Comparison of the retrieving precision of potato leaf area index derived from several vegetation indices and spectral parameters of the continuum removal method

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ABSTRACT
Leaf area index (LAI) is one of the important variables for crop growth monitoring and yield estimating. In this article, the potato LAI was retrieved by several vegetation indices (VIs) and spectral parameters of the continuum removal method (SPCRM) to provide accurate estimates. A comparison of the two methods of retrieving precision was completed. The data source for computing VIs and SPCRM was hyperspectral reflectance data for the life cycle, derived from two potato cultivars, Favorite (early maturing variety) and Yanshu 4 (late maturing variety), through field experiments. Sensitive bands were identified to indicate seven VIs by correlation analysis. Additionally, seven SPCRM were computed. Based on these methods, the potato LAI was retrieved and tested. Meanwhile, a comparison of the retrieving precision was implemented. The results showed that compared with the filtered spectral reflectance and VIs, the correlation between the potato LAI and the continuum removal spectral reflectance and its retrieved SPCRM were higher. The determination coefficients ($R^2$) of the retrieving models of four parameters, the total area (S), the left area (Sl), the right area (Sr) and the depth area ratio (W), derived from the continuum removal method were all above 0.801, and their fitting coefficients ($r$) were all above 0.868, with the mean relative errors (MRE) all <0.14. It was identified that W was the most suitable parameter for retrieving the potato LAI. Although the effectiveness of SPCRM requires further research, this study manifests that SPCRM have the potential to accurately retrieve the potato LAI.

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Introduction
Leaf area index (LAI), whose mathematical meaning is the sum of the area of a single side of a leaf per unit of surface area (Chen & Black, 2010), is a crucial parameter reflecting the biochemical status and physical processes of crop populations (Liu, Zhou, Wu, Xia, & Tang, 2016). It can provide vital theoretical indicators for the field management of crops, water and fertilizer regulation, growth monitoring and yield estimation. Thus, the LAI is regarded as the most commonly used comprehensive parameter in growth monitoring via hyperspectral remote sensing as it varies with the spectral reflectance of the crop canopy. Conventional LAI was acquired by a ground survey method, which is not only inefficient and costly but also only able to obtain a small range of the LAI accurately. Furthermore, hyperspectral remote sensing can obtain data and information from objects of interest with a number of very narrow electromagnetic wavebands (Du, Gong, et al., 2016).

It provides a path for crop growth monitoring in real time and estimating crop agronomic parameters with its strong continuity and large amount of information generated. Generally speaking, there are two ways to obtain crop LAI for the time being: statistical model and physical model. Statistical model, namely empirical regression model including simple linear regression (Broge & Leblanc, 2001), multiple linear regression (Heiskanen, 2006), and partial least squares regression (Cho, Skidmore, Corsi, Wieren, & Sobhan, 2007), uses a regression expression obtained from the relationship between the spectral reflectance at the crop canopy level and LAI measured by field experiments (Maki & Homma, 2014). Direct inversion of physical model requires a lot of resources and time due to its own complexity. However, statistical model needs less input variables. Therefore, it may be a simpler and more inexpensive method for laypersons other than researchers in remote sensing to estimate crop LAI. Certainly, for some multispectral data, machine learning methods,
such as decision tree learning, artificial neural networks (ANNs) (Kimes, Nelson, Manry, & Fung, 1998), support vector machines (SVMs, Durbha, King, & Younan, 2007), and random forests (RFs) (Liang et al., 2015) are also increasingly employed to optimize the use of spectral information with the goal of minimizing prediction uncertainty (Li et al., 2016).

Also, scholars have a great deal of research on crop LAI simulation utilizing hyperspectral data. Hyperspectral remote sensing has attracted increasing attention for LAI retrieving because of its continuous spectral coverage and high spectral resolution. Theoretically, hyperspectral data can yield more spectral details obscured in multispectral data. At present, however, it is mainly carried out in grain crops such as wheat (Guo et al., 2016), corn (Li et al., 2014) and rice (Wang et al., 2015) and leguminous crops such as soybeans (Du, Xia, et al., 2016). There is very little related research on solanaceous crops, and no reports have been published on potato. With the implementation of the “potato staple food” strategy in China, it is urgent to carry out research on area extraction, yield estimation, planting suitability, pest control and growth monitoring of potato crops (He et al., 2017). Hence, the estimation of the potato LAI is of great significance.

