

## **CLASSIFICATION OF OIL PALM NITROGEN STATUS FROM SPOT-6 SATELLITE USING SUPPORT VECTOR MACHINE AND SPECTRAL INDICES**

Amiratul Diyana Amiruddin<sup>1</sup> and Farrah Melissa Muharam<sup>1, 2\*</sup>

<sup>1</sup>*Department of Agriculture Technology, Faculty of Agriculture, Universiti Putra Malaysia, 43400 Serdang, Malaysia*

*amiratul\_diyana@yahoo.com*

<sup>2</sup>*Laboratory of Science and Technology, Institute of Plantation Studies, Universiti Putra Malaysia, 43400 Serdang, Malaysia*

*farrahm@upm.edu.my*

**Abstract:** Nitrogen (N) management is important in sustaining oil palm production. Remote sensing based approaches such as spectral index has promise in assessing the N nutrition content of many crops. The objectives of this study are to examine the N classification capability of three spectral indexes (SI): visible (Vis), near infrared (NIR) and a combination of visible and NIR (Vis+NIR) using data from the SPOT-6 satellite. N treatments varied from 0 to 2 kg per palm and were applied to both mature palms. The N-sensitive SIs tested in this study were age-dependent. The Vis index such as BGRI<sub>1</sub> (CVA= 79.55%) and the Vis+NIR indices such as NDVI, NG, IPVI and GNDVI (CVA= 81.82%) were the best indices to assess N status of young and prime mature palms through the SVM classifier. Nonetheless, the SVM classifier showed promising potential in classifying foliar N content of mature palms that can possibly be used further for developing a new index in assessing N content of oil palms.

**Keywords:** nitrogen; oil palm; satellite; machine learning; spectral index

### **INTRODUCTION**

To our knowledge, nutrient assessments concerning oil palm is not well studied. Asraf, Nooritawati, and Rizam (2012) has manipulated support vector machine (SVM) for classifying N, P, and magnesium (Mg) status of oil palm nutrition on foliar samples, obtaining accuracies of 97.8%, 87.2%, and 100%, respectively. Recently, Amiruddin, Muharam, and Mazlan (2017) evaluated data mining approaches, i.e. SVM and linear discriminant analysis (LDA) for discrimination of the sensitive spectral bands and classification of the N status of multiple oil palm ages, using a handheld spectroradiometer. The authors reported that the discriminant analysis (DA) produced higher accuracies (73-97%) compared to SVM in assessing N status of all ages of palms, yet the latter yielded reasonable accuracy ranges between 71-88% with a lesser number of spectral bands. These most recent studies, nevertheless, employed ground based sensors such as a digital camera and a spectroradiometer that still requires extensive and expensive ground sampling. Bearing in mind that oil palm plantations involve vast cultivation areas, evaluation via platforms such as satellites is required. Earlier in 2003, Nor Azleen et al. (2003) tested a limited number of spectral indices generated from the SPOT satellite; and used the normalised difference vegetation index (NDVI), soil adjusted vegetation index (SAVI) and atmospherically resistant vegetation index (ARVI). They reported that only SAVI performed the best with an accuracy of  $R^2 = 0.91$ . Nonetheless, this study was conducted on 23 year old oil palms that are close to replanting age, and therefore did not represent the ideal assessment of N foliar status.

In the light of current evaluations of oil palm N status of which a limited number of spectral indices and data mining were tested, we formulated our study to achieve a specific objective as that is to assess the performance of spectral indices generated from the visible (Vis), near infrared (NIR) and combination of visible and NIR bands (Vis+NIR) derived from SPOT-6 for N classification of mature oil palms.

## **METHODS**

The experiment involved *Tenera* palms cultivated in two different fields representing different ages: 9 years (MP05; 2.377779°N and 102.265658°E) and 12 years (MP02; 2.380374°N and 102.238012°E) in Melaka Pinda Estate, United Malacca Berhad plantation in Melaka, Malaysia. Samples represented young mature and prime mature palms. To induce differences in foliar N contents, N treatments were applied in 3 rates: 0, 1 and 2 kg N per palm. The treatments were replicated three times and arranged in Randomized Completely Block Design (RCBD) to result in eighteen experimental subplots comprised 16 uniform palms each. N treatments were assigned randomly to these experimental subplots. Ammonium chlorite (AC) was applied as the source of N around the weeding circle in four split applications made in November 2013, and March, Jun and September 2014. To ensure optimum plant growth, phosphorus (P), potassium (K), magnesium (Mg) and boron (B) were applied uniformly as single fertilisers based on the following rate: 0.049 kg, 0.467 kg, 0.054 kg and 0.004 kg, respectively.

