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Review Paper

Hyperspectral imaging: A potential tool for monitoring crop infestation, crop yield and macronutrient analysis, with special emphasis to Oilseed Brassica

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Abstract

Due to increase in human population at an alarming rate, there is tremendous pressure on the agriculture sector for increasing production of agricultural commodities. Oilseed Brassica is an important oilseed crops in India. Although, India occupies third position with about 10.3 % share in the acreage, and production of rapeseed-mustard in the world after China, and Canada, with the average yield of 1188 kg per hectare, which is low as compared to world average 1994 kg/ha. The major reasons for low exploitable yield are infestation by various pathogens, and pests, improper weed management, degradation of soils due to excessive use of pesticides, fertilizers, and emerging pesticide resistance. Hyperspectral imaging system (HIS), also known as imaging spectroscopy or 3D spectroscopy, combines imaging, and spectroscopy into a single system. Through its multi-spectral, multi-temporal, and multi-resolution observation capability, the technology provides an alternative to traditional methods for facilitating sustainable agriculture by mapping, and monitoring the agricultural situation, retrieval of biophysical parameter, and management/ decision support for agricultural development**.** For oilseed rape, the technology has been found to be useful for disease forecasting, monitoring infestation induced damages, predicting seed yield, detection of fungal pathogens, weeds and macronutrient analysis for monitoring fertilizer application.

Key words: *Crop infestation, crop yield, hyperspectral imaging, macronutrient analysis, oilseed rape*

Introduction

The world population is increasing at an alarming rate, and expected to reach around 11.2 billion by 2100. It has been estimated that India's human population would reach, and stabilize around 1.5 billion by 2035. Whereas the average rate of increase of crop production is only 1.3% per year, and it can't keep pace with population growth. Therefore, there is a big challenge for researchers to ensure the crop poduction is sufficient to satisfy the need of increasing human population. Non-scientific cropping practices has affected the sustainability, especially by depleting the ground water, degrading the soils, decreasing nutrient use efficiency, and increased pest and disease incidences. In order to make the land sustainable, the agricultural activity today should be considered as a system, rather than a single crop-producing unit. A system approach to manage the agriculture is essential for long-term sustainability, and achieving an evergreen revolution. Seed variety, growth environment, and field management are major concerns in crop growth. The acquisition of spatial and temporal variability of crop growth is one of the goals in precision agriculture (Zhang *et al*., 2002). The detection of nutrient condition, and disease diagnosis have significant meaning for crop growth. The different growth stages could influence the yield of the crops, and the physiological index including leaf chlorophyll, soluble sugar, soluble protein, enzyme activity, and others affecting the crop growth could be used to understand crop growth status. Remote sensing (RS), which is defined as the collection of information about an object without physical contact, has been a very effective source of information. RS data, through its multi-spectral, multi-temporal, and multi-resolution observation capability, provides an alternative to traditional methods for collection of information related to agriculture (Navalgund and Ray, 2000; Ray, 2004b). RS data can be used for facilitating sustainable agriculture in three different ways: mapping and monitoring the agricultural situation, retrieval of biophysical parameter, and management/decision support for agricultural development (Parihar and Ray, 2002). A decision-support system using remote sensing, and Geographical Information System (GIS), super-imposing favorable weather parameter can be useful for disease prediction followed by crop protection activities or disease management. Furthermore, the imaging spectroscopy has been successfully applied in estimating the crop yield. Examples included the prediction of biomass, and yield of winter wheat under different nitrogen supplies using spectral indices (Serrano *et al*., 2000). This technique has attracted the growing interests of researchers as a powerful tool for agriculture products analysis (Ariana and Lu, 2010; Barbina *et al*., 2012; Del Fiore *et al*., 2010; Wu *et al*., 2012a). Numerous studies have illuminated the relationships between the spectral data from vegetation leaves, and various biophysical, and physiological parameters of the crops (Goel *et al*., 2003; Jago *et al*., 1999; Lee *et al*., 2004; Thenkabail *et al*., 2000; Vigneau *et al*., 2011; Zou *et al*., 2011).

Hyperspectral immaging approach

Oilseed Brassica (*Brassica* sp.) is one of the important oilseed crops in India (FAO, 2011), which constitutes a major source of edible oil for human consumption. The processed byproducts served as the high energy, and protein meal for livestock. Besides, rapeseed oil is recently being increasingly processed as a renewable resource in many applications owing to its very good biodegradability, oleochemical application (e.g. detergents, soaps, cosmetics or polymers), and fuels (Hogya *et al*., 2010). Therefore, increasing yield in oilseed rape is significant for both vegetable oil, and biodiesel production. Though, India occupies a major position in the acreage, and production of mustard in the world, the average yield per hectare is low as compared to other mustard growing countries. The major reasons for low yield are infestation by various pathogens and pests, improper weed management, degradation of soils due to excessive use of pesticides, insecticides, fertilizers, and emerging pesticide resistance. Hyperspectral remote-sensing approach, using remotely sensed reflectance for many continuous narrow wavelength bands, has been proposed for various aspects of crop management such as the detection of various kinds of pests and pathogens, identification and classification of plant species, yield estimation, as well as estimation of different crop bio-physical and bio-chemical parameters. Effect of pest and disease status on the spectral properties of the crop can be used to control site-specific application of insecticide (Pinter *et al*., 2003). Using remote sensing instruments, it is possible to monitor changes in crop health over the course of a growing season (Richardson *et al*., 2004). The presence of disease or insect feeding on a plant or canopy surface causes changes in chlorophyll, chemical concentrations, cell structure, nutrient and water uptake, and gas exchange, which leads to differences in colour, and temperature that can modify canopy reflectance characteristics (Raikes and Burpee, 1998). Hyperspectral imaging techniques has been found to be useful for detection of various biotic stresses caused due to pathogens and pests (Kumar *et al*., 2013; Baranowski *et al*., 2015), detection of weed emergence, and to quality factors, such as oil, protein, and total glucosinolate content of rapeseed (Petisco *et al*., 2010), chlorophyll of rape leaves (Fang *et al*., 2007), acetolactate synthase activity, protein content, and total amino acids in herbicide-stressed oilseed rape leaves (Liu *et al*., 2008, 2011). This review covers all potential applications of hyperspectral imaging for monitoring crop infestation, crop yield, and macronutrient analysis, with special emphasis to Oilseed rape.

