Estimating litchi canopy nitrogen content using simulated multispectral remote sensing data

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***Abstract**. This study aims at evaluating the performance of seven highly spatial resolution remote sensing data in litchi canopy nitrogen content estimation. The litchi canopy reflectance were collected by ASD field spectrometer. Then the canopy spectral data were resampled based on the spectral response functions of each satellite sensors (Geo-eye, GF-WFV1, Rapid-eye, WV-2, Landsat 8, WV-3, and Sentinel-2). The spectral indices in literature were derived based on the simulated data. Meanwhile, the successive projection algorithm (SPA) was used to extract the sensitive variables. The partial least square regression (PLSR) was used to develop the nitrogen estimation model. The results indicated that the Worldview-3 and Sential-2 provided the better prediction of nitrogen content (R^2c=0.60, RMSEc=0.18, R^2cv=0.55, RMSEcv=0.20) than the other simulated satellite data. The bands in visible and near infrared region played an important role in nitrogen estimation since the absorption of chlorophyll. And the usage of bands in SWIR together with bands in VNIR can improve the performance of nitrogen estimation model.*

***Keywords**: nitrogen, canopy, remote sensing, SWIR*

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Introduction

Nitrogen is the mineral nutrient in greatest demand in litchi growth, which has an important effect on litchi growth, flowering and fruit development (Jia et al., 2015; Zheng et al., 2001). The fast and effective monitoring the nitrogen status and making fertilizer plan are very important to maintain the stable and high yield (Chen et al., 1999). The nitrogen inversion based on remote sensing data is one key point of quantitative remote sensing (Yamdagani et al., 1980; Yao et al., 2017; Knyazikhin et al., 2013). Previous studies have presented some successful implementation of nitrogen remote sensing from a variety of vegetation. The physical model, statistical regression model, and vegetation index model are the most three used methods in nitrogen estimation (He et al., 2016; Jay et al., 2017）. The physical model is general and has explicit physical meaning. While many input parameters and complicated form limit its application. And the nitrogen status is estimated indirectly by the variation of the relationship between Chlorophyll and nitrogen (Chen et al., 2017). The estimation error of nitrogen is large when there is no significant correlation between nitrogen and Chlorophyll (Li et al., 2016). The regression model is simple and easy to use, but poor general performance. The sensitive bands may lack physical significance. The authenticity of the estimation model is difficult to guarantee under high signal to noise ratio conditions. The spectral index is the combination of specific spectral bands. The model is vulnerable to vegetation types, growing environment, growth stages and so on. While it is simple and easy to use with the high accuracy in nitrogen estimation and a physical meaning. Thus, the spectral index is the widest used methods in nitrogen estimation.

Many researchers have evaluated the ability of canopy structure vegetation indices and pigment vegetation indices in nitrogen estimation, and tried to construct the new spectral indices based on canopy curve shape characteristics (such as, the red edge, canopy double peak) (Chen et al., 2010; Feng et al., 2016; Guo et al., 2017). Meanwhile, considering the useful of bands in SWIR in nitrogen estimation as some researchers proved, some nitrogen spectral indices were also proposed by using the combination of bands in SWIR (Herrmann et al., 2010) . While seldom studies investigated the ability of satellite remote sensing data to estimate litchi nitrogen status. Thus, in this study, we compared the performance of the several high spatial resolution satellite remote sensing data by spectral indices and PLS models.

Materials and Methods

2.1 Experimental datasets

Experimental datasets obtained in Guangdong Province were used for this study. The canopy leave around the litchi canopy were evenly collected after the canopy spectra measurement. About 20 pieces leave were sampled as one sample to analyze the N content. Experiments were conducted in experimental fields in yangdong county, Huidong County and Baiyun District in Guangdong Province under a wide range of agricultural management practices and environmental conditions during periods in

2006, 2011, 2013 and 2014 (Li et al., 2016).

Table 1 Descriptive statistics for canopy nitrogen contentof litchi at each growth stage.

Growth Stage	n	Min.	Max.	Range	Mean	SD	CV
Terminal autumn shoot maturation stage	15	1.43	1.76	0.33	1.54	0.09	0.01
Flower bud differentiation stage	15	1.39	1.89	0.50	1.61	0.15	0.02
Flower spike growing stage	16	0.98	1.84	0.86	1.29	0.26	0.07
Flowering stage	20	1.36	1.97	0.61	1.70	0.16	0.03
Fruit maturation stage	8	1.39	1.89	0.50	1.61	0.15	0.02

SD, standard deviation; CV, coefficient of variation.