As for characteristic parameters and methods of LAI retrieval, vegetation indices (VIs) were widely employed by most scholars in retrieving LAI of a variety of vegetation types on account of the significant correlations with LAI. For example, Li et al. selected sensitive VIs of winter wheat by means of a segmentation mode to build the best VI combination to improve the precision of LAI retrieval (Li et al., 2012). Zhao et al. compared the results of LAI retrieval of winter wheat with the normalized difference vegetation index (NDVI), which was extensively employed, in the whole growth stage and with different VIs at different growth stages (Zhao, Huang, Zhang, & Jing, 2013). In addition, Xin et al. used spectral derivative and statistical analysis techniques to confirm the relationship between the hyperspectral reflectance, VI and LAI of rice. Next, the LAI simulation models were established, and the simulation results were compared (Xin et al., 2015). Xia, Wu, Zhou, and Zhou (2013) employed two methods of regression analysis and a back propagation (BP) neural network to construct LAI simulation models for regional winter wheat. Xie et al. (2014) retrieved the winter wheat LAI via four ways, the SVM, continuous wavelet transformation (CWT), discrete wavelet transformation (DWT) and principal component analysis (PCA), and tested the authenticity of the models computed by those different algorithms. On the other hand, when constructing-related models, Eklundh, Hall, Eriksson, Ardö, and Pilesjö (2003), Haboudance, Miller, Pattey, Zarco-Tejada and Strachan (2004), Tillack, Clasen, Kleinschmit, and Förster (2014) all used linear regression models to retrieve LAI. Both Feng et al. (2013) and Herrmann et al., 2012 used linear regression and exponential models. Houborg and Boegh (2008) used a polynomial model for LAI retrieval.

The continuum removal method (CRM) is generally applied in the estimation of crop nutrient and nitrogen content and has not been utilized in LAI retrieval studies so far (Peng, Chi, Xiang, Teng, & Shi, 2014). According to the filtered spectral reflectance and canopy LAI data, we could find the sensitive bands that reflected the changes in LAI based on the correlation analysis, then construct different VIs for LAI retrieval based on these bands. Simultaneously, the corresponding spectral parameters of the continuum removal method (SPCRM) were initiated and the LAI retrieval models were constructed by those parameters. Finally, the comparison between SPCRMs and VIs for retrieving LAI of potato was carried out. Although different spectral characteristics have been used to estimate LAI with varying success, especially for VIs, SPCRMs have rarely been employed in vegetation field. The goal of this study was to comparatively assess the predictive power of SPCRM and VIs in simulating potato LAI. The results are intended to provide theoretical and technical support for remote sensing monitoring of potato growth and to provide a new idea for remote sensing retrieval of vegetation LAI.

Materials and methods

Field experiment design

Field trials were conducted at the Agricultural Science and Technology Demonstration Park (125°00’E, 43°40’ N) in Fanjiatun Town, Gongzhuling City, Jilin Province, China from May to September in 2017. In the experiments, two potato cultivars, Favorite (early maturing variety, FWRT) and Yanshu 4 (late maturing variety, YS4), which are widely planted in Jilin Province, were selected as the target crop. As shown in the field schematic (Figure 1), each potato cultivar planting was repeated three times with 32 cells in each repeat area. There was a total of 96 cells in the whole area, and each cell, containing 10 strains of potatoes, was arranged in the form of 4 rows × 8 columns. The ridge width of the potato is 75–80 cm and the plant spacing is 30–35 cm. To avoid interference from other factors, the potato management mode of the experiment referenced the general field mode with superior fertility, irrigation and drainage conditions.

Data acquisition and preprocessing

The spectral reflectance data of the potato canopy were obtained using a miniature fiber spectrometer, USB 2000+ from Ocean Optics Inc. in USA, whose fastest sampling speed is 1 ms with a spectral sampling interval
of 0.46 nm. When the USB2000+ spectrometer is connected to the computer via the USB 2.0 interface, the user can store 1000 spectra per second, which is highly flexible and is ideal for applications requiring high-speed processing. When measuring the spectral reflectance, it was clear, cloudless and windless and the measurement period was selected from 10:00 to 14:00 daily. During the measurement, the sensor probe was vertically downward and approximately 0.5–1 m above the top of the canopy in order to minimize the effect of soil background. To reduce the measurement error to the greatest extent, each cell was measured three times in the field of view, and three random points were selected for each measurement. Moreover, three curves were obtained from each observation point and the average was taken as the canopy spectral reflectance. For the time of our experiments, the duration of the measurements included the entire growth period of the potato. During the measurement process, when the measurement of each point was finished, the standard whiteboard calibration was performed in time (the standard whiteboard reflectance is 1, so the obtained target spectrum is the relative reflectance), so we could accurately measure the next position.