2. Hyperspectral imaging theory and principals

The technique, Hyperspectral imaging system (HIS) is also called as imaging spectroscopy, which combines properties of imaging, and spectroscopy. It studies and measures spectra acquired through reflection of the electromagnetic radiation from the object under study. A typical HIS encompasses: (i) a source of light to illuminate the object, (ii) a lens for focusing and delineating field view, (iii) a spectrograph for splitting the light into different spectral bands, (iv) a camera for capturing final spatial-spectral images, and (v) a software for monitor the image acquisition. Choice of the mode applied for image acquisition relies largely on properties of the sample being analyzed. Basically, there are three modes for acquisition: 1) Reflectance, 2) Transmittance, and 3) Interactance, mainly differs in configurations of lighting, and detector systems. The differences between these 3 acquisition modes lead to dissimilar effects of data acquisition from the same object. In the interactance mode, which is a blend of reflectance, and transmittance modes, the source of light, and the detector are on the same side of the object under study (Nicola *et al*., 2007). HIS in reflectance mode is able to detect external properties of the target like shape, color, size, etc. but is not able to determine internal quality parameters effectively. On the other hand, transmittance mode is useful in detecting internal characteristics as well (Ariana and Lu, 2008). The interactance mode is suitable for measuring turbid liquids, semi-solid, and solid substances as well (Reich, 2005).

The technology involves acquisition of images in the visible, and near-infrared/ infrared regions. Then these images are combined to form a 3 dimensional hyperspectral cube, and finally the images are visualized as sections of the hypercube with its two spatial (x,y) and one spectral dimension (*ë*). Each spectral pixel of the hypercube refers to a spectral signature, i.e., spectrum, of the corresponding spatial region, and it records complete measured spectrum of the spatial point which is imaged. The measured spectrum specifies the sample's ability for absorbing or scattering the exciting light, thus characterizing the inherent properties of the sample. With combined properties of imaging, and spectroscopy, the technique HIS results in unparalleled capabilities for sample detection, which is not possible with either spectroscopy or imaging alone. Appropriate qualitative, as well as, quantitative information can be retrieved from the hypercube to determine distribution of numerous constituents within the sample. The precision of HIS sensors is typically measured as spectral resolution. The spectral resolution is defined as the thickness of the narrowest spectral feature which can be resolved by sensor. The bands in the HIS images are very narrow (ranging from 5nm-20nm), and range from UV to thermal IR regions (Muhammad *et al*., 2012)**.** Due to narrow bands, hyperspectral images acquire a very high spectral resolution leading to better identification and discrimination of the target.

Remote sensing hyperspectral technology for disease forecasting

Ensuring crop protection by disease forecasting is important for maintain the crop productivity and quality. Sudden changes in weather conditions leads to onset, and spread of plant diseases, which are regulated largely by weather anomalies occurring during a crop growth cycle. The disease incidences above certain threshold levels, results in poor crop yield, and grain quality. Prediction of diseases on spatial scales either depends on observation of weather conditions from *in situ* measurements or from estimates based on satellite monitoring (Green and Hay, 2002) or forecasts obtained through meso-scale models (Strand, 2000). Infection of crops with various diseases alter thermal and/oroptical properties of leaves, canopies in spectral regions due to necrotic or chlorotic lesions, canopy dryness, and premature senescence orbrowning (Malthus and Madeira, 1993; West *et al*., 2003). In comparison to multispectral imaging, hyperspectral systems are fairly promising in detection of diseases in crops (Thenkabail *et al*., 2002; Laudien *et al*., 2004, Kanemasu *et al*., 1974; Nageswara Rao and Rao, 1982; Franke and Menz, 2007). Satellite-based systems based on hyperspectral imaging have been used to identify different diseases such as late blight (*Phytophthora infestans*) in tomato (Zhangand Qin, 2004), rice diseases (Qin *et al*., 2003), and orange rust in sugarcane (Apan *et al*., 2004). Sclerotinia rot is one of the major diseases affecting the crop. Typical symptoms of the disease includes dryness, discolouration, and shrinkage of canopies. Outbreak of the disease is largely accompanied by a period of persistent minimal temperature which occurs mainly during the month of January and February in India (Chattopadhyay, 2008). Periods of alternating cloudy, and clear sky with intermittent drizzle are the main duration for the spread of this disease (Venette *et al*., 1998). A three stage detection system using combination of satellite-based remote sensing observations, and minimum air temperature was developed for detecting Sclerotinia rot (*Sclerotinia sclerotiorum*) in Indian mustard (Baranowski *et al*., 2015). The researchers developed a new technique for tracking Sclerotinia rot at multiple stages in mustard growing fields. The surface weather data along with collective satellite based imaging data, over the period of five years,based on analysis of surface reflectance's in red (R), shortwave infrared (SWIR), and near infrared (NIR) regions as well as land surface temperature (LST) from Moderate Resolution Imaging Spectro radiometer (MODIS) AQUA were utilized for characterization of disease outbreak (Baranowski *et al*., 2015).