2.2 Ground-based hyperspectral and plant measurements

Canopy reflectance spectra were obtained under clear-sky conditions around midday (10:00-14:00 LST) using portable spectroradiometers (Fieldspec-FR 3, ASD). The spectral range of sensor was 350-2500 nm, with a field of view of 25°. Spectral resolution (full width at half maximum, FWHM) was 3 nm for the region of 350–1000 nm and 10 nm for the region of 1000–2500 nm for the FieldSpec-FR. The resembling interval was 1nm. Reflectance measurements were taken at a nadir-looking angle from 2m above the canopy. More than 15 measurements were made in each observation by moving over each canopy, to derive the representative reflectance spectra for each canopy. Spectral reflectance was derived as the ratio of reflected radiance to incident radiance estimated by a calibrated white reflectance (Spectralon, Labsphere). After the spectral measurements, the leave at the litchi canopy were put in a paper bag. Plant nitrogen content was determined by Micro-Kjeldahl method.

2.3 Analytical methods

Hyperspectral signatures will be analyzed using some published spectral indices that are particularly useful in other plant and ecosystem (Table1). The PLS regression will be used to develop the nitrogen estimation model. The determination coefficient and RMSE in calibration and leave one cross validation were used to evaluate the ability of spectral indices. The best performance model has the smaller RMSE and the larger R^2 at the same time. The field hyperspectral data were resampled based on the seven sensors (Geo-eye, GF-WFV1, Rapid-eye, WV-2, Landsat 8, WV-3, and Sentinel-2).

Table 2 The spectral indices used in this study

Type	Spectral index	Equation	Reference
Structural vegetation index	NDVI	$\left(R_{nir}-R_{red}\right)/(R_{nir}+R_{red})$	Baret et al., 1989
	OSAVI	$\left(1+0.16\right)\left(R_{nir}-R_{red}\right)/(R_{nir}+R_{red}+0.16)$	Baret et al., 1989
	RVI	R_{nir}/R_{red}	Broge et al., 2001
	TVI	$0.5\left[120\left(R_{750}-R_{550}\right)-200(R_{670}+R_{550})\right]$	Broge et al., 2001
	EVI	$2.5\times\dfrac{R_{nir}-R_{red}}{R_{nir}+6R_{red}-7.5R_{blue}+1}$	Main et al., 2011

	GNDVI	$\frac{R_{nir}\text{-}R_{green}}{R_{nir}+R_{green}}$	Maire et al., 2004
	WDRVI	$\frac{0.1R_{nir}\text{-}R_{red}}{0.1R_{nir}+R_{red}}$	Herrmann et al., 2010
Nitrogen vegetation index	MTVI	$(1.5\frac{1.2(R_{800}\text{-}R_{550})-2.5(R_{670}-R_{550})}{\sqrt{(2R_{800}+1)^2-(6R_{800}-5\sqrt{R_{670}})-0.5}})$	Hunt et al., 2013
	NDRE	$\frac{R_{nir}-R_{rededge}}{R_{nir}+R_{rededge}}$	Fitzgerald et al.2010
	Wang	$\frac{(R_{nir}-R_{rededge}+2R_{blue})}{(R_{nir}+R_{rededge}-2R_{blue})}$	Wang et al., 2007
Chlorophyll vegetation index	MCARI	$(1.5\frac{2.5(R_{800}-R_{670})-1.3(R_{800}-R_{550})}{\sqrt{(2R_{800}+1)^2-(6R_{800}-5\sqrt{R_{670}})-0.5)}}$	Hunt et al., 2013
	NPCI	$\frac{R_{red}\text{-}R_{blue}}{R_{red}+R_{blue}}$	Maire et al., 2004
	PSRI	$\frac{R_{red}\text{-}R_{green}}{R_{nir}}$	Sims & Gamon, 2002
	SPVI	$0.4(3.7(R_{800}-R_{670})-1.2(R_{530}-R_{670})$	Main et al., 2011
	CCCI	$\frac{\mathrm{NDRE}-\mathrm{NDRE}_{\min}}{NDRE-NDRE_{\min}}$	Fitzgerald et al.2010
	GI	$\frac{R_{green}}{R_{red}}$	Maire et al., 2004