The acquisition of the potato canopy LAI was synchronized with the measurements of the canopy spectral reflectance. LAI was collected by the SUNSCAN canopy analysis system (Delta Inc., UK), which acquires LAI using the distribution equation of the elliptical foliage angle so that it can be used on cloudy days and in other conditions without consideration of the weather. To ensure the accuracy of collected LAI data, each experiment cell contained nine evenly selected points, which were measured three times and each measurement was parallel and perpendicular to the ridge. Similarly, the average value was regarded as LAI of the point.

In the spectral reflectance measurement process, noise and external confounding factors are inevitable. Therefore, it is necessary to smooth the spectral curve to reduce the impact on later comparisons and analyses. Savitzky-Golay filtering is a comprehensive filtering method based on local polynomial least-squares fitting within the time domain, and the most prominent feature is that it can maintain the shape and width of the signal while filtering out any noise (Li, Xie, & Qiao, 2017). To minimize the influence of noise, the reflectance curves of the wavelength range of 400–950 nm were intercepted from the original reflectance data and processed with Savitzky-Golay filtering method to obtain the filtered curves, making the spectral data conducive to mathematical modeling analysis.

**Regression analysis**

Regression analysis can be divided into two major categories: one-dimensional regression analysis and multiple regression analysis, which is mainly used...
for establishing the mapping relationship between two variables (the independent and dependent variables) (Huang et al., 2013). In this article, VIs or SPCRM constructed by the canopy spectral reflectance are independent variables and LAI is the dependent variable (Hocking, 1976; Thenkabail, Smith, & Pauw, 2000). Taking the LAI retrieval of VI as an example, first, the correlation analysis between the spectral reflectance and LAI of the canopy was implemented. The sensitive bands were found according to the variation trend of the correlation coefficient (CC), and then the VIs were computed on the basis of the reflectance of the sensitive bands. Finally, VIs and LAI were used to construct the regression models and their accuracy was verified.

In accordance with the results of previous research and the variation characteristics of the spectral reflectance, the following seven representative and widely adopted VIs (Table 1) were selected to initiate the estimation models for the potato LAI. The ratio vegetation index (RVI) can accurately reflect the vegetation coverage and growth, to a certain extent (Anderson, Hanson, & Haas, 1993). When vegetation coverage exceeds 50%, RVI is very sensitive to vegetation. In contrast, when vegetation coverage is <50%, the sensitivity is reduced. The difference vegetation index (DVI) is a great indicator to reflect the change in the vegetation-soil background (Richardson, 1977). The NDVI is used to study the growth of the vegetation due to the elimination of most radiation errors (Miller, Hare, & Wu, 1990). The green normalized difference vegetation index (GNDVI) is generally used to manifest the health and biomass of vegetation (Gitelson & Merzlyak, 1996). The green ratio vegetation index (GRVI) is sensitive to the change in vegetation under the condition that the LAI exceeds 3 (Gitelson, Kaufman, & Merzlyak, 1996). The enhanced vegetation index (EVI) can effectively avoid the saturation of the atmosphere and soil (Huete, Justice, & Liu, 1994). The soil-adjusted vegetation index (SAVI) can reduce the effects of the soil background (Huete, 1988). In this article, the soil-adjusted coefficient (L) was 0.5.

**Continuum removal method**

The CRM, also known as the envelope removal method, is commonly used for analyzing the hyperspectral data of minerals and rocks to remove the effects of background absorption and to separate the absorption of characteristic matter (Han, Zhu, Wang, & Zhao, 2016). This method was proposed by Roush and Clark for the normalization of the original spectral curve, which means that bulgy peaks absorbed or reflected with a changing wavelength are connected with straight line to ensure all the outside angles at the peaks are more than 180°. The range of the reflectance value is 0–1 after the spectral reflectance data are processed by CRM. The relative reflectance at the peak is 1, and at other points, it is <1. The absorption and reflection of the spectrum can be highlighted and facilitate the comparison with other spectrums by this transformation. The formula of the continuum removal spectral reflectance is as follows:

\[
Scr = \frac{R}{Rc}
\]  

(1)

Here, Scr is the continuum removal spectral reflectance; R is the original spectral reflectance; and Rc is the continuum linear reflectance.