3. Hyperspectral imaging for identification of biotic and abiotic stress

In natural, uncontrolled conditions, crops, and other plants are exposed to a combination of various biotic, and abiotic stresses that affect host metabolism, and lead to large yield losses (Bravo *et al*., 2003; Glazebrook *et al*., 2005; Mitchell, 1998). Biotic stresses are caused by living organisms, such as fungi, bacteria, viruses, and insects, which infect plants. During plant stress, absorption of incident light changes in both the visible, and NIR ranges, which is due to the decrease in leaf chlorophyll concentration, and changes in other pigments (Carter *et al*., 2001; Gitelson *et al*., 2001; Larsolle *et al*., 2007; Steddom *et al*., 2003; 2005). The change of absorption consequently influences the reflectance of stressed plants, which can be visualised by hyperspectral imaging systems as locally changed spectral characteristics of leaf surfaces (Delalieux *et al*., 2009; Penuelas *et al*., 1995; Wang *et al*., 2008; Wolf and Verreet, 2002). As the plant grows, a number of pests and pathogens pose a threat to brassica, and such pests are unmanageable without applications of insecticides, pesticides, and chemical treatments (Alford *et al*., 2003). However, indiscriminate use of these pesticides, and chemicals, have led to resistance among insect populations to the prevailing pesticides. Pesticide resistance due to superfluous treatments is an emerging issue for pest management programs (Valantin-Morison *et al*., 2007). To control the unnecessary chemical application, a prototype method for detection of infestation seriousness in crops is need of the hour. Though visual pest identification is easy, and convenient, however, there are some chances for biasness, and lack of accuracy (Richardson *et al*., 2001; Steddom *et al*., 2005). Various alternative techniques, which have been applied for monitoring damage detection of crops include, methods established on digital image analysis (Diaz-Lago *et al*., 2003), spectral technology (Guanand Nutter, 2002; Riedell and Blackmer, 1999), hyperspectral imaging techniques (Zhao *et al*., 2011; Reisig and Godfrey, 2010; Liu *et al*., 2010), and multi-spectral imaging technology (Kim *et al*., 2000). The technology of digital image analysis focusing on color features, and morphology of targets can be employed for qualitative as well as quantitative information on pest identification by recognition of the edge of pests (Habib *et al*., 2000; Habib, 2000). Apart from digital image analysis, technologies based on spectral, multispectral, and hyperspectral imaging also have potential for quantifying damages by pests. Reflectance spectral features characterizing aphid infestation of wheat leaves have been studied (Mirik *et al*., 2007, 2006a). Further, the reflectance spectral data has been utilized to estimate the injury severity during heat field infestation by sunny pests (Genc *et al*., 2008). Other potential studies include utilization of spectral data sets for detection of minute damages in tomato leaves due to pests (Xu *et al*., 2007), damage caused by thrips in sugarcane (Abdel-Rahman *et al*., 2010), aphid and spider on cotton vegetation (Reisig and Godfrey, 2007). The technology has also been used for detection of green bug (Yang *et al.*, 2005; Yang, 2005), and aphid-infested wheat (Mirik *et al.*, 2005, 2006b). Further, Elliott *et al*. (2007, 2009) demonstrated infestation of aphid in wheat fields by analyzing airborne remote sensing data, is an another application of spectral, and hyperspectral techniques for large scale analysis. Kumar *et al*. (2013) recently found that remote sensing using hyperspectral data can be a useful tool for monitoring the effect of aphid infestation in mustard crops. Aphid infested crop had low leaf area index (LAI), chlorophyll concentration, seed yield, and per cent oil content as compared to healthy crop. The reflectance for healthy crop was found to be more in visible as well as NIR region as compared to aphid infested canopy. The most significant spectral bands for the aphid infestation in mustard are in visible (550–560 nm), and near infrared regions (700–1250 nm and 1950–2450 nm). The different level of aphid infestation can be identified in 1950–2450 nm spectral regions. Spectral indices viz., NDVI (Normalised difference vegetation index), RVI (Ratio vegetation index), AI (Aphid Index), and SIPI (Structural independent pigment index) had significant correlation with aphid infestation (Kumar *et al*., 2013).

Cabbage caterpillar is an important pest affecting oilseed rape, however, no uniform criteria exist for judging the extent of damage caused due to cabbage caterpillars. Several researchers have shown that hyperspectral imaging combined with digital image analysis gives better performance for pest infestation detection (Mirik *et al.*, 2006c). Further, researchers have also found that neural network modeling method for HIS data analysis is ideal, and results in higher accuracies for agriculture pattern recognition (Velioglu *et al*., 2011; Arribas *et al*. 2011; Tyystjarvi *et al*., 2011; Jeon *et al*., 2011). Neural network modeling method has also been utilized for assessing growth of insect (Patten *et al*., 2011). The researchers have applied the combination of hyperspectral imaging, digital image analysis, and neural networks for detection of Cabbage caterpillar pest infestation detection on oilseed rape. This is useful study for evaluation of severity of damage induced by cabbage caterpillars in oilseed rape.

Another potential application of hyperspectral imaging technologies in mustard is early detection of biotic stresses caused by major plant fungal pathogen *Alternaria* (Baranowski *et al*., 2015). The genus *Alternaria* is ubiquitous, saprophytic, and included plant-pathogenic species (*A. alternata*, *A. brassicae*, *A. brassicicola*, *A. dauci*), which may affect crops in the field or cause harvest and postharvest decay of plant products. Alternaria infecion on leaves of oilseed rape causes obstruction, and disfunction of stomata, which affects the physiological processes in plants. Baranowski *et al*. (2015) used thermal (8-13 μm), and hyperspectral imaging in visible, and near infrared (VNIR), and short wavelength infrared (SWIR) ranges were used to develop a method ofearly detection of biotic stresses caused by fungal species belonging to the genus *Alternaria*. These results revealed the good applicability of thermography, and hyperspectral imaging in the VNIR and SWIR regions for studying the development of *Alternaria* infection on leaves of oilseed rape within a 3-week period after inoculation.