Eight oil palm stands in each subplot were sampled during the field campaign. Six leaflets from frond 17 for each palm sample were analysed for foliar N content by applying the wet digestion method following Miller and Miller (1948). The solutions then were placed in an auto-analyser machine to measure N content. Based upon von Uexkull and Fairhurst (1991), there were only two levels of leaf N threshold available for this study: deficient (<2.3%) and optimum (2.4 – 2.8 %). 320 and 50 of the samples collected from young mature oil palms were classified as deficient (2.01 % ± 0.16) and optimum (2.33 % ± 0.07), respectively. On the other hand, for the mature tree samples, 680 and 273 of the samples were deficient (2.10 % ± 0.14) and optimum (2.41 % ± 0.10), respectively.

A satellite image was obtained from a SPOT-6 pan-sharp image with 1.5 m spatial resolution on 20th November 2014. The imagery underwent pre-processing such as atmospheric correction, geometric correction and cloud masking. Finally, the digital numbers were converted to the reflectance using an equation proposed by Coeurdevey and Soubirane (2013).

The indices tested for this study were calculated following Table 1. In this study, the indices were evaluated individually rather than as subsets of spectral indices.

**Table 1: A summary of indices evaluated in this study.**

<b>Index Name</b>	<b>Acronym</b>	<b>Equation</b>	<b>Reference</b>
<b>Vis indices</b>			
<b>Single blue</b>	Blue	B	Mercado-Luna et al. (2010)
<b>Single green</b>	Green	G	Mercado-Luna et al. (2010)

**INTERNATIONAL CONFERENCE ON BIG DATA APPLICATIONS IN AGRICULTURE (ICBAA2017)  
5-6 DECEMBER 2017**

<b>Single red</b>	Red	R	Mercado-Luna et al. (2010)
<b>Redness index</b>	RI	$(R-G)/(R+G)$	Escadafal and Huete (1994)
<b>Vegetation index green</b>	VIG	$(G-R)/(G+R)$	Gitelson et al. (2002)
<b>Blue green index</b>	BGI <sub>1</sub>	B/G	Patane and Vibhute (2015)
	BGI <sub>2</sub>	G/B	Auearunyawat et al. (2012)
<b>Green red index</b>	GRI	G/R	Adamsen et al. (1999)
<b>Blue red index</b>	BRI	R-B	Kawashima and Nakatani (1998)
<b>Blue green red index</b>	BGRI <sub>1</sub>	$G/(R+B)$	Patane and Vibhute (2015)
	BGRI <sub>2</sub>	$G/(R+G+B)$	Kawashima and Nakatani (1998)
	BGRI <sub>3</sub>	$R/(R+G+B)$	Kawashima and Nakatani (1998)
	BGRI <sub>4</sub>	$2B/(R+G+B)$	Vibhute and Bodhe (2013)
<b>NIR indices</b>			
<b>Single NIR</b>	NIR	NIR	
<b>Combination of Vis and NIR indices (Vis+NIR)</b>			
<b>Normalized difference vegetation index</b>	NDVI	$(NIR-R)/(NIR+R)$	Rouse et al. (1974)
<b>Normalized green</b>	NG	$G/(NIR+R+G)$	Sripada et al. (2006)
<b>Difference vegetation index</b>	DVI	NIR-R	Tucker (1979)
<b>Green difference vegetation index</b>	GDVI	NIR-G	Sripada et al. (2006)
<b>Infrared percentage vegetation index</b>	IPVI	$NIR/(NIR+R)$	Crippen (1990)
<b>Green normalized difference vegetation index</b>	GNDVI	$(NIR-G)/(NIR+G)$	Buschmann and Nagel (1993)
<b>Normalized near infrared</b>	NNIR	$NIR/(NIR+R+G)$	Sripada et al. (2006)