The continuum removal spectra were converted by normalization of the filtered spectral data. After that, seven SPCRM were extracted for comparative analysis. (i) The maximum absorption depth (Dh): the maximum absorption value of the absorption peak. (ii) The absorption wavelength (λ): the value of the wavelength corresponding to Dh. (iii) The total area (S): the integral of the band depth in the starting and ending wavelength range. (iv) The left area (Sl): the left area of Dh of the total area. (v) The right area (Sr): the right area of Dh of the total area. (vi) The symmetry (V): the ratio of left area to right area. (vii) The depth area ratio (W): the ratio of Dh to S. In this article, the more intense absorption valley of two of interception bands was selected to extract SPCRM.

**Model construction and verification**

The measured LAI data were separated into two groups and each one included 36 sets of data, which were used to simulate and verify the LAI models. The index model, linear model, logarithmic model, polynomial model, power model, and so on were established to estimate the LAI of potato. The precision of the verification was quantitatively conducted using

| Hyperspectral vegetation index | Calculation formula |
|-------------------------------|--------------------|
| Ratio vegetation index (RVI)  | RVI = NIR/Red      |
| Difference vegetation index (DVI) | DVI = NIR – Red   |
| Normalized difference vegetation index (NDVI) | NDVI = (NIR – Red)/(NIR + Red) |
| Green normalized difference vegetation index (GNDVI) | GNDVI = (NIR – Green)/(NIR + Green) |
| Green ratio vegetation index (GRVI) | GRVI = NIR/Green – 1 |
| Enhanced vegetation index (EVI) | EVI = 2.5 × \( \frac{NIR + 2 × Red – 1.5 × Blue + 1}{NIR + 2 × Red} \) |
| Soil-adjusted vegetation index (SAVI) | SAVI = \( \frac{NIR – Red}{NIR + 2 × Red} \) (1 + L) |

Note: NIR, red, green and blue are near infrared, red, green and blue band reflectance, respectively; L is the soil-adjusted coefficient.
three factors: the determination coefficient ($R^2$), the fitting coefficient ($r$) and the mean relative error (MRE). The closer $R^2$ is to 1, the better the regression model. In contrast, the closer $R^2$ is to 0, the worse the regression model. The fitting coefficient ($r$) is the CC between the simulated value and the measured value of LAI. In a similar manner, the closer $r$ is to 1, the better the simulated result. The closer $r$ is to 0, the worse the simulated result. For the MRE, as it gets smaller the simulation result is more precise. The regression model with the largest $R^2$, the largest $r$ and the smallest MRE was taken as the final model. The related mathematical equations are as follows:

\[
R^2 = \frac{SSE}{SST} = 1 - \frac{SSR}{SST} \quad (2)
\]

Here, $R^2$ is the determination coefficient; SSE is the sum of squares for error; and SST is the sum of squares for total. SSR is the sum of squares for regression.

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x}_i)^2} \quad (3)
\]

\[
MRE = \frac{RMSE}{\bar{x}_i} \quad (4)
\]

Here, RMSE is the root mean square error; $x_i$ is the measured value; $\bar{x}_i$ is the simulated value; and $\bar{x}_i$ is the average of the measured value.

Results

Vegetation index calculation and correlation analysis

The correlation analysis between the spectral reflectance of potato at different growth stages and the corresponding LAI was implemented to look for the sensitive bands. The result of the correlation analysis is shown in Figure 2. It can be observed that, in the range of visible band (400–760 nm), the filtered spectral reflectance of the potato canopy was by and large negatively correlated with LAI overall ($P < 0.05$). In the visible range of green band (500–560 nm), the curve showed a small peak, which is due to the strong absorption of chlorophyll. There was a significant negative correlation ($P < 0.05$) in the visible range of red band (620–690 nm), and the maximum absolute value occurred at the 690 nm with a value of approximately −0.5. In the range of 690–760 nm, the absorption ability of pigments of potato leaves gradually weakened, yet the reflecting ability of cells increased slightly. In this range, the CC increased with the increasing wavelength, increasing to 0 at 710 nm and reaching a maximum value of 0.52 at 773 nm, near the infrared wavelength. The CC maintained relatively large values near the infrared band (760–850 nm), which was most sensitive to the canopy LAI of potato. Consequently, the sensitive bands of 417.34, 547.34, 683.62 and 773.28 nm were selected to calculate VIs.

The seven VIs selected in this study were computed according to the reflectance of the above sensitive bands and the correlation analyses with the potato LAI data were executed. As shown in Table 2, the CC ranged from 0.318 to 0.669. In accordance with statistical precedent, two variables are highly correlated when $|r| \geq 0.8$, moderately correlated when $0.5 \leq |r| < 0.8$, slightly correlated when $0.3 \leq |r| < 0.5$, and not correlated when $|r| < 0.3$. Therefore, DVI, NDVI, EVI and SAVI were moderately correlated with the potato LAI, while RVI, GNDVI and GRVI were slightly correlated. In summary, the seven VIs (DVI, NDVI, EVI, SAVI, RVI, GNDVI and GRVI) could be used to retrieve the potato LAI.

