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APPLICATION OF HYPERSPECTRAL IMAGING TECHNIQUE IN AGRICULTURAL REMOTE SENSING

LI ZHANG, TENI GEER[1], XIAOXU SUN, CHUNGUANG SHOUAND HUISHI DU*

Jilin Normal University, College of Tourism and Geographical Science, Siping, Jilin136000, China

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Abstract

Hyperspectral imaging technique plays an essential role in agricultural production. This article analyzed the research progress of hyperspectral imaging technique at home and abroad and summarized the development status of hyperspectral technique in precision agriculture, crop disaster detection, and crop growth status. For example, hyperspectraltechnique can measure the content of trace elements such as nitrogen, phosphorus and potassium in the soil, and determine the crop growth stage according to the leaf area index (LAI) and the crop nitrogen content. Hyper-spectrum could tell whether a crop was affected by disasterand the degree of impact. The present study also outlined the problems that hyperspectral imaging technique faced with agriculture, namely complicated spectral data, relatively easily interfered by external environment, and inaccurate image interpretation, providing a reference for the application of hyperspectral remote sensing in agriculture.

Hyperspectral remote sensing is an image data technique for obtaining digital images in many narrow bands across the visible, near-infrared (NIR), mid-infrared (MIR) and thermal infrared (TIR) regions of the electromagnetic spectrum (Yao *et al*. 2008, Du *et al*. 2016). It has outstanding features of multiple spectra, high resolution and the “consistency between images and spectra” (Teng *et al*. 2009). With the development of hyperspectral technology, its application has expanded to a variety of fields, especially in agriculture. Hyper-spectrum could be used to calculate the organic matter content of different types of soil, determine the nutrient content in crops, monitor the growth of crops, estimate the crop yield, and investigate the impact of pests and diseases on crops (Pang *et al*. 2012), so that timely response measures could be taken to increase the crop yield and promote the sustainable development of agriculture (Du *et al*. 2016). In the present study the applications of hyperspectral remote sensing in precision agriculture, agricultural disasters and crop growth, providing references for the future development of hyperspectral imaging technique in agriculture were reviewed.

Hyperspectral imaging technique is a potential soil attribute mapping tool that can invert SOM content (Gomez *et al*. 2016), helping to assess soil quality in real time and serve precision agriculture (Rajeev *et al*. 2015). Combined with classification and regression tree or multivariate statistical analysis methods, hyper-spectrum can be used to identify mineral composition, organic matter content and moisture (water) content of soil, and estimate the concentrations of nitrogen, carbon, carbonate and organic matter in soil (Gmur *et al*. 2012). Studies have shown that different soil types have distinct spectral curves. The spectral curve features of different farmland soil types in Northeast China measured by hyper-spectrum exhibited different reflectance for different soil types. With respect to the black soil, the response of organic matter content was more significant at 400-1000 nm than that at 1100-2500 nm, and some scholars have further narrowed the most significant range down to 400-750 nm (Yang *et al*. 2013, Liu *et al*. 2014). Hyperspectral imaging

*Author for correspondence: < duhs@163.com >. [1]College of Civil and Transportation Engineering, Beijing University of Civil Engineering and Architecture, Beijing 100044, China.

technique could remotely estimate the leaf chlorophyll content, and further perform nutrient diagnosis and crop yield evaluation (Chi *et al*. 2016). Chlorophyll fluorescence is correlated to photosynthesis, therefore, there is a certain relationship between plant leaves and net photosynthetic rate (Zarco-Tejada *et al*. 2013). Hyperspectral imaging technique could perform non-destructive detection of nitrogen content in plant leaves (Tian *et al*. 2011). Combined with regression analysis it may assess the nitrogen content, accurately collecting nitrogen content information of plant leaves (Cilia *et al*. 2014, Wang *et al*. 2017). Taking advantages of the neural network model, it could estimate the nitrogen content at various stages of corn growth. Investigation showed that the nitrogen content had greatest impact on corn growth (Liang *et al*. 2010).