<b>Simple ratio</b>	SR	NIR-R	Birth and McVey (1968)
<b>Green ratio vegetation index</b>	GRVI	NIR/G	Sripada et al. (2006)
<b>Optimized soil adjusted vegetation index</b>	OSAVI	$[(NIR-R)/(NIR+R+L)] \times (1+L)$	Rondeaux et al. (1996)
<b>Soil adjusted vegetation index</b>	SAVI	$[(NIR-R)/(NIR+R+L)] \times (1+L)$	Huete (1988)
<b>Normalized red</b>	NR	$R/(NIR+R+G)$	Sripada et al. (2006)

For training and validating the accuracy of the trained models, N status data were separated by the ratio 70:30, respectively, by using Waikato Environment for Knowledge Analysis (WEKA) 3.6 software (Hall et al. 2009). Prior to the classification, feature selection concerning significant spectral band was conducted on the training datasets. Furthermore, classifications were performed on the selected spectral bands following the previous procedure and on spectral indices highlighted in Table 1. Training accuracy (TA %) and cross validation accuracy (CVA %) obtained from the classifications of raw bands and indices were compared to find the best spectral and classification approach in determining N sufficiency levels of oil palms.

Spectral classification in this study was based on the SVM-Recursive Feature Elimination (SVM-RFE) (Guyon et al. 2002), where the processes were performed using the WEKA 3.6.9 software. The classification is based on the principle to seek the optimum separating hyperplane (OSH) that best distinguishes two sufficiency classes. In seeking for the OSH, the SVM optimises C that is the penalty value and  $\gamma$  that is a predetermined smoothness parameter that controls the width of the RBF kernel. Generally, a large C value gives a higher penalty to classification errors, which minimises the number of misclassified data, whereas a small C value maximises the margin so that the OSH is less sensitive to the errors from the learning data set (Ivanciuc 2007). The optimisation of these two parameters was done using the Grid Search procedure within WEKA program by the performance of the SVM model with each pair of (C,  $\gamma$ ). The optimised C and  $\gamma$  parameters were selected by choosing the combination pair that yielded the highest  $R^2$  value.

## **RESULTS AND DISCUSSION**

Generally, most of the indices depicted a similar pattern in which the CVA was lower than the TA regardless of types of index and maturity class (Table 2 and 3). Therefore, the results and discussion were focused on the CVA. Overall, the classification of N status in oil palm trees using spectral index was age dependant because there was no single index that could classify both palm maturity classes with consistently high accuracy. The best indices to classify N sufficiency levels of young and prime mature palms were the Vis (BGRI<sub>1</sub> and BGRI<sub>2</sub>; CVA = 79.55%) and Vis+NIR (NDVI, NG, IPVI and GNDVI, CVA = 81.82%). According to the types of index, the finest Vis indices that could explain N variations in young mature palm were BGRI<sub>1</sub> and BGRI<sub>2</sub> (CVA = 79.55%), while RI and VIG indices (CVA = 77.27%) for prime mature. It is also worthy to note that regardless of palm maturity classes, the NIR index produced useful N classification models with CVA of 72.73%. Meanwhile, for the Vis+NIR indices, indices such as NDVI, NG, DVI, GDVI, IPVI, GNDVI, NNIR, SR, GRVI, OSAVI, SAVI and NR produced a similar classifying accuracy (CVA = 72.73%) for young mature palm, whereas the NDVI, NG, IPVI and GNDVI were beneficial for classifying

N variations in prime mature palms (CVA = 81.82%). Generally, as palm trees get older, the classification accuracies of most of the Vis indices demonstrated a declining trend, while the Vis+NIR indices depicted an increasing pattern. For example, the Vis index such as BGRI<sub>4</sub> tended to decrease in accuracy as the palm gets older for both classifiers (72.73 to 63.64%). A similar observation also was made on the BGI<sub>1</sub> and BGI<sub>2</sub> where the accuracy decreased from 72.73 to 63.64%. Nevertheless, the NDVI and IPVI index increased in CVA from 72.73 to 81.82%, whereas the SAVI index increased from 72.73 to 79.55% SVM. Likewise, a similar observation was also made on the GDVI and GNDVI index. The sensitivity of the N models was found to be age-dependent. These results signified the essentiality of the age factor in oil palm N status classification; none of the indices worked for both of the two age groups and the shift of the spectral region sensitive to N content to longer wavelengths as palms mature. One of the reasonable hypotheses is that saturation of chlorophyll content occurred in the prime mature palms, whereas it was noticeable that prime mature palms had darker green coloured and thicker leaflets than the young one palms. The other explanation to these findings is that while the oil palm foliar is the main N sink for young palms, N will remobilise to other developing sinks such as trunk, rachis or cabbage in older palms (Hartley 1988; Foster 2002), indicating the age-N allocation relationship. Hence, this result might suggest that for certain age of perennials, the use of foliar alone for indicating the N status is inadequate and should be used to complement measurement of plant growths such as the size of trunk.