Potato LAI retrieval based on vegetation index

The above seven VIs were individually fitted with the potato LAI over the whole growth period and different
retrieving models were initiated with largest $R^2$, largest $r$ and smallest MRE to make the simulation value of LAI as close to the true value as possible. In this study, 36 sets of sample data were selected from the datasets to construct the simulation models of LAI, and the final models are shown in Table 3. It can be seen that except for GNDVI and GRVI, the potato LAI was retrieved by the other remaining VIs with good outcomes for $R^2$ ranging from 0.4407 to 0.5568. Meanwhile, the fitting coefficients of those models were above 0.64 with the MRE <0.2161. Therefore, among the chosen VIs, SAVI, NDVI, EVI and DVI had the most salient fitting effects of comprehensiveness. All the models in the following table were nonlinear since LAI and VIs appeared to have nonlinear variation throughout the whole growth period.

The simulation models of the four VIs with good performance are shown in Figure 3. One primary reason for lower retrieval precision of GNDVI and GRVI is that they were calculated by the spectral reflectance of the wavelength at the peak of green band, which was lowly correlated with LAI. Additionally, the CC between RVI and LAI was 0.318, which is close to the critical value for a low correlation. Therefore, the effect of RVI retrieval of LAI of the potato was not very good. For one thing, DVI, EVI and SAVI took the influence of soil, atmosphere and surrounding environmental factors into account. However, for another, NDVI

| Vegetation indices | Combined bands (unit: nm) | Retrieving models | Determination coefficient ($R^2$) | Fitting coefficient ($r$) | Mean relative error (MRE) |
|--------------------|---------------------------|-------------------|-------------------------------|-------------------------|--------------------------|
| RVI                | 773, 683                  | $y = -0.0017x^2 + 0.148x + 1.3836$ | 0.4407                       | 0.6639                  | 0.2075                   |
| DVI                | 773, 683                  | $y = -18.292x^2 + 26.122x - 5.27$ | 0.4507                       | 0.6714                  | 0.2056                   |
| NDVI               | 773, 683                  | $y = 4.9025x^2 + 0.643$          | 0.5261                       | 0.6400                  | 0.2155                   |
| GNDVI              | 773, 547                  | $y = 6.8267x^2 - 0.72$           | 0.2005                       | 0.4208                  | 0.2548                   |
| GRVI               | 773, 547                  | $y = -0.1567x^2 + 1.7889 - 1.1884$ | 0.1949                       | 0.4415                  | 0.2489                   |
| EVI                | 773, 683, 417             | $y = 4.2511x^{1.3117}$          | 0.5183                       | 0.6410                  | 0.2161                   |
| SAVI               | 773, 683                  | $y = 5.7913x^{1.9057}$          | 0.5568                       | 0.6739                  | 0.2070                   |

![Figure 3](image-url)
eliminated most of the impact of background irradiation, and the spectral data used for constructing these four VIs were very strongly correlated with LAI, thus their retrieval results were great.

Parameters extraction of continuum removal method and correlation analysis

Before acquiring the continuum removal spectra, the original spectral reflectance data were processed by the Savitzky-Golay filtering method to obtain the filtered spectral data with less noise. As shown in Figure 4, after the continuum transformation, two absorption valleys emerged for chlorophyll strongly absorbing blue light (450 nm) and red light (600 nm), forming a “double-valley” structure in the range of 380–850 nm of the continuum removal spectra. The spectral curve of the continuum removal showed a higher peak at 550 nm than that of the filter spectral curve. In this article, the more intense absorption valley of two was used to extract the seven SPCRM.

As with the correlation analysis of VIs and LAI, a similar result was seen for the spectral reflectance of the continuum removal and LAI. It can be seen from Figure 5 that the correlation between the spectral reflectance of the continuum removal and LAI was stronger than the filtered spectral reflectance as a whole. In the context of the total observation bands, the spectral reflectance of the continuum removal was negatively correlated with LAI (P < 0.01), especially in the range of 600–700 nm, reaching a maximum absolute value of the CC at a wavelength of 617.44 nm with a value of −0.78. The results showed that CRM has great potential for improving the correlation with LAI.