Hyperspectral imaging technique may generate distinct spectral curves of plants during various growing seasons. Taking the Saskatchewan test field in Canada as the study area, leaf area indexes (LAIs) were measured for barley, wheat and rapeseed, during the early growing season (June), the vigorous growing season (July), and the late growing season (August), respectively. Firstly, a plant canopy analyzer was used to measure the LAI, and an ADS portable hyperspectral instrument was used to fetch remote sensing data. The variance analysis based on normalized vegetation index (NDVI) was used to obtain the significant differences. Byimage analysis, it can be seen that during the early growing season, photosynthesis was strong, the plants were at jointing stage, and the distribution of the plant spectral curves was similar to those of the barren lands. In the vigorous growing season, the chlorophyll only took a small amount of absorption and the plant spectra displayed a typical vegetation spectral curve distribution (Fig. 1). During the late growing season, the spectra curves in the visible and NIR regions were relatively smooth due to the harvest of wheat and barley (Zheng *et al*. 2007). It was found that during wheat germination the spectral curve exhibited a significant absorption valley at 675 nm, while no such phenomenon existed for non-germinated wheats, indicating that wheat could be clearly detectable at 675 nm (Wu *et al*. 2012). Hyper-spectrum could be manipulated to indirectly study the crop growth stages by monitoring the amount of irrigation water required during the growth (Sudipta *et al*. 2013). The information bands and their combinations based on hyperspectral remote sensing technology could be assembled to extract the spatial information of crop growth and perform growth monitoring of rice (Li *et al*.2006). The above-ground biomass in canopy of crops changes at various growing seasons, hence, the growth stage of rice could be determined indirectly by measuring the above-ground canopy biomass with hyper-spectrum (Martin*et al*.2014). Hyper-spectrum was also used to explore the crop growth in the polar regions. The biomass measurements in the polar regions showed significantly different biomass-spectra relationships in the early growing season (Sara *et al*.2017). Hyper-spectrum may detect crop growth, implement crop management, improve crop quality, and make production more scientific.

Hyperspectral imaging technique is one of the important technical means for pest and disease detection. Hyperspectral data could be used to prove the spectral changes of crops during pest and disease invasions, explore the severity of damage, and determine the sensitive bands and sensitive periods for crops affected by pests and diseases. The relationship between crop hyperspectral reflectance and pest and disease invasion could be learnt by comparing the crop hyperspectral curves in the background of crop growth (Hamed *et al*. 2005). The spectra of leaves and trunksof trees varied when affected by pests and diseases (Zhang *et al*. 2017). Therefore, the damage degree of forest pests and diseases can be detected by hyperspectral remote sensing (e.g. DNVI, RVI). Further, combined with first derivative and data dimensionality analysis, it was concluded that the most significant band to study forest pests and diseases was 759nm (Pan *et al*. 2014). Hyper-spectrum was also used to detect the degree of late blight infection in California tomatoes in the United States. The results demonstrated that hyperspectral technique could effectively manage crop pests and diseases, indicating that the hyperspectral-based classification method served well for crop disease identification (Zhang *et al*. 2003). The impact of pests and diseases in tea was detected with hyperspectral technique. Further by first-order differential derivative conversion, it was found that the regions of 715 - 763 nm and 776 - 778 nm worked best to tell the impact of pests and diseases on tea (Liu *et al*. 2016). Hyper-spectrum has been used to detect the effects of pests and diseases on various vegetations. The spectral bands for inversion of different vegetations affected by pests and diseases are different, and the corresponding analysis model varies as well.

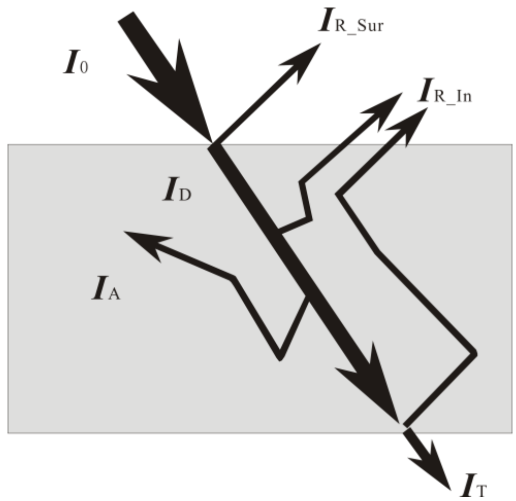

Fig. 1. Radiate transfer of light within a blade: (I0) total energy incident on the blade surface; (ID) energy that passes through the surface of a blade and into the interior of the blade; (IR_Sur) energy directly reflected; (IA) energy absorbed inside the blade; (IR_In) energy that enters the blade and is scattered multiple times and reflected back; (IT) energy that is scattered many times and passes through the blade.