4. Hyperspectral imaging for weed detection

Aerial remote sensing platforms were first used for weed detection in the early 1980s. Menges *et al*. (1985) utilized conventional color (CC), and color infrared (CIR) photography as a means to distinguish weeds from agricultural crops in experimental plots. They found that the 850 nm, NIR reflectance between weed, and weed/crop canopies was more variable than the visible reflectance at 550 nm, supporting the use of CIR over CC photography. Initial work in remote sensing for weed detection within crop canopies was accomplished using CIR video systems similar to those used over the southern range lands. Brown *et al*. (1994) used filters to separate still-video images into red, green, blue, and NIR narrow-band components for detection of weeds in no-till corn. The classified image was visually comparable to a full-color photograph of the same area. Supporting the need for newer technology, they cite difficulty in converting between video, and digital formats. With advances in digital technology in 1990s, Lamb and Weedon (1998) used a four-camera airborne digital imaging system to record blue, green, red, and NIR wave bands over a fallow field of weeds (*Pancium effusum* R. Br.) in oilseed brassica stubble. Image analysis included an unsupervised classification of a NDVI, and supervised classifications of multi-band images. Ground referencing was accomplished by visually mapping weedy areas with a GPS unit on an all-terrain vehicle (ATV). Overall classification accuracy assessments for this pre-emergence weed detection application ranged from 85 to 87%. Therefore, the hyperspectral image technology can also be used as potential tool for weed emergence detection.

5. Detecting macronutrients content and distribution in oilseed rape leaves using hyperspectral imaging

Apart from their ideal performance to detect many kinds of crop diseases, spectral, and hyperspectral imaging technologies have also been used to analyze chemical composition for crops and foods (Liu *et al*., 2008; 2011a; 2011b; Liu and He, 2008). Nitrogen (N), phosphorus (P), and potassium (K) are the most important macronutrients for maintaining plant growth status, and enhancing crop yield. Nitrogen is a key element in all organisms, and in different physiological processes of plants, where it is required consistently, and in large amounts (Bondada & Oosterhuis, 2001; Evans, 2001; Feng *et al*., 2006; Fismes *et al*., 2000; Hezewijk *et al*., 2008). Phosphorus is a crucial ingredient of some macro-molecules such as nucleic acids, phospholipids, and sugar phosphates (Raghothama and Karthikeyan, 2005). Organic P compounds are involved in energy transfer reactions, and in respiration. Potassium plays an essential role in enzymatic reactions, the maintenance of osmotic potential, and water uptake during plant development (Dong, *et al*., 2010; Pettigrew, 2008). In recent decades, a rapid increase in production of oilseed rape has required the improvement of fertiliser management to optimise the crop yield, and product quality. The traditional uniform application of fertiliser's in a field can't match the requirements of individual plants, and result in over-or under application, which tends to bring about soil quality degradation, ground water pollution, and fluctuation or even reductionin yield (Dong *et al*., 2010; Farruggia *et al*., 2004; Jorgensen *et al*., 2007; Rathke *et al*., 2006). It is important to understand leaf nutrition of oilseed rape in order to optimise the fertilisation process. However, conventional chemical analysis for the determination of leaf nutrient content is time consuming, and destructive. Therefore, a precise, and rapid method for detecting specific nutrient concentration is of significant importance for precision diagnosis, real-time fertilisation, and productivity prediction which can lead to economic, and environmental benefits. The measurement of leaf, and canopy spectral reflectance is a promising technique to estimate the concentrations or biochemical composition in foliage. Good results have been obtained for the quantification of oleuropein in olive leaves (Aouidi *et al*., 2012), measurement of N content in wheat crops (Hansena and Schjoerring, 2003; Mistele and Schmidhalter, 2008; Tarpley *et al*., 2000), and evaluation of plant water status (Cheng *et al*., 2011; Feret *et al*., 2011). There has also been a number of surveys to determine quality factors in oilseed rape based on spectral techniques, such a soil, protein, and total glucosinolate content of rapeseed (Petisco *et al*., 2010), chlorophyll of rape leaves (Fang *et al*., 2007), acetolactate synthase activity, and protein content, and total amino acids in herbicide-stressed oilseed rape leaves (Liu *et al*., 2008; Liu *et al*., 2011a; Liu *et al*., 2011b). Therefore, site-specific fertilisation management in precision farming systems could benefit from spectroscopy, a fast, and non-destructive method, for obtaining the variability of leaf nutrient status during crop growth. Hyperspectral imaging is an emerging technology that integrates both spectroscopy, and imaging techniques in one system to provide spectral, and spatial information simultaneously (Barbina *et al*., 2012). Since each hyperspectral image contains information about the spatial distribution of chemical constituents in the object as well as spectral information for each pixel in hundreds of contiguous discrete spectral bands, chemical composition analyses can be more reliable than using only spectral reflectance or traditional machine vision. Examples include detection of chlorophyll distribution in cucumber leaves (Zou *et al*., 2011), and estimation of leaf nitrogen accumulation in wheat (Yao *et al*., 2010). Recently, researchers has reported on quantitative assessment of the three essential macronutrients (N, P and K) in oilseed brassica leaves, and determining their concentration distribution (Zhang *et al*., 2013). The hyperspectral imaging was used to provide N, P, and K concentration information to show the nutrient distribution in oilseed rape leaves. Partial least square regression (PLSR), and least-squares support vector machines (LS-SVM) calibration models were developed to quantitatively relate spectral features to N, P, K, and identify the most significant wavelengths linked to each chemical constituent in fresh leaves, The results demonstrated that it is possible to apply hyperspectral imaging technique in VIS/NIR region for nutrient analysis in oilseed rape. Correlations between the spectral features, and macronutrient content of leaf samples were established by using PLSR, and LS-SVM analysis, and reasonable accuracy was obtained for nutrient content detection. It indicates the potential of hyperspectral imaging to be used as a rough screening tool for estimation of N, P, and K content *in situ* in living plant samples non-destructively. The distribution maps can provide data on spatial localisation of nutrient accumulation, and would be helpful to understand the changing of nutrient content in leaves under different fertilizer treatments.