To improve the precision of the potato LAI retrieval on the basis of VIs, we took advantage of the seven SPCRM to estimate the potato LAI. As shown in Table 4, the correlation of SPCRM and LAI was analyzed to find the best inversion index. The results showed that the CC of these 7 parameters with LAI ranged from 0.282 to 0.863. The absorption wavelength (λ) is irrelevant to LAI, as it had the lowest value (0.282). Beyond that, the remaining six SPCRM all had the great correlation with LAI. To be specific, symmetry (V) and LAI were lowly correlated, and a moderate correlation was observed for the maximum absorption depth (Dh). The total area (S), left area (Sl), right area (Sr) and depth area ratio (W) were highly correlated with LAI, and all of them were significant at 0.01 level. In conclusion, other than the absorption wavelength (λ), the other six parameters can be used to establish retrieval models for the potato LAI.

Figure 4. Canopy spectral curve of potato: (a) filtered spectral curve; (b) continuum removed spectral curve.

Figure 5. Correlation between spectral reflectance and LAI.
Potato LAI retrieval based on parameters of the continuum removal method

The LAI retrieval of potato was performed using SPCRM with a strong correlation to LAI as seen in Table 4. For retrieval models, a comprehensive analysis of Table 5 suggested that six SPCRM, regardless of the absorption wavelength ($\lambda$), could retrieve the potato LAI effectively. In addition to the models of the area ratio ($V$) and the maximum absorption depth ($D_h$), $R^2$ of the other four models were above 0.8. Furthermore, the fitting coefficients were above 0.86, with the MRE <0.14. Compared to other inversion models based on VIs, SPCRM have a better potential for the simulation of the potato LAI due to improved fitting effects and reduced errors. Among them, the maximum $R^2$ of the inversion models occurred with the parameter of total area (S) with a value of 0.8435, whereas the fitting coefficient of the depth area ratio (W) is highest with a value of 0.9105 and its MRE of 0.1147 is the minimum.

The inversion results of the four parameters with better fitting effects were illustrated in Figure 6. The retrieval models of the above six parameters are all nonlinear models, as well as VIs, because of the non-linear variation of LAI and the continuum removal spectra. In summary, the main cause of the higher precision of SPCRM inversion compared to VIs is that the correlation between spectral reflectance and LAI was greatly enhanced after the continuum transformation. What's more, the extracted parameters also increased the correlation with LAI, so the accuracy of the inversion model was improved with the increasing correlation.

Table 5. Fitting models between LAI and parameters of the continuum removal method.

| Parameters | Retrieving models | Determination coefficient ($R^2$) | Fitting coefficient ($r$) | Mean relative error (MRE) |
|------------|-------------------|----------------------------------|--------------------------|--------------------------|
| Dh         | $y = 4.9115x^{2.3899}$ | 0.6811 | 0.7363 | 0.1897 |
| S          | $y = 20.531e^{-0.024x}$ | 0.8435 | 0.8808 | 0.1324 |
| Sl         | $y = 8.6874e^{-0.036x}$ | 0.8176 | 0.8791 | 0.1336 |
| Sr         | $y = 68.759e^{-0.064x}$ | 0.8012 | 0.8683 | 0.1398 |
| V          | $y = 9.4642e^{-1.832x}$ | 0.4421 | 0.6287 | 0.2177 |
| W          | $y = -26956x^2 + 1033.4x - 5.1892$ | 0.8290 | 0.9105 | 0.1147 |

Note: ** indicates a significant correlation at 0.01 level, * indicates a significant correlation at 0.05 level.
Discussion

