIR/Red	–0.5532*
D_r	0.4623	NIR/Blue	0.6662**
λ_r	0.4601	SD_r/SD_b	–0.2692
D_y	0.3781	SD_r/SD_y	0.2122
λ_y	–0.2322	R_g/R_o	0.3461
R_g	0.8262**	(NIR–Green)/(NIR+Green)	–0.7341**
λ_g	–0.2171	(NIR–Red)/(NIR+Red)	–0.5581*
R_o	0.8591**	(NIR–Blue)/(NIR+Blue)	0.6641*
λ_o	0.3101	$(SD_r–SD_b)/(SD_r+SD_b)$	0.2321
SD_b	0.3772	$(SD_r–SD_y)/(SD_r+SD_y)$	0.3165
SD_y	0.3712	$(R_g–R_o)/(R_g+R_o)$	0.3341
SD_r	0.3912		

Note: r, Pearson correlation coefficient. ** means that correlation is highly significant at P<0.01 level; * means that correlation is significant at P<0.05 level.

3.1.4 Fruit near-maturity stage

As Table 5 depicted, leaf K concentration exhibited significant positive correlations with D_y and SD_b (P<0.05), and highly significant positive correlations with D_r, R_g, R_o, SD_y (yellow edge area), SD_r, and NIR/Blue (P<0.01) at the fruit near-maturity stage.

Table 5 Pearson correlation coefficients between leaf K concentration and spectral parameters of Ping'ou hybrid hazelnut at the fruit near-maturity stage

Spectral parameter	r	Spectral parameter	r
D_b	0.4951	RNIR/Green	0.0042
λ_b	0.3011	RNIR/Red	0.0641
D_r	0.7982**	NIR/Blue	0.4553
λ_r	–0.4791	SD_r/SD_b	–0.2691
D_y	0.6011*	SD_r/SD_y	0.5212
λ_y	–0.4225	R_g/R_o	0.4761
R_g	0.9201**	(NIR–Green)/(NIR+Green)	0.0209
λ_g	0.0011	(NIR–Red)/(NIR+Red)	0.0712
R_o	0.9101**	(NIR–Blue)/(NIR+Blue)	0.4481
λ_o	0.0012	$(SD_r–SD_b)/(SD_r+SD_b)$	–0.2461
SD_b	0.6681*	$(SD_r–SD_y)/(SD_r+SD_y)$	0.4392
SD_y	0.6871**	$(R_g–R_o)/(R_g+R_o)$	0.4701
SD_r	0.7912**		

Note: r, Pearson correlation coefficient. ** means that correlation is highly significant at P<0.01 level; * means that correlation is significant at P<0.05 level.

3.2 Comparison of fitting degree among different models of leaf K concentration and spectral parameters at different fruit growth stages

In this study, the leaf K concentration of Ping'ou hybrid hazelnut was considered as the dependent variable (y), and the spectral parameters that had significant correlations with leaf K concentration were selected as the independent variables (x). The regression models were established using six different modelling equations: power function, exponential function, logarithmic function, linear function, quadratic function, and cubic function. As shown in Table 6, all four fruit growth stages showed the highest fitting degree (R^2) values for the regression model established by the cubic function. The best estimators were as follows: D_y for the fruit setting stage; D_y for the fruit rapid growth stage; R_o for the fruit fat-change stage; and R_g for the fruit near-maturity stage.

3.3 Validation for the optimal estimation model of leaf K concentration

Residuals of the estimation model of leaf K concentration established by the cubic regression equation with the highest fitting degree (R^2) values were tested. As can be seen from Table 7, the residuals of the model all followed a normal distribution; the residuals were independent of each other, there was no first-order autocorrelation, and the variance difference was not significant. The results showed that the regression model between leaf K concentration and spectral parameters established by the cubic regression equation is valid.