The advantages of high resolution and abundant information of hyper-spectrum equip it with a broad application prospect in agricultural pest monitoring. It was shown that hyper-spectrum can clearly identify whether cotton was affected by freezing, however, it cannot determine the degree of freezing injury (Li *et al*. 2008). Together with first derivative, second derivative, and reciprocal logarithm, hyperspectral imaging technique was employed to obtain the sensitive bands of identifying the effects of freeze damage to winter wheat (Li *et al*. 2014). The sensitive bands were 578.37, 571.93 and 684.92 nm, among which the band of 684.92nm gave the most accurate results. In addition, the principal component analysis method was applied to establish a hyperspectral inversion model of the severity of winter wheat freeze injury, and it has been verified (Wang *et al*. 2014). Besides the detection of freeze damage to crops, hyper-spectrum was applied to droughts and floods of crops as well. Hyper-spectrum was used to determine whether maize was affected by flood during the jointing stage and measure the degree of impact. Studies have shown that the maize was affected by flood at jointing, and the severer the flood, the smaller the chlorophyll content in maize, which also dropped sharply with the increase of flood time (Meng *et al*. 2017). It was found that beet and maize followed this rule at various growth stages (Jiang *et al*. 2013).

The application of hyper-spectrum in agricultural production estimation focuses on two areas, crop type identification and area extraction, and crop growth detection and yield estimation. The crop leaves may be effectively identified in the NIR region. The internal structures of leaves are different regarding different crops. Hyper-spectrum is capable of detecting internal structures, therefore it could be used to identify different crops accurately. Based on this, combined with MODIS data and Back propagation (BP) neural network model, it could be used to estimate the crop yield (Table 1). A cotton yield estimation model based on canopy spectral index measured by hyperspectral imaging technique was established, and the spectrum and yield of cotton from the germination peak period to the late bloom period were analyzed by spectral reflectance (Zhuang *et al*. 2011). Hyper-spectrum was used to estimate the winter wheat yield too. As shown in studies, the spectral reflectance was negatively correlated with yield in the visible, NIR and shortwave infrared (SWIR) regions, and the NDVI and yield defined in the NIR region were extremely significant (Zhang *et al*. 2014).

Table 1. Agricultural directional remote sensing demand.

Target	Spectrum requirements	Suitable satellite data
Optimum harvest time	Hyperspectral, multispectral, visible-near infrared	Proba Chris, Hyperion, Landsat TM, Quickbird; MODIS, ASTER, etc.
Yield	Hyperspectral, multispectral, visible-near infrared	Proba Chris, Hyperion, Landsat TM,GF-5, IKONOS, CBERS, etc.
Quality	Hyperspectral, multispectral, optical, thermal infrared	Proba Chris, Hyperion, Landsat TM, Quickbird, ASTER, etc.

There are many spectral bands in hyper-spectrum, such as visible, near infrared, mid-infrared and thermal infrared. It can be used to identify crop types and is useful for the agricultural product yield estimation and the optimal band determination. Classification of wheat varieties with hyperspectra demonstrated that the NIR spectroscopic information could reflect the differences among varieties, while different parts of crops may affect the crop classification results. Studies showed that it is achievable to distinguish some crops by hyper-spectrum. Easily the crops could be distinguished by their different spectral curves and absorption bands. However, it is hard to tell apart crops with similar spectral absorption bands (Dong *et al*. 2015). The spectral reflection and absorption analysis revealed major spectral characteristic bands in the visible to NIR regions, including the green peak at 510 - 560 nm, the red valley at 650 - 690 nm, the red edge at 680-760 nm, the chlorophyll absorption band in the blue light region of 400 - 530 nm and in the red light region of 500 - 730 nm, weak water absorption band at 930-1000nm, narrow water and oxygen absorption band at 1100 -1250 nm.

The application of hyperspectral imaging technique in agriculture has made some progress, but it still has a long way from maturity (Shi *et al*. 2015). The impact of surrounding environments such as weather on hyper-spectrumim pairs the accuracy of the prediction model. Besides, the information interference of surrounding objects complicates the spectral data, making data processing cumbersome and setting high technique requirement (Yan *et al*. 2019). In addition, the large amount of collected images is a burden for data storage (Cheng *et al*. 2001). Moreover, the measured crop itself has a complex metabolic regulation mechanism, which may cause deficiency of some elements and excessive of other elements, resulting in inaccurate measurement of plant spectral curve, which leads to errors in image interpretation.

With the development of hyperspectral technology, the integration of theory and practice should be improved to enhance the ability to transfer experimental results into actual productivity (Hong *et al*. 2010). It is of great benefit to accelerate the establishment of agronomic hyperspectral database, improve the mining power and application efficiency of hyperspectral data, and combine 3S technology to analyze agricultural information in a timely fashion. Though the application of hyperspectral imaging technique in agriculture is more precise and accurate than the previous multi-spectral technique, it still needs further improvement in agricultural yield estimation, crop growth detection, and crop damage investigation. Agriculture is heading for conservation tillage and sustainable agricultural development in China. Conservation tillage has the superiority of reducing air pollution, increasing crop yield, and promoting sustainable agricultural development. Hyperspectral imaging technique can accurately measure the nutrient contents of crops, crop growth, and the implementation of conservation tillage.

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