Further, the hyperspectral technologies can be used to embody several other features of the oilseed rape for further analysis. However, few research endeavours have been reported on prediction of yield in oilseed rape from spectral features of leaves obtained by hyperspectral imaging. The technique has also been used very recently for determination of concentration of pigments of Oilseed rape (Heet *et al*., 2015). A hyperspectral imaging system covering the spectral range 380-1030 nm was used to estimate leaf pigment concentration. Spectral information of rape leaves were extracted from the hyperspectral images. Partial least squares (PLS), least squares-support vector machine (LS-SVM), and extreme learning machine (ELM) were applied to build calibration models using spectra of 500-900 nm to determine the concentrations of chlorophyll a (Chl a), chlorophyll b (Chl b), total chlorophyll (tChl), and carotenoids (Car). The overall results indicated that hyperspectral imaging with ELM method was an efficient technique for leaf pigment content determination, and the selected sensitive wavelengths would be helpful to develop portable instrument or on-field monitoring sensors in the precise agricultural management.

6. Hyperspectral imaging for yield estimation

Early researchers have found that leaves contribute to seed development during the ripening phase, including the number of pods per plant, and seed weight per pod (Brar and Thies, 1977; Clarke, 1978; Diepenbrock, 2000; Freyman *et al*., 1973). However, to predict the yield of oilseed rape on individual plants using the potential crop growth information in rape leaves in earlier stage is a challenging job for growers and researchers. Economic and environmental benefit will be both obtained if the individual oilseed yield can be estimated accurately. Farmers can contact their bulk handlers and marketers can determine the price of their product ahead of their harvest season. Yield estimation can provide valuable information for planning harvest schedules, and generating prescription maps for management practices. It is difficult to record the yield of individual plant because manual measurement of yield is laborious, and time-consuming. Therefore, an approach for early, and rapidly estimating oilseed rape yield is highly desirable and beneficial. Hyperspectral imaging is an emerging technology that simultaneously acquires spatial information, as regular imaging systems, and spectral information for each pixel in the image. Comparison of conventional RGB imaging, NIR spectroscopy, and multispectral imaging, hyperspectral imaging has many advantages such as containing spatial, spectral, and multi-constituent information, and sensitivity to minor components (Gowen *et al*., 2007).

Furthermore, imaging spectroscopy has been successfully applied in estimating the crop yield. Examples included the prediction of biomass, and yield of winter wheat under different nitrogen supplies using spectral indices (Serrano Examples *et al*., 2000). Ye *et al*. (2006) obtained the reasonable estimation of citrus yield using the hyperspectral data with a high R^2 in regression analysis. Meanwhile, Weber *et al.* (2012) predicted the grain yield using reflectance spectra of canopy, and leaves in maize plants grown under different water regimes, and got the most relevant wave lengths for predicting the yield. Recently, Zhang and He (2013) developed a technique to early and rapidly estimate seed yield using hyperspectral images of oilseed rape leaves in the visible, and near infrared (VIS–NIR) region (380–1030 nm). Among the hyperspectral images in four growing stages, the hyperspectral images obtained in flowering stage demonstrated the highest correlation with seed yield. This suggests that leaf spectral features at the flowering stage provide more relevant information on the yield variability among individual plants, hence, the hyperspectral imaging can be applied for yield estimation.

References

Abdel-Rahman EM, Ahmed FB, van den Berg M, Way MJ. 2010. Potential of spectroscopic data sets for sugarcane thrips (*Fulmekiola serrata* Kobus) damage detection. *Intl J Remote Sensing* **31**: 4199–4216.

Alford DV, Nilsson C, Ulber B. 2003. Insect pests in oilseed rape crops. In: Alford, D.V. (Ed.), Biocontrol of Oilseed Rape Pests. Blackwell Science, pp. 9–41

Aouidi F, Dupuy N, Artaud J, Roussos S, Msallem M, Gaime IP, Hamdi M. 2012. Rapid quantitative determination of oleuropein in olive leaves (Oleaeuropaea) using mid-infrared spectroscopy combined with chemometric analyses. *Industrial Crops and Products* **37**: 292-297.

Apan A, Held A, Phinn S, Markley J. 2004. Detecting sugarcane 'orange rust'disease using EO-1 Hyperion hyperspectral imagery. *Intl J Remote Sensing* **25**: 489–498.

Ariana DP, Lu RF. 2010. Evaluation of internal defect and surface color of whole pickles using hyperspectral imaging. *J Food Eng* **96**: 583-590.

Arribas JI, Sanchez-Ferrero GV, Ruiz-Ruiz G, Gomea-Gil J. 2011. Leaf classification in sunflower crops by computer vision and neural networks. *Computers and Electronics in Agric* **78**: 9–18.

Baranowski P, Jedryczka M, Mazurek W, Babula-Skowronska D, Siedliska A , Kaczmarek J. 2015. Hyperspectral and thermal imaging of Oilseed rape (*B. napus*) response to fungal species of the genus *Alternaria*. *PLoS ONE* **10**: e0122913.

Barbina DF, ElMasry G, Sun DW, Allen P. 2012. Predicting quality and sensory attributes of pork using near-infrared hyperspectral imaging. *Anal Chim Acta* **719**: 30–42.

Bondad BR, Oosterhuis DM. 2001. Canopy photosynthesis, specific leaf weight, and yield components of cotton under varying nitrogen supply. *J Plant Nutrition* **24**: 469-477.

Bradford MMA. 1976. Rapid and sensitive method for the quantification of microgram quantities of protein utilizing the principle of protein-dye binding. *Anal Biochem* **72**: 248–254.

Bravo C, Moshou D, West J, McCartney A, Ramon H. 2003. Early disease detection in wheat fields using spectral reflectance. *Biosyst Eng* **84**: 137–145.

Brown RB, Steckler JPGA, Anderson GW. 1994. Remote sensing for identification of weeds in no-till corn. *Trans ASAE* **37**: 297–302.

Carter GA, Knapp AK. 2001. Leaf optical properties in higher plants: Linking spectral characteristics to stress and chlorophyll concentration. *American J Bot* **88**: 677–684.