Samples were randomly and independently selected to test the spectral characteristic estimation model for leaf K concentration at the selected four fruit growth stages (Fig. 1). The RMSE values of the spectral characteristic estimation model were 0.2236, 0.4311, 0.1151, and 0.0175 g/kg, at the fruit setting stage, fruit rapid growth stage, fruit fat-change stage, and fruit near-maturity stage, respectively; the RE values of the spectral characteristic estimation model were 4.1941%, 7.0608%, 0.2406%, and 0.7044% for the four growth stages, respectively. The data showed that the model has a relatively high estimation accuracy.

4 Discussion

The results showed that there was a strong correlation between leaf K concentration and D_y at the fruit setting stage and fruit rapid growth stage. This is largely because the main factors affecting the

Table 6 Fittings of regression models using spectral parameters associated with leaf K concentration of Ping'ou hybrid hazelnut at different fruit growth stages

Growth stage	Spectral parameter	Fitting degree R^2					
		Power function	Exponential function	Logarithmic function	Linear function	Quadratic function	Cubic function
Fruit setting stage	λ_o	0.4523	0.4525	0.4551	0.4551	0.4558	0.4571
	R_g	0.5869	0.5891	0.6167	0.6225	0.6235	0.6247
	D_y	0.9201	0.8643	0.9253	0.8881	0.9091	0.9436
	SD_b	0.4923	0.5245	0.5221	0.5571	0.5678	0.5691
	SD_r/SD_b	0.4489	0.4151	0.4737	0.4385	0.4935	0.4977
	$(SD_r–SD_b)/(SD_r+SD_b)$	0.4541	0.4563	0.4793	0.4821	0.4821	0.5166
Fruit rapid growth stage	D_y	0.9291	0.8845	0.9341	0.8941	0.9498	0.9511
	R_g	0.5659	0.5691	0.5817	0.5855	0.5865	0.6037
	SD_b	0.4781	0.5163	0.4893	0.5301	0.5391	0.5596
	R_g/R_o	0.4605	0.4608	0.4653	0.4661	0.4662	0.5217
	$(R_g–R_o)/(R_g+R_o)$	0.4561	0.4609	0.4581	0.4641	0.4651	0.5091
Fruit fat-change stage	R_g	0.7091	0.6818	0.7031	0.6817	0.7021	0.7098
	R_o	0.7512	0.7411	0.7421	0.7371	0.7491	0. 8028
	RNIR/Green	0.5591	0.5541	0.5397	0.5335	0.5415	0.5637
	RNIR/Blue	0.4341	0.4333	0.4413	0.4431	0.4432	0.4641
Fruit near-maturity stage	D_r	0.6332	0.6151	0.6521	0.6361	0.6541	0.7028
	R_g	0.8501	0.8311	0.8647	0.8465	0.8865	0.9247
	R_o	0.8191	0.8203	0.8253	0.8271	0.8282	0.8401
	SD_r	0.4908	0.4801	0.4822	0.4719	0.5094	0.7791
	SD_y	0.6201	0.6059	0.6396	0.6257	0.6398	0.6821

Table 7 Residual inspection of the regression relationship between leaf K concentration and the most effective spectral parameters established by the cubic regression equation at different fruit growth stages

	Fruit setting period	Fruit rapid growth period	Fruit fat-change period	Fruit near-maturity period
R^2	0.9436	0.9511	0.8028	0.9247
n	42	42	42	42
P value	0.0001	0.0001	0.00075	0.0001
$\hat{\sigma}^2$	0.1149^2	0.1124^2	0.4046^2	0.1149^2
Normal distribution chi-square test of residuals	χ^2=1.2049<$\chi^2_{0.1}$(6)=10.64 e~N(0, 0.6852^2)	χ^2=0.7365<$\chi^2_{0.1}$(6)=10.64 e~N(0, 0.3415^2)	χ^2=1.7299<$\chi^2_{0.1}$(6)=10.64 e~N(0, 0.4206^2)	χ^2=1.2049<$\chi^2_{0.1}$(6)=10.64 e~N(0, 0.5217^2)
First-order autocorrelation test of residuals	DW=2.003 ∈ [1.468, 2.532] α=0.01	DW=1.4904 ∈ [1.468, 2.532] α=0.01	DW=1.6603 ∈ [1.468, 2.532] α=0.01	DW=2.0124 ∈ [1.468, 2.532] α=0.01
Test for homogeneity of variance	W=0.3573<$F_{0.05}$(13, 28)=2.09	W=0.4229<$F_{0.05}$(13, 28)=2.09	W=0.0582<$F_{0.05}$(13, 28)=2.09	W=0.3573<$F_{0.05}$(13, 28)=2.09