In assessing between raw spectral band and spectral index, the latter generated higher accuracy (CVA above 75%) irrespective of age groups. These highest accuracy models were attributed to the Vis and Vis+NIR indices. Of all the indices measured, the Vis+NIR index i.e. NDVI, NG, IPVI, GNDVI and SAVI (CVA =81.82%) were the best in classifying foliar N content of prime mature palms compared to use raw spectral band alone such B index (CVA = 75.00%). For young mature palm, N status classification was best performed using a Vis index i.e. BGRI<sub>1</sub> and BGRI<sub>2</sub>.

The combination of different visible regions with NIR into spectral indices showed inconsistency in terms of the capability to classify N status for different palm age classes. The combination of red and NIR terms for classifying N status of both mature palms increased the model's accuracy ranging from 68.18 to 81.82% instead of using the red terms alone (CVA=63.64%). Likewise, the CVA of the Vis+NIR index i.e. IPVI for prime mature palm increased to 81.82% in comparison to the use of the Vis based index alone. Similarly, the combination of two or three spectral bands in Vis index also illustrated inconsistency in classifying N status of different palm age classes. Mostly, the CVA of indices engaged with the blue term decreased in comparison to the use of the single B index. A similar pattern also was observed on the accuracy of BRI index that integrates the blue and red bands. Meanwhile, the indices that engage red and green bands depicted a contrary trend, where combined red and green terms increased the classification accuracies instead of using the single R index. On the other hand, for the prime mature palm, the VIG index increased from 63.64 to 77.27%. A similar observation also was made for the RI and GRI index. Implementation of spectral indices such as such NDVI, NG and GNDVI depicted better classification accuracy compared to the raw spectral bands, either individually or collectively. The application of spectral indices has been proven in enhancing the signal of biochemical properties of the plant pigments such chlorophyll, nitrogen and carotenoids by reducing the variation among images and enhancing the contrast between vegetation and the ground (Rouse et al. 1974; Gitelson, Kaufman, and Merzlyak 1996; Hunt et al. 2010). Regardless of palm age groups and classifiers, the combination of red and NIR band indices increased classification accuracy

instead of using single raw spectral. NIR reflectance that is sensitive to structural properties of the leaf, branch and canopy improves the capability of classification model in assessing foliar N content of oil palm. The main reason behind this is due to the high sensitivity of NIR to the canopy structure as the function of LAI but not to chlorophyll content. Moreover, the N application has been proven to increase the leaf area as well as the LAI of the oil palm (Corley and Mok 1972; Goh and Hårdter 2003).

Meanwhile, the SVM portrayed a robust classification for N status of oil palm. The results from these studies were parallel to the several publicised studies that highlighted the advantages of SVM over other classifiers in determining the relationship between the spectral feature and nutrient nutrition status in crops (Zhai et al. 2013; Wang et al. 2013; Axelsson et al. 2013). The good performance demonstrated by the SVM was attributed to the structural risk minimisation (SRM) principle employed in the SVM. SRM benefits the controlling process of the generalisation ability of the SVM and thus avoids over-fitting and multi-dimensional problems when dealing with spectral data (Smola and Vapnik 1997; Vapnik 2000; Zhang et al. 2008).

**Table 2: Classification of spectral index on young mature palm.**

<b>Accuracy (%)</b>	<b>TA</b>	<b>CVA</b>
<b>Vis Indices</b>		
<b>Blue</b>	90.00	72.73
<b>Green</b>	90.00	72.73
<b>Red</b>	90.00	72.73
<b>RI</b>	90.00	72.73
<b>VIG</b>	91.00	72.73
<b>BGI<sub>1</sub></b>	90.00	72.73
<b>BGI<sub>2</sub></b>	90.00	72.73
<b>GRI</b>	90.00	72.73
<b>BRI</b>	90.00	72.73
<b>BGRI<sub>1</sub></b>	90.00	79.55
<b>BGRI<sub>2</sub></b>	90.00	79.55
<b>BGRI<sub>3</sub></b>	90.00	72.73
<b>BGRI<sub>4</sub></b>	90.00	72.73
<b>NIR Indices</b>		
<b>NIR</b>	90.00	72.73
<b>Combination of Vis and NIR Indices (Vis+NIR)</b>		
<b>NDVI</b>	90.00	72.73
<b>NG</b>	90.00	72.73
<b>DVI</b>	90.00	72.73
<b>GDVI</b>	90.00	72.73
<b>IPVI</b>	90.00	72.73
<b>GNDVI</b>	90.00	72.73
<b>NNIR</b>	90.00	72.73
<b>SR</b>	90.00	72.73
<b>GRVI</b>	90.00	72.73
<b>OSAVI</b>	90.00	72.73