Chattopadhyay C. 2008. Management of diseases of rapeseed-mustard with special reference to Indian conditions. In: Kumar A, Chauhan JS, Chattopadhyay C. (Eds.), Sustainable Production of Oilseeds: Rapeseed-Mustard Technology. Agrotech Publ. Acad., Udaipur, India, 364–388 p.

Cheng T, Rivard B, Sa´nchez-Azofeifa A. 2011. Spectroscopic determination of leaf water content using continuous wavelet analysis. *Remote Sensing of Environment* **115**: 659-670.

Del Fiore A, Reverberi M, Ricelli A, Pinzari F, Serrantie S, Fabbri AA, Bonifazi G, Fanelli C. 2010. Early detection of toxigenic fungi on maize by hyperspectral imaging analysis. *Int J Food Microbiol* **144**: 64–71.

Delalieux S, Somers B, Verstraeten WW, Van Aardt ANJ, Keulemans W, Coppin P. 2009. Hyperspectral indices to diagnose leaf biotic stress of apple plants considering leaf phenology. *Int J Remote Sens* **30**: 1887–1912.

Dong HZ, Kong XQ, Li WJ, Tang W, Zhang DM. 2010. Effects of plant density and nitrogen and potassium fertilization on cotton yield and uptake of major nutrients in two fields with varying fertility. *Field Crops Res* **119**: 106-113.

Elliott N, Mirik M, Yang ZM, Dvorak T, Rao M, Micheis J, Walker T, Catana V, Phoofolo M, Giles K, Royer T. 2007. Airborne multi-spectral remote sensing of Russian wheat aphid injury to wheat. *South Western Entomologist* **32**: 213–219.

Elliott N, Mirik M, Yang ZM, Jones D, Phoofolo M, Catana V, Giles K, Michels GJ. 2009. Airborne remote sensing to detect greenbug stress to wheat. *South Western Entomologist* **34**: 205-211.

Evans RD. 2001. Physiological mechanisms influencing plant nitrogen isotope composition. *Trends in Plant Sci* **6**: 121-126.

Fang H, Song HY, Cao F, He Y, Qiu ZJ. 2007. Study on the relationship between spectral properties of oilseed rape leaves and their chlorophyll content. *Spectroscopy and Spectral Analysis* **27**: 1731-1734.

Farruggia A, Gastal F, Scholefield D. 2004. Assessment of the nitrogen status of grassland. *Grass and Forage Sci* **59**: 113-120.

Feret JB, Francois C, Gitelson A, Asner GP, Barry KM, Panigada C, Richardson AD, Jacquemoud S. 2011. Optimizing spectral indices and chemometric analysis of leaf chemical properties using radiative transfer modeling. *Remote Sens Env* **115**: 2742-2750.

Feng L, Fang H, Zhou WJ, He Y. 2006. Nitrogen stress measurement of canola based on multi-spectral charged coupled device imaging sensor. *Spect Spec Anal* **26**: 1749-1752.

Fismes J, Vong PC, Guckert A, Frossard E. 2000. Influence of sulfur on apparent N-use efficiency, yield and quality of oilseed rape (*Brassica napus* L.) grown on a calcareous soil. *European J Agron* **12**: 127-141.

Franke J, Menz G. 2007. Multi-temporal wheat disease detection by multi-spectral remote sensing. *Precision Agric* **8**: 161–172.

Genc H, Genc L, Turhan H, Smith SE, Nation JL. 2008. Vegetation indices as indicators of damage by the sunn pest (Hemiptera: Scutelleridae) to field grown wheat. *African J Biotech* **7**: 173-180.

Gitelson AA, Merzlyak NM, Chivkunova BO. 2001. Optical properties and non-destructive estimation of anthocyanin content in plant leaves. *Photochem Photobiol* **74**: 38-45.

Glazebrook J. 2005. Contrasting mechanisms of defence against biotrophic and necrotrophic pathogens. *Annu Rev Phytopathol* **43**: 205-227.

Goel PK, Prasher SO, Landry JA, Patel RM, Viau AA. 2003. Estimation of crop biophysical parameters through airborne and field hyperspectral remote sensing. *Trans. ASAE* **46**: 1235-1246.

Gomez NV, Miralles DJ. 2011. Factors that modify early and late reproductive phases in oilseed rape (*B. napus* L.): its impact on seed yield and oil content. *Ind Crops Prod* **34**: 1277-1285.

González-Lara R, González LM. 1991. Analysis of the soluble proteins in grape musts by reversed-phase HPLC. *Chromatographia* **32**: 463-465.

Gowen AA, O'Donnell CP, Cullen PJ, Downey G, Frias JM. 2007. Hyperspectral imaging—an emerging process analyticaltool for food quality and safety control. *Trends Food Sci Technol* **18**: 590-598.

Green RM, Hay SI. 2002. The potential of Pathfinder AVHRR data for providing surrogate climatic variables across Africa and Europe for epidemiological applications. *Remote Sens Env* **79**: 166-175.

Guan J, Nutter FW. 2002. Relationships between defoliation, leaf area index, canopy reflectance, and forage yield in the alfalfa-leaf spot pathosystem. *Comp Electron Agric* **37**: 1-3.

Gulen H, Turhan E, Eris A. 2006. Changes in peroxidase activities and soluble proteins in strawberry varieties under salt-stress. *Acta Physiol. Plant* **28**: 109-116.

Habib G. 2000. A soft Computing Approach for Classification of Insects in Agricultural Ecosystems. PhD thesis, New Mexico State University.

Habib G, Nadipuram RP, John JE. 2000. A neuro-fuzzy approach for insect classification. In: World Automatic Congress, 3rd International Symposium on Soft Computing foe Industry, Maul, Hawaii.

Hansena PM, Schjoerring JK. 2003. Reflectance measurement of canopy biomass and nitrogen status in wheat crops using normalized difference vegetation indices and partial least squares regression. *Remote Sen Env* **86**: 542-553.

Hoff JE. 1975. A simple method for the approximate determination of soluble protein in potato tubers. *Potato Res* **18**: 428-432.