Note: χ^2, normal distribution chi-square test of residuals. DW (Durbin-Watson) was used to test the independence; W (Levene's test) was used to test the homogeneity of variance.

spectral reflectivity in the visible light band are lutein, lycopene, anthocyanins, and other pigments. Lutein and lycopene have absorption bands at approximately 450 nm; the main absorption band of chlorophyll is also at 450 nm, which leads to the absorption of light by lutein, and the masking of lycopene by chlorophyll. Therefore, in the visible range, chlorophyll becomes the decisive factor affecting the reflectivity of green plants. However, at the fruit setting stage and fruit rapid growth stage of Ping'ou hybrid hazelnut, the leaves were just beginning to grow and were mostly young leaves with low chlorophyll concentration and yellow color. Moreover, the water content in the

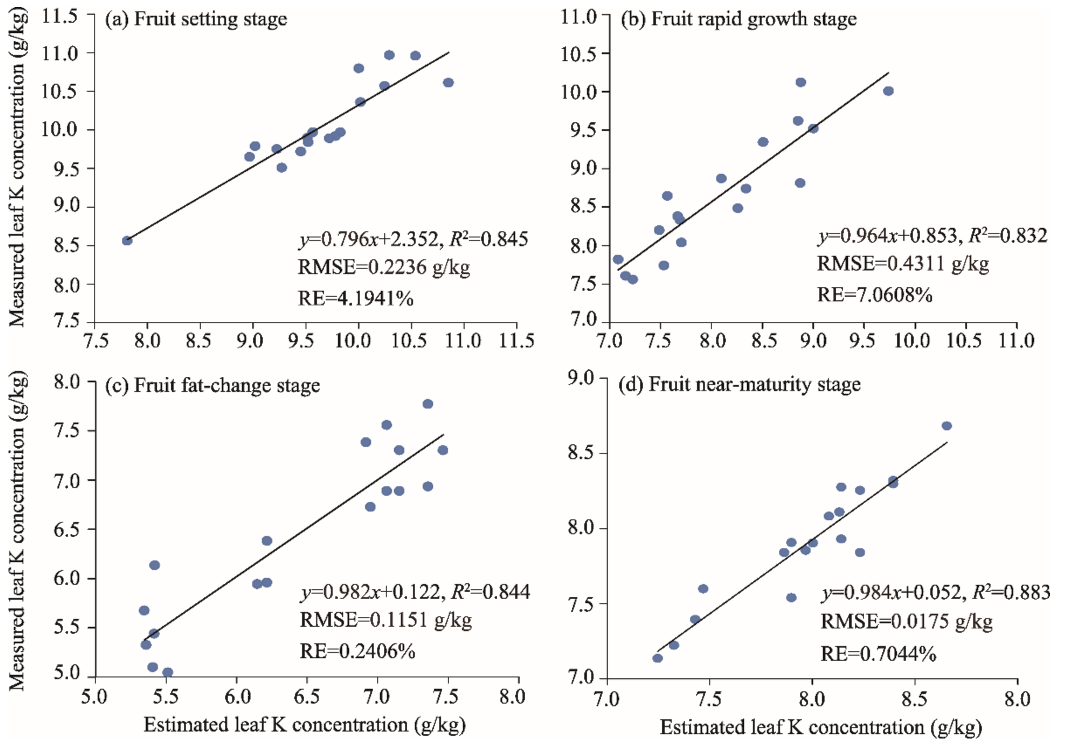

Fig. 1 Relationships between estimated and measured values for leaf K concentration of Ping'ou hybrid hazelnut at different fruit growth stages

leaves was high, the structure was relatively unstable, and the leaves were relatively thin, leading to a strong correlation between leaf K concentration and D_y at the fruit setting stage and fruit rapid growth stage.