**Parameters selection for LAI retrieving and correlation analysis**

It was observed that spectral reflectance was negatively correlated with LAI in the visible band and positively correlated in the near-infrared band in the whole observation region after conducting a correlation analysis. The spectral reflectance of the visible band and the near-infrared platforms can better reflect the dynamic changes in LAI (Bai et al., 2007; Walburg, Bauer, & Daughtry, 1981). In this study, LAI sensitive bands existed in the visible light blue band (417.34 nm), the visible light green peak (547.34 nm), the visible light red trough (683.62 nm) and the near-infrared band (773.28 nm). These results are of great significance to the real-time monitoring of potato growth in this area. In crop LAI estimation studies, the variables that most scholars have adopted are VIs except for parameters that describe the characteristic spectra of vegetation like red-edge position, red-well position (Pu, Gong, Biging, & Larrieu, 2003) and red-edge amplitude (Filella & Penuelas, 1994), and some features derived from PCA or wavelet transform (WT) (Pu & Gong, 2004). However, PCA and WT cannot enhance the spectral characteristics of the data (Fan, Yan, & Xu, 2010; Johnson & Billow, 1995). Therefore, using these data on sensitive bands of potato LAI, correlation analyses of DVI, NDVI, EVI, SAVI, RVI, GNDVI, GRVI and LAI were performed. Different VIs have specific sensitivities and resistances to different factors or disturbances, resulting in various relationships with LAI. It was found that DVI, NDVI, EVI and SAVI were moderately correlated with potato LAI, while RVI, GNDVI and GRVI were slightly correlated. The results were basically consistent with those of wheat and peanut (He, Liu, & Li, 2014; Lv et al., 2016). DVI, NDVI, EVI and SAVI can eliminate the influence of soil background and irradiance well, so relatively speaking their correlations with LAI were significant, and the precision of the final inversion models was very high, especially for SAVI. But overall, the reasons for the low correlation between VI and LAI in this article can be summarized as two aspects. On the one hand, the VI is easily affected by factors, such as differences in surface properties and sun position, as well as viewing geometry. On the other hand, there is a certain limit to the correlation between VI and LAI. It can be seen from Figure 3 that when the LAI is >3, NDVI, EVI and SAVI have obvious saturation phenomena, which cannot effectively reflect the change of LAI.

CRM has the effect of eliminating unrelated background information and enhancing the absorption features of interest, and has been widely used in spectroscopy of ground object information (Jing et al., 2010). As for the continuum removal method, the potato reflectance of the canopy was mapped to the continuum line and the differences of partial absorption feature were enlarged by normalization. Through correlation analyses between the continuum removal spectra and LAI, the overall correlation was greatly improved and negatively correlated as a whole, which was consistent with the correlation between the canopy spectra and nitrogen content of winter wheat (Li & Chang, 2017). In view of the limited correlation of VIs with LAI, SPCRM (Dh, λ, S, Sl, Sr, V, W) derived from continuum removal spectral reflectance data were applied to the studies of correlation analyses with LAI. The results showed that the correlation between SPCRM and LAI was greatly improved compared with VIs and LAI (λ was approximately 670 nm and its correlation with LAI was very weak). The CC between S, W, Sl, Sr and LAI were all >0.8. We know that the stronger the correlation between two variables, the easier it is to build a fitting model. According to each VI, a variety of inversion models of potato LAI were established. The model with larger $R^2$, larger $r$ and smaller MRE was selected as the final one. Different VIs can reduce the influence of noise, such as soil background and aerosol, to different degrees (Mannschatz, Pflug, Borg, Feger, & Dietrich, 2014). In the VI simulation models, the accuracy of the optimal model was close to 80% (while the accuracy of the optimal SPCRM model had increased by approximately 10%, approaching 90%). This result indicated that CRM has certain advantages in the LAI simulation study, especially the SPCRM.

**Model performance comparison of LAI retrieving**

To verify the accuracy of the four VIs (DVI, NDVI, EVI, SAVI) inversion models with good performance, 36 sets verification data of LAI from datasets were put into their corresponding inversion models to obtain the simulated LAI data. Afterwards, the simulated LAI data were compared with measured LAI, and the results were shown in Figure 7. $R^2$ of the 4 verification models below ranged from 0.4096 to 0.4541 with good performance, and the maximum value of $R^2$ was from the model of SAVI. Indeed, its simulation effect and verification effect were both best possibly resulting from effectively reducing the effect of soil background for SAVI when $L$ is equal to 0.5 (Xia et al., 2013). Although the LAI inversion accuracy of the potato via VIs was close to 80% and different VIs have diverse adaptation ranges for LAI estimation, there is still a lot to be improved upon.

Likewise, 36 sets of observed LAI data were utilized to verify the retrieving models of SPCRM and four verification models (S, Sl, Sr, W) with good simulation effects were generated as shown.
It can be seen that $R^2$ of these four verification models ranged from 0.7539 to 0.829, higher than those of verification models of VIs on the whole. The optimal verification result was identified as the model of W, with the maximal $R^2$ of 0.829 and minimal MRE of 0.1147 possibly resulting from better quantitative prediction ability of the model built by W (Xiang et al., 2016). Compared to the LAI retrieving results of VIs and SPCRM, it can be seen that the accuracy of the latter method was close to 90%, which was greatly improved on the basis of VIs inversion.

**Figure 7.** Comparison of verification models of vegetation indices for measured LAI and estimated LAI: (a) DVI, (b) NDVI, (c) EVI, (d) SAVI.