Results and Discussions

The performance of PLSR models developed by the each simulated satellite bands were listed in Table 3. Since spectral indices can improve the response of reflectance to the variation of biochemical (Yu et al., 2014). The spectral indices listed in Table 2 were calculated for each type of satellite sensor. These spectral indices are all derived by the reflectance in visible and near infrared spectral region. For each dataset, the PLSR model of nitrogen estimation was developed based on the derived spectral indices. And the performance of these models were presented in Table 4.

The nitrogen estimation models via combining spectral indices and simulated satellite bands were presented in Table 5. Meanwhile, considering the data redundancy of dataset in which the spectral indices and simulated bands were used together, we proposed to select the sensitive variable to the nitrogen variation by SPA. The sensitive variables for each dataset and the performance of PLSR models by the sensitive variables were showed in Table 6.

Table3 The PLS models developed by the simulated bands

Data Set	R^2c	RMSEc	R^2cv	RMSEcv
All spectra	0.499	0.203	0.412	0.222
WV-3	0.483	0.206	0.401	0.226
Geo-eye	0.367	0.228	0.298	0.242
GF-WFV	0.361	0.229	0.305	0.240
Rapid eye	0.366	0.228	0.345	0.236

Landsat 8	0.489	0.205	0.413	0.223
Sentinel-2	0.481	0.206	0.415	0.221
WV-2	0.444	0.214	0.388	0.228

Table 4 The PLS models developed by the spectral indices

Data Set	R^2c	RMSEc	R^2cv	RMSEcv
WV-3	0.616	0.178	0.487	0.209
Geo-eye	0.359	0.229	0.296	0.241
GF-WFV	0.439	0.215	0.223	0.258
Rapid eye	0.361	0.229	0.252	0.254
Landsat 8	0.376	0.226	0.272	0.248
Sentinel-2	0.376	0.227	0.325	0.238
WV-2	0.423	0.217	0.299	0.244

Table 5 The PLS models developed by the simulated bands and spectral indices

Data Set	R^2c	RMSEc	R^2cv	RMSEcv
WV-3	0.65	0.170	0.507	0.204
Geo-eye	0.39	0.223	0.309	0.241
GF-WFV	0.44	0.215	0.217	0.260
Rapid eye	0.36	0.229	0.296	0.243
Landsat 8	0.51	0.201	0.367	0.23
Sentinel-2	0.43	0.22	0.351	0.232
WV-2	0.45	0.21	0.381	0.227

Table 6 The PLS models developed by the spectral variables selected by SPA.

Dataset	Spectral variable	R^2c	RMSEc	R^2cv	RMSEcv
WV-3	NDRE, Wang, CCCI, R_{482}, R_{1661}	0.60	0.18	0.55	0.197
Geo-eye	GNDVI, NPCI	0.32	0.236	0.29	0.244
Rapid-eye	OSAVI,TCARI, SPRI, SPVI, GI	0.40	0.22	0.35	0.23
GF-WFV	OSAVI, SPRI, SPVI, GI, R_{655}	0.37	0.227	0.298	0.243
Landsat 8	GNDVI, R_{442}, R_{863}, R_{1609}	0.497	0.210	0.423	0.221
Sentinel-2	NDRE, R_{444}, R_{1613}	0.498	0.203	0.428	0.218
WV-2	Wang, PRSI, SRPI, R_{721}	0.33	0.23	0.25	0.25

From Table 3-6, we found that all seven datasets didn't provide the accurate nitrogen estimation. The performance of all nitrogen estimation model couldn't perform well. The R^2c and R^2cv were relatively low (R^2cv max= 0.55). The dataset contained the data collected in different growth stages, cultivars, and planting environments. The relationships among nitrogen and other biochemical which have the specific absorption features varied with these factors, which affect the ability of spectral data in nitrogen estimation (Li et al., 2016). Meanwhile, the nadir viewing of canopy can only provide the top information of canopy, which cannot give the whole information of canopy (He et al., 2016). And the distribution of canopy nitrogen is varied with canopy height (Yu et al., 2014). Both two factors makes the inconformity of canopy spectra and nitrogen status, which have the influence of nitrogen inversion accuracy (Jay et al., 2017; Chen et al., 2017).