Högya P, Franzaring J, Schwadorf K, Breuer J, Schütze W, Fangmeier A. 2010. Effects of free-air CO2 enrichment on energy traits and seed quality of oilseed rape. *Agric Ecosyst Env* **139**: 239-244.

Kumar J, Vashisth A, Sehgal VK, Gupta VK. 2013. Assessment of aphid infestation in mustard by hyperspectral remote sensing. *J Indian Soc Remote Sens* **10**.1007/s12524-012-0207-6.

Jago RA, Cutler MEJ, Curran PJ. 1999. Estimating canopy chlorophyll concentration from field and airborne spectra. *Remote Sens Env* **68**: 217-224.

Jeon HY, Tian LF, Zhu HP. 2011. Robust crop and weed segmentation under uncontrolled outdoor illumination. *Sensors* **11**: 6270-6283.

Jørgensen RN, Christensen LK, Bro R. 2007. Spectral reflectance at sub-leaf scale including the spatial distribution discriminating NPK stress characteristics in barley using multiway partial least squares regression. *Intl J Remote Sens* **28**: 943-962.

Kanemasu ET, Niblett CL, Manges H, Lenhert D, Newman MA. 1974. Wheat: its growth and disease severity as deduced from ERTS-1. *Remote Sens Env* **3**: 255-260.

Kim YS, Reid JF, Hansen A, Zhang Q. 2000. On-field crop stress detection system using multi-spectral imaging sensor. *Agril Biosys Eng* **2**: 88-94.

Knogge W. 1996. Fungal infection of plants. *Plant Cell* **8**: 1711-1722.

Kumar A, Bhatia SC. 2006. Polypeptide markers for low temperature stress during seed germination in sunflower. *Plantarum* **50**: 81-86.

Lamb DW, Weedon M. 1998. Evaluating the accuracy of mapping weeds in fallow fields using airborne digital imagery: *Panicum effusum* in oilseed rape stubble. *Weed Res* **38**: 443-451.

Larsolle A, Muhammed HH. 2007. Measuring crop status using multivariate analysis of hyperspectral field reflectance with application to disease severity and plant density. *Precis Agric* **8**: 37-47.

Laudien R, Bareth G, Doluschitz R. 2004. Comparison of remote sensing based analysis of crop diseases by using high resolution multispectral and hyperspectral data - case study: Rhizoctoniasolani in sugarbeet. In: Proc.12th International Conference on Geoinformatics–Geospatial Information Research: Bridging the Pacific and Atlantic, University of Gavle, Sweden, 7–9 June, pp. 670-676.

Ledoux M, Lamy F. 1986. Determination of proteins and sulfobetaine with the Folin-phenol reagent. *Anal Biochem* **157**: 28-31.

Lee KS, Cohen WB, Kennedy RE, Maiersperger TK, Gower ST. 2004. Hyperspectral versus multispectral data for estimating leaf area index in four different biomes. *Remote Sens Env* **91**: 508-520.

Liu F, He Y. 2008. Classification of brands of instant noodles using vis/NIR spectroscopy and chemometrics. *Food Res Intl* **41**: 562-567.

Liu F, Jin ZL, Naeem MS, Tian T, Zhang F, He Y, Fang H, Ye QF, Zhou WJ. 2011a. Applying near-infrared spectroscopy and chemometrics to determine total amino acids in herbicidestressed oilseed rape leaves. *Food and Bioprocess Technol* **4**: 1314-1321.

Liu F, Nie PC, Huang M, Kong WW, He Y. 2011. Nondestructive determination of nutritional information in oilseed rape leaves using visible/ near infrared spectroscopy and multivariate calibrations. *Sci China Inform Sci* **54**: 598-608.

Liu F, Zhang F, Jin ZL, He Y, Fang H, Ye QF, Zhou W. 2008. Determination of acetolactate synthase activity and protein content of oilseed rape (*B. napus*) leaves using visible/ near-infrared spectroscopy. *Analytica Chimica Acta* **629**: 56-65.

Liu ZY, Shi JJ, Zhang LW. 2010. Discrimination of rice panicles by hyperspectral reflectance data based on principal component analysis and support vector classification. *J Zhejiang Univ Sci* B **11**: 71-78.

Malthus TJ, Madeira AC. 1993. High resolution spectroradiometry: spectral reflectance of field bean leaves infected by *Botrytis fabae*. *Remote Sen Env* **45**: 107-116.

Menges RM, Nixon PR, Richardson AJ. 1985. Light reflectance and remote sensing of weeds in agronomic and horticultural crops. *Weed Sci* **33**: 569-581.

Mirik M, Michels GJ, Mirik SK, Elliott NC, Catana V, Jones DB, Bowling R. 2006a. Using digital image analysis and spectral reflectance data to quantify damage by greenbug (Hemitera: Aphididae) in winter wheat. *Comp Electr Agric* **5**: 86-98.

Mirik M, Michels GJ, Mirik SK, Elliott NC, Catana V. 2006c. Spectral sensing of aphid (Hemiptera: Aphididae) density using field spectrometry and radiometry. *Turkish J Agric Forestry* **30**: 421-428.

Mirik M, Michels GJ, Mirik SK, Jones D, Elliott NC, Catana V, Bowling R. 2005. Hyperspectral field spectrometry for estimating greenbug (Homoptera: Aphididae) damage in wheat. In: 29 Biennial Workshop on Aerial Photography, Videography, and High Resolution Digital Imagery for Resource Assessment, Texas.

Mirik M, Michels GJ, Sabina KM, Elliott NC, Bowling R. 2006b. Hyperspectral spectrometry as a means to differentiate uninfested and infested winter wheat by greenbug (Hemiptera: Aphididae). *J Econ Ento* **99**: 1682-1690.

Mirik SK, Elliott NC. 2007. Reflectance characteristics of Russian wheat aphid (Hemiptera: Aphididae) stress and abundance in winter wheat. *Comp Electr Agric* **57**: 123-134.