The spectral parameters that were significantly correlated with leaf K concentration were D_y, R_g, SD_b, R_g/R_o, $(R_g–R_o)/(R_g+R_o)$, and RNIR/Green at the fruit rapid growth stage, RNIR/Blue at the fruit fat-change stage, and D_r, R_g, R_o, SD_y, and SD_r at the fruit near-maturity stage. The spectral characteristics of plant leaves were mainly influenced by their physiological and biochemical properties, such as the absorption, reflection, and conduction of light waves by chloroplast pigments and water, proteins, nucleic acids, sugars, and other substances in the leaves (Thomas and Oerther, 1972; Jiao et al., 2006). K element has a great influence on the above factors because of their participation in physiological and biochemical reactions and material transport in plants. The accumulated leaf K concentration in plant cell fluid is as high as 60–150 mmol/L, which can promote the formation of chlorophytes (Walker, 1996). If the leaf K concentration is low, the epidermal cells will change, the leaf surface thickness will increase, and the cells of palisade and sponge tissue will shrink and rupture locally. K in plants usually exists in the form of cations (Marschner, 2011) with strong fluidity, flowing from mature tissues to young tissues for their growth and development (Mengel and Kirkby, 1987) and providing an electron balance during the flow without promoting solute accumulation (Stiles and Van, 2004). In addition, K is the basic motive force promoting the increase in plant cell volume, the fluctuation of its ions, and the change in water flux which could lead to the expansion and rapid increase of plant cell volume. Therefore, leaves of Ping'ou hybrid hazelnut increase rapidly at the fruit growth periods, and the cell structure in the leaves also changes rapidly. Moreover, K ions are not only an important factor in the regulation of plant cell expansion by osmotic pressure (the interaction between cell expansion and the surrounding cell wall can maintain tissue hardness) but also the main factor in maintaining the balance of cell permeability. K is involved in an important regulatory mechanism of plant CO_2 and water wherein stomatal movement occurs through the plasma membrane (Fisher, 1968; Tallman, 1972). It is also an important driving force that maintains enzyme, protein, and nucleic acid activity, and is an important element in controlling the water balance of plants (Davies and Zhang, 1991). The morphology of leaf cells also has a significant influence on spectral reflectance. At different fruit growth stages, the leaf cells of Ping'ou hybrid hazelnut showed diverse shapes, sizes, and arrangements. As a result, the spectral characteristics of fruits at each fruit growth stage were different, and the parameters that were significantly correlated with leaf K concentration were different at each growth stage.

5 Conclusions

Our results revealed that the mathematical relationship between leaf K concentration and the most effective spectral characteristic parameters established by the cubic function was of the highest precision. The most effective spectral characteristic parameters of leaf K concentration were D_y, D_y, R_o and R_g at the fruit setting stage, fruit rapid growth stage, fruit fat-change stage, and fruit near-maturity stage. Results from the RMSE and RE showed that the regression estimation model of leaf K concentration established by the cubic function had a relatively high estimation accuracy and can be used to predict leaf K concentration properly. In this study, we only established the measurement error model of spectral inversion based on the statistical relation, without considering the theoretical model, which should be further studied in the future.

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References

Alex C W. 2006. Plant Nutrition. New York: InfoBase Publishing, 14–17.

Allen V B, David J P. 2007. Handbook of Plant Nutrition. Florida: Chemical Rubber Company Press, 21–50.

Davies W, Zhang J. 1991. Root signals and the regulation of growth and the development of plants in drying soil. Annual Review of Plant Physiology and Plant Molecular Biology, 42: 55–76.