By comparing the performance of nitrogen estimation model, we found that WV-3 had the best performance among seven type simulated data. Sentinel-2 showed the relatively better performance than the other five datasets. We concluded the relatively good performance of WV-3 and Sentinel-2 to the contribution of the absorptions of chlorophyll in VIR and the absorptions of nitrogen, cellulose, etc. in SWIR. In Table 4, there were no significant difference of the nitrogen models among the six dataset except WV-3. Since the spectral indices are mainly calculated by the bands in visible and near infrared region. And the useful of bands in visible and near infrared region are mainly related to the important role of nitrogen in chlorophyll (Maire et al., 2004).

The performance of model developed by simulated Landsat 8 OLI data is lower than those of Sentinel-2 and WV-3, while is higher than those of Geo-eye and GF-WFV. Which indicated that the bands in SWIR is useful in litchi nitrogen estimation. From Table 6, we found that the variables selected by SPA are mainly related to the absorption features of chlorophyll in visible and near infrared region. Meanwhile, the bands in SWIR were also selected for Landsat 8, WV-3 and Sentinel-2, which also indicated the important role of SWIR in litchi nitrogen estimation (Li et al., 2016).

Conclusions:

We collected the canopy reflectance spectra and canopy leaf nitrogen concentration from different growth stages of litchi, planting environment, and cultivars. The simulated bands of seven satellite sensors were derived by the each spectral response function. Then the spectral indices were calculated by the reflectance in VNIR region. The nitrogen estimation models were developed by the simulated bands, and spectral indices, respectively. The results indicated that the bands in visible and red edge regions are important in nitrogen estimation. While, the usage of the bands in SWIR, together with the bands in visible and red edge region can improve the performance of nitrogen estimation. The nitrogen estimation models are related to the absorption features of chlorophyll in visible and near infrared regions and those of protein, cellulose, etc. in SWIR. Although the accuracy of nitrogen estimation model is relatively low, SPA is useful in feature selection. Which can reduce data redundancy and improve the modelling efficiency and performance to a certain extent. In further study, the usage of multi-angular remote sensing data can be used to improve the accuracy of nitrogen estimation.

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References:

[1] Jia T., Zhang X.M., Fu G.N., Long Q.C., Effects of Nitrogen Forms on Absorption and Distribution Characteristics of Litchi Nitrogen. Tillage and Cultivation, 2015(5):7-10.

[2] Zheng Y.J., Lin L.W., Luo W., The nutrition characteristics of *litchi Chinensis* and the fertilizer practice. Soil and Environmental Sciences, 2001, 10(3): 204-206.

[3] Chen L.,Liu X., Effect of water stress on nitrogen and nucleic acid metabolisms in litchi (*Litchi chinensis Sonn.*) leaves and their relations to drought-resistance. Acta Photophysiologica Sinica, 1999. **25**: 49-56.

[4] Yamdagani R., Balyan D.S..Jindal P.C., A note on the effect of nitrogen on litchi (Litchi chinensis Sonn.). Haryana Journal of Horticultural Sciences, 1980.