**INTERNATIONAL CONFERENCE ON BIG DATA APPLICATIONS IN AGRICULTURE (ICBAA2017)  
5-6 DECEMBER 2017**

<b>SAVI</b>	90.00	72.73
<b>NR</b>	90.00	72.73



**Table 3: Classification of spectral index on prime mature palm.**

<b>Accuracy (%)</b>	<b>TA</b>	<b>CVA</b>
<b>Vis Indices</b>		
<b>Blue</b>	77.00	75.00
<b>Green</b>	77.00	63.64
<b>Red</b>	77.00	63.64
<b>RI</b>	78.00	77.27
<b>VIG</b>	77.00	77.27
<b>BGI<sub>1</sub></b>	77.00	63.64
<b>BGI<sub>2</sub></b>	77.00	63.64
<b>GRI</b>	77.00	68.18
<b>BRI</b>	77.00	72.73
<b>BGRI<sub>1</sub></b>	77.00	63.64
<b>BGRI<sub>2</sub></b>	77.00	65.91
<b>BGRI<sub>3</sub></b>	77.00	63.64
<b>BGRI<sub>4</sub></b>	77.00	63.64
<b>NIR Indices</b>		
<b>NIR</b>	76.00	72.73
<b>Combination of Vis and NIR Indices (Vis+NIR)</b>		
<b>NDVI</b>	77.00	81.82
<b>NG</b>	77.00	81.82
<b>DVI</b>	76.00	70.45
<b>GDVI</b>	76.00	72.74
<b>IPVI</b>	78.00	81.82
<b>GNDVI</b>	77.00	81.82
<b>NNIR</b>	77.00	70.45
<b>SR</b>	76.00	70.45
<b>GRVI</b>	77.00	63.64
<b>OSAVI</b>	78.00	68.18

<b>SAVI</b>	78.00	79.55
<b>NR</b>	77.00	68.18

## **CONCLUSIONS**

The current findings of this study highlighted the prospect of spectral measurement obtained from the satellite imagery with a combination of spectral indices and machine learning analysis in discriminating foliar N sufficiency levels of mature oil palms. The results of this study suggest that in general the Vis (BGRI<sub>1</sub> and BGRI<sub>2</sub>) and Vis+NIR (NDVI, NG, IPVI and GNDVI) indices are beneficial in discriminating N status in young and prime mature palms. Hence, more attention should be given to the age factor when dealing with the N study of perennial crops such oil palm. Despite of the age limitation, the result revealed that the spectral measurement acquired from the space-borne sensor could classify the N status of oil palm with satisfactory accuracy despite the fact that the measurement taken from the canopy level are normally confounded with the soil background, canopy structure, leaf structure and branch characteristics.