Fisher R A. 1968. Stomatal opening: role of potassium uptake by guard cells. Science, 160(3829): 784–785.

Hu Z Z, Pan C D, Zhao S C. 2019. Spectral inversion of the water content of Hazelnut leaves at various phenolobical periods of fruit development. Northern Horticulture, 2019(09): 20–26. (in Chinese)

Izhar A, Frans J M M. 2014. Cellular and tissue distribution of potassium: Physiological relevance, mechanisms and regulation. Journal of Plant Physiology, 171(9): 708–714.

Jiao W J, Min Q W, Lin K, et al. 2006. Progress and perspective on nutrition diagnosis of plant nitrogen. Chinese Agricultural Science Bulletin, 22(12): 351–355. (in Chinese)

Lu J S, Li W Y, Yu M L, et al. 2020. Estimation of rice plant potassium accumulation based on non-negative matrix factorization using hyperspectral reflectance. Precision Agriculture, 5: 1–24.

Koch K, Mengel K. 1974. The influence of the level of K supply to young tobacco plants on short-term uptake and utilization of nitrate. Journal of the Science of Food and Agriculture, 25: 465–471.

Maathuis F J M, Oosterhuis D, Berkowitz G. 1999. Frontiers in Potassium Nutrition: New Perspectives on the Effects of Potassium on Physiology of Plants. Georgia: Potash and Phosphate Institute, 58−95.

Marschner H. 2011. Mineral Nutrition of Higher Plants. (3rd ed.). San Diego: Academic Press, 35−49.

Mengel K, Kirkby E A. 1987. Principles of Plant Nutrition. Bern: International Potash Institute, 481–511.

Nieves-Cordones M, Alemán F, Martínez V, et al. 2014. K^+ uptake in plant roots. The systems involved, their regulation and parallels in other organisms. Journal of Plant Physiology, 171(9): 14–22.

Payal B, Bably P. 2020. Determination of concentration of total sodium and potassium in surface and ground water using a flame photometer. Applied Water Science, 10(1): 16–21.

Shan X C, Song F H, Shi Y J, et al. 2015. Effects of spraying plant growth regulators on photosynthetic characteristics traits and fructify growth of the major Hybrid Hazel. Xinjiang Agricultural Sciences, 52(6): 1063–1070. (in Chinese)

Stiles K A, Van V E. 2004. Role of K^+ in leaf growth: K^+ uptake is required for light-stimulated H^+ efflux but not solute accumulation. Plant Cell and Environment, 27: 315–325.

Tallman G. 1992. The chemiosmotic model of stomatal opening revisited. Critical Reviews in Plant Sciences, 11(1): 35–57.

Thomas J R, Oerther G F. 1972. Estimating nitrogen concentration of sweet pepper leaves by reflectance measurements. Agronomy Journal, 64(1): 11–13.

Walker D J, Leigh R A, Miller A J. 1996. Potassium homeostasis in vacuolate plant cells. Proceedings of the National academy of Sciences of the United States of America, 93: 10510–10514.

Wang L Z, Song F H, Shi Y J, et al. 2020. Effects of different N P K fertilizer application rates on photosynthetic characteristics, yield and quality of *Corylus heterophylla* × *C. avellana*. Forest Research, 33(1): 55–61. (in Chinese)

Wang Z, Zhou L D, Li H. 2011. Predicting nitrogen concentrations in fresh peach leaf from hyper spectral remote sensing. Chinese Agricultural Science Bulletin, 27(4): 85–90. (in Chinese)

Zhang S F, Jiang R F, Chen X P, et al. 2011. Soil Testing and Fertilization. Beijing: China Agricultural University Press, 80. (in Chinese)

Zhao H B, Wang J, Dong C X, et al. 2014. Fast determination of potassium content in fresh pear leaves using visible/near infrared spectroscopy technique. Soil, 46(2): 256–261. (in Chinese)