[5] Yao L.X., Zhou C.M., He Z.H., Li G.L., Bai C.H., Annual nutrient demand of the growth of autumn branch, spica and fruit in litchi. Journal of Plant Nutrient and Fertilizer, 2017, 23(4): 1128-1134.
[6] Knyazikhin Y., Schull M.A., Stenberg P., Mõttus M., Rautiainen M., Yang Y., . . . Lewis P., Hyperspectral remote sensing of foliar nitrogen content. Proceedings of the National Academy of Sciences of the United States of America, 2013. **110**(3): 185-92.
[7] He L., Zhang H.Y., Zhang Y.S., Song X., Feng W., Kang G.Z., . . . Guo T.C., Estimating canopy leaf nitrogen concentration in winter wheat based on multi-angular hyperspectral remote sensing. European Journal of Agronomy, 2016. **73**: 170-185.
[8] Jay S., Maupas F., Bendoula R..Gorretta N., Retrieving LAI, chlorophyll and nitrogen contents in sugar beet crops from multi-angular optical remote sensing: Comparison of vegetation indices and PROSAIL inversion for field phenotyping. Field Crops Research, 2017. **210**: 33-46.
[9] Chen Y.Z., Fu B.J., Feng X.M., Overview and outlook of remote sensing inversion of vegetation nitrogen content, Acta Ecologica Sinica, 2017, 37(18): 6240-6252.
[10] D. Li, C. Wang, W. Liu, Z. Peng, S. Huang, J. Huang, S. Chen, Estimation of litchi (Litchi chinensis Sonn.) leaf nitrogen content at different growth stages using canopy reflectance spectra, European Journal of Agronomy, 2016, 80: 182-194.
[11] P. Chen, D. Haboudane, N. Tremblay, J. Wang, P. Vigneault, B. Li, New spectral indicator assessing the efficiency of crop nitrogen treatment in corn and wheat, Remote Sensing of Environment, 2010, 114(9): 1987-1997.
[12] W. Feng, H.Y. Zhang, Y.S. Zhang, S.L. Qi, Y.R. Heng, B.B. Guo, D.Y. Ma, T.C. Guo, Remote detection of canopy leaf nitrogen concentration in winter wheat by using water resistance vegetation indices from in-situ hyperspectral data, Field Crops Research, 2016, 198: 238-246.
[13] B.-B. Guo, S.-L. Qi, Y.-R. Heng, J.-Z. Duan, H.-Y. Zhang, Y.-P. Wu, W. Feng, Y.-X. Xie, Y.-J. Zhu, Remotely assessing leaf N uptake in winter wheat based on canopy hyperspectral red-edge absorption, European Journal of Agronomy, 2017, 82: 113-124.
[14] I. Herrmann, A. Karnieli, D.J. Bonfil, Y. Cohen, V. Alchanatis, SWIR-based spectral indices for assessing nitrogen content in potato fields, International Journal of Remote Sensing, 2010, 1(19): 5127-5143.
[15] F. Baret, G. Guyot, D.J. Major, Crop biomass evaluation using radiometric measurements, Photogrammetria, 1989, 43(5): 241-256.
[16] N.H. Broge, E. Leblanc, Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density, Remote Sensing of Environment, 2001, 76(2): 156-172.
[17] R. Main, M.A. Cho, R. Mathieu, M.M. O’Kennedy, A. Ramoelo, S. Koch, An

investigation into robust spectral indices for leaf chlorophyll estimation, Isprs Journal of Photogrammetry & Remote Sensing, 2011, 66(6): 751-761.
[18] G.L. Maire, C. François, E. Dufrêne, Towards universal broad leaf chlorophyll indices using PROSPECT simulated database and hyperspectral reflectance measurements, Remote Sensing of Environment, 2004, 89(1):1-28.
[19] Hunt, E. Raymond, Jr, Doraiswamy, C. Paul, McMurtrey, E. James, Daughtry, S.T. Craig, Akhmedov, A visible band index for remote sensing leaf chlorophyll content at the canopy scale, International Journal of Applied Earth Observations & Geoinformation, 2013, 21(1): 103-112.
[20] Fitzgerald G, Rodriguez D, O'Leary G. Measuring and predicting canopy nitrogen nutrition in wheat using a spectral index - the canopy chlorophyll content index (CCCI).[J]. Field Crops Research, 2010, 116(3):318-324.
[21] Wang F M, Huang J F, Tang Y L, Wang X.Z. New Vegetation Index and Its Application in Estimating Leaf Area Index of Rice [J]. Rice Science, 2007, 14(3):195-203.
[22]Sims, Daniel A.; Gamon, John A. - Relationships between leaf pigment content and spectral reflectance across a wide range of species, leaf structures and developmental stages
[23]Yu K, Lenz-Wiedemann V, Chen X, Bareth G., Estimating leaf chlorophyll of barley at different growth stages using spectral indices to reduce soil background and canopy structure effects [J]. Isprs Journal of Photogrammetry & Remote Sensing, 2014, 97:58-77.
[24] Wang J.H., Huang W.J., Lao C.L., Zhang L.D., Luo C.B., Wang T., Liu L.Y., Song X.Y., Ma Z.H., Inversion of winter wheat foliage vertical distribution based on canopy reflected spectrum by partial least squares regression method. Spectroscopy and Spectral Analysis, 2007, 27(7): 1319-1322.