Mistele B, Schmidhalter U. 2008. Estimating the nitrogen nutrition index using spectral canopy reflectance measurements. *Europ J Agron* **29**: 184-190.

Mitchell MT. 1998. Machine Learning. Singapore: McGraw Hill. 352 p.

Nageswara Rao PP, Rao VR. 1982. Identification of brown plant hopper and bacterial leaf blight affected rice crop on LANDSAT false colour composites. In: Proc. 3rd Asian Conference of Remote Sensing, Dhaka, Bangladesh, 4-7 Dec, pp. 1-12.

Navalgund RR, Ray SS. 2000. *Proceedings of Geomatics-2000*. 21-22 January, 2000, Pune, pp. NR1-NR14

Parihar JS and Ray SS. 2002. *Lecture Note of ISPRS Pre-Symposium tutorial on Sustainable Agriculture.* Dec 2, 2002. Hyderabad.

Patel SJ, Subramanian RB, Jha YS. 2011. Biochemical and molecular studies of early blight disease in tomato. *Phytoparasitica* **39**: 269-283.

Patten T, Li WJ, Bebis G, Hussain M. 2011. Assessing insect growth using image analysis. *Intl J Artificial Intellig Tools* **20**: 511-530.

Penuelas J, Baret F, Filella I. 1995. Semiempirical indexes to assess carotenoids/ chlorophyll-a ratio from leaf spectral reflectance. *Photosynthetica* **31**: 221-230.

Petisco C, Garcý´a-Criado B, Va´zquez-de-Aldana BR, Haro A de, Garcý´a-Ciudad A. 2010. Measurement of quality parameters in intact seeds of Brassica species using visible and near-infrared spectroscopy. *Ind Crops Products* **32**: 139-146.

Pettigrew WT. 2008. Potassium influences on yield and quality production for maize, wheat, soybean and cotton. *Physiologia Plantarum* **133**: 670-681.

Pinter P Jr, Hatfield JL, Schepers JS, Barnes EM, Moran MS, Daughtry CST, Upchurch DR. 2003. Remote sensing for crop management. *Photogrammetry Remote Sens* **69**: 647-664.

Qin Z, Zhang M, Christensen T, Li W, Tang H. 2003. Remote sensing analysis of rice disease stresses for farm pest management using wide-band airborne data.In: Proceedings of Geoscience and Remote Sensing ymposium, IGARSS, IV, July, Toulouse, France, pp. 2215-2217.

Raghothama KG, Karthikeyan AS. 2005. Phosphate acquisition. *Plant and Soil* **274**: 37-49.

Raikes C, Burpee LL. 1998. Use of multispectral radiometry for assessment of Rhizoctonia blight in creeping bentgrass. *Phytopathol* **88**: 446-449.

Rathke GW, Behrens T, Diepenbrock W. 2006. Integrated nitrogen management strategies to improve seed yield, oil content and nitrogen efficiency of winter oilseed rape (*B. napus* L.): a review. *Agric Ecosys Env* **117**: 80-108.

Ray SS, Singh JP, Das G, Panigrahy S. 2004. *The Int Arch Photogram Rem Sens & Spatial Inform Syst* **35**: 127-231.

Reisig D, Godfrey L. 2007. Spectral response of cotton aphid (Homoptera: Aphididae) and spider mite (Acari: Tetranychidae) infested cotton: controlled studies. *Envl Ent* **36**: 1466-1474.

Reisig D, Godfrey L. 2010. Remotely sensing arthropod and nutrient stressed plants: a case study with nitrogen and cotton aphid (Hemiptera: Aphididae). *Envl Ent* **39**: 1255-1263

Richardson AD, Aikens M, Berlyn GP, Marshall P. 2004. Drought stress and paper birch (*Betula papyrifera*) seedlings: effects of an organic biostimulant on plant health and stress tolerance, and detection of stress effects withinstrument-based, noninvasive methods. *J Arboricult* **30**: 52-61.

Richardson MD, Karcher DE, Purcell LC. 2001. Quantifying turfgrass cover using digital image analysis. *Crop Sci* **41**: 1884-1888.

Riedell WE, Blackmer TM. 1999. Leaf reflectance spectra of cereal aphid damaged wheat. *Crop Sc* **39**: 1835-1840.

Steddom K, Bredehoeft WM, Khan M, Rush MC. 2005. Comparison of visual and multispectral radiometric disease evaluations of Cercospora leaf spot of sugar beet. *Plant Dis* **89**: 153-158.

Steddom K, Heidel G, Jones D, Rush MC. 2003. Remote detection of rhizomania in sugar beets. *Phytopathol* **93**: 720-726.

Steddom K, Bredehoeft MW, Khan M, Rush CM. 2005. Comparison of visual and multispectral radiometric disease evaluations of cercospora leaf spot of sugar beet. *Plant Dis* **89**: 153-158.

Strand JF. 2000. Some agrometeorological aspects of pest and disease management for the 21st century. *Agril Forest Meteorol* **103**: 73-82.

Tarpley L, Reddy KR, Sassenrath-Cole GF. 2000. Reflectance indices with precision and accuracy in predicting cotton leaf nitrogen concentration. *Crop Sci* **40**: 1814-1819.

Taulavuori E, Tahkokorpi M, Laine K, Taulavuori K. 2010. Drought tolerance of juvenile and mature leaves of a deciduous dwarf shrub *Vacciniummyrtillus*L. in a boreal environment. *Protoplasma* **241**: 19-27.

Thenkabail P, Smith RB, De Pauw E. 2002. Evaluation of narrow band and broad band vegetation indices for determining optimal hyperspectral wave bands for agricultural crop characterisation. *Photogrammetry Eng Remote Sens* **68**: 607-627.

Thenkabail PS, Smith RB, De Pauw E. 2000. Hyperspectral vegetation indices and their relationships with agricultural crop characteristics. *Remote Sens Environ* **71**: 158-182.

Tyystjarvi E, Norremark M, Mattila H, Keranen M, Hakala-