## **REFERENCES**

- Amirruddin AD, Muharam FM, Mazlan N. 2017. Assessing leaf scale measurement for nitrogen content of oil palm: performance of discriminant analysis and support vector machine classifiers. *Int J Remote Sens* 38(23): 7260-7280. doi:10.1080/01431161.2017.1372862.
- Asraf, HM, Nooritawati MT, Rizam SBS. 2012. A comparative study in kernel-based support vector machine of oil palm leaves nutrient disease. *Procedia Eng.* 41: 1353–1359. doi:10.1016/j.proeng.2012.07.321.
- Axelsson C, Skidmore AK, Schlerf M, Fauzi A. 2013. Hyperspectral analysis of mangrove foliar chemistry using pls and support vector regression and support vector regression. *Int J Remote Sens.* 34 (5): 1724–1743. doi:10.1080/01431161.2012.725958.
- Coeurdevey L. 2013. SPOT 6/7 Imagery - user guide technical report No. SI/DC/13034-v1.0. France: Astrium Services.
- Corley RHV, Mok CK. 1972. Effects of nitrogen, phosphorus, potassium and magnesium on growth of the oil palm. *Exp Agr* 8(4): 347–353. doi:10.1017/S0014479700005470.
- Foster H. 2002. Assessment of oil palm fertilizer requirements. In: Fairhurst T, Härdter R, editors. *Oil palm: management for large and sustainable yields*. Singapore: Potash & Phosphate Institute (PPI). p. 231–257.
- Gitelson AA, Kaufman YJ, Merzlyak MN. 1996. Use of a green channel in remote sensing of global vegetation from EOS-MODIS. *Remote Sens Environ.* 58 (3): 289–298. doi:10.1016/S0034-4257(96)00072-7.
- Goh KJ, Härdter R. 2003. General oil palm nutrition. In: Fairhurst T, Härdter R, editors. *Oil palm: management for large and sustainable yields*. Singapore: Potash & Phosphate Institute (PPI). p. 191-230.
- Guyon I, Weston J, Barnhil S, Vapnik V. 2002. Gene selection for cancer classification. *Mach. Learn.* 46 (1-3): 389–422.

**INTERNATIONAL CONFERENCE ON BIG DATA APPLICATIONS IN AGRICULTURE (ICBAA2017)  
5-6 DECEMBER 2017**

- Hall M, Frank E, Holmes G, Pfahringer B, Reutemann P, Witten IH. 2009. The WEKA data mining software. SIGKDD Explorations Newsletter 11(1): 10–18. doi:10.1145/1656274.1656278.
- Hartley C. 1988. The oil palm: world agriculture series. 3rd ed. London, (UK): Longman Scientific & Technical.
- Hunt ER, Hively WD, Fujikawa SJ, Linden DS, Daughtry CS, McCarty GW. 2010. Acquisition of NIR-Green-Blue digital photographs from unmanned aircraft for crop monitoring. Remote Sens. 2(1): 290–305. doi:10.3390/rs2010290.
- Ivanciuc O. 2007. Applications of support vector machines in chemistry. Reviews in Computational Chemistry. 23: 291–400. doi:10.1002/9780470116449.ch6.
- Miller G, Miller E. 1948. Determination of nitrogen in biological materials. Anal. Chem. 20 (5): 481–488. doi:10.1021/ac60017a022.
- Nor Azleen W, Wahid AR, Tarmizi BO, Basri AM. 2003. Remote sensing for oil palm foliar nitrogen. Bangi, Malaysia: MPOB. (MPOB Information Series 190).
- Rouse JW, Haas RH, Schell JA, Deering DW. 1974. Monitoring vegetation systems in the Great Plains with ERTS. In: Freden SC, Mercanti EP, Becker M, editors. Third Earth Resources Technology Satellite (ERTS)–1 Symposium. Volume I: Technical Presentations, NASA SP-351, Washington (DC), USA: NASA. p. 309–317
- Smola A, Vapnik VN. 1997. Support vector regression machines. Advances in Neural Information Processing Systems 13 (9):155–161.
- von Uexkull HR, Fairhurst T. 1991. Fertilizing for high yield and quality : The Oil Palm, Bern, Switzerland: International Potash Institute. (IPI Bulletin 12).
- Vapnik VN. 2000. The nature of statistical learning theory. New York, NY: Springer-Verlag.
- Wang F, Huang J, Wang Y, Liu Z, Zhang F. 2013. Estimating nitrogen concentration in grape from hyperspectral data at canopy level using support vector machines. Precis Agric 14(2): 172–183. doi:10.1007/s11119-012-9285-2.
- Zhai Y, Cui L, Zhou X, Gao Y, Fei T, Gao W. 2013. Estimation of nitrogen, phosphorus, and potassium contents in the leaves of different plants using laboratory-based visible and near-infrared reflectance spectroscopy : comparison of partial least-square regression and support vector machine regression. Int J Remote Sens 34 (7): 2502–2518. doi:10.1080/01431161.2012.746484.
- Zhang Y, Cong Q, Xie YF, Yang JX, Zhao B. 2008. Quantitative analysis of routine chemical constituents in tobacco by near-infrared spectroscopy and support vector machine. Spectrochim Acta A Mol Biomol Spectrosc 71 (4): 1408–1413. doi:10.1016/j.saa.2008.04.020.