**Figure 8.** Comparison of verification models of the parameters of the continuum removal method for measured LAI and estimated LAI: (a) $S$, (b) $Sl$, (c) $Sr$, (d) $W$. 
Limitations and prospects of potato LAI retrieving

Continuum removal is a spectral analysis method that effectively enhances the absorption features of interest (Jiang, Li, Guo, Liu, & Chen, 2012). In this article, we used this method to enhance the correlation between SPCRM and LAI and obtained good simulation models. Compared with VIs, although SPCRM showed better potential to some extent, verification of the applicability of this method needs to be carried out continuously. A universal optimal index or parameter for LAI estimation in any situation may not exist because hyperspectral data contains a great amount of information. Thus, how to select the most effective and suitable variable from these data to establish an inversion model still remains to be determined (He et al., 2014). In addition to research methods, there are also possible factors that limit the accuracy of LAI inversion in this article. First, unlike other staple food crops (such as wheat and rice), the potato tubers grow underground, and we cannot directly observe the morphological characteristics of the potato with our eyes. Therefore, there are certain difficulties in subdividing the growth period, and LAI can only be estimated during the entire growth period. The problem of saturation is inevitable due to using the entire growth period data. Second, if the study is conducted using hyperspectral data of multi-year time series, the accuracy of potato LAI simulation may be further improved. Finally, in this experiment, the potato cultivars, planting region and various conditions limited the inversion precision. Of course, the inversion models constructed in this study need to be tested and refined in different regions with different potato cultivars and different tillage methods.

The potato LAI retrieving by hyperspectral remote sensing technique should be more diversified to acquire higher precision and more universal models. Certain more effective methods that can handle mixed effects can be considered in future analyses (Hajjem, Bellavance, & Larocque, 2014; Isik & Ozden, 2013). In addition to methods, other aspects should also be taken into account. For example, the experiment should be carried out in areas with large differences in water and temperature conditions. Taking after other crops, the LAI inversion models should be constructed for different growth stages of potato with regression analysis, neural networks and other methods to obtain a higher accuracy and better stability.

Conclusions

Based on the correlation analyses, the LAI of potato was inverted by remote sensing using VIs and SPCRM, respectively. Then, the comparison of precision was implemented. The results showed the following:

1) VIs selected in this article improved the correlation with the potato LAI compared to the canopy spectral reflectance. DVI, NDVI, EVI and SAVI were moderately correlated with the potato LAI, whereas RV1, GNDVI and GRVI were lowly correlated. The CC between LAI and SAVI was the highest with a value of 0.669. The spectral reflectance of CRM further improved the correlation with LAI, especially in the range of 600--700 nm. The strongest negative correlation with LAI was located at 617.44 nm with a value of −0.78. In all the variables, the correlation between SPCRM and LAI was the most significant. The parameters of total area (S), left area (Sl), right area (Sr) and depth area ratio (W) were highly correlated with LAI, with the maximum CC of 0.863 between total area (S) and LAI. Consequently, CRM and SPCRM have greater potential in the potato LAI retrieving.

2) SPCRM enhanced the inversion ability of the potato LAI, and six parameters, other than the absorption wavelength (λ) of SPCRM, could simulate the change in the potato LAI effectively. In addition to the area ratio (V) and the maximum absorption depth (Dh) of above six parameters, \( R^2 \) of the inversion models were above 0.8, while the fitting coefficients were above 0.86 with the MRE <0.14. Compared to the inversion models of VIs, SPCRM had obvious advantages on the potato LAI retrieval, with the fitting effect greatly improved and the error significantly reduced. \( R^2 \) of total area (S) inversion model was highest up to 0.8435. However, the fitting coefficient of the depth area ratio (W) inversion model was higher, reaching 0.9105 with the smallest MRE of 0.1147. In terms of verification models, \( R^2 \) of the four models (Figure 8) ranged from 0.7539 to 0.829 with good performance. The verification result of the depth area ratio (W) was the best with the highest \( R^2 \) of 0.829 and the smallest inversion error of 0.1147. In conclusion, the depth area ratio (W) was the most suitable parameter for retrieving the potato LAI in this article.

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Author Contributions

Shanjun Luo, Yingbin He, Shengli Zhang and Jingke Zhang conceived and designed the experiments; Shanjun Luo, Dingding Duan, Zhuozhuo Wang, Fei Xu and Jing Sun performed the experiments; Shanjun Luo, Dingding Duan, Yuantao Zhang, Yaqiu Zhu and Jinkuan Yu analyzed the data; Yingbin He contributed materials/
analysis tools; Weihua Jiao contributed to the discussion; and Shanjun Luo wrote the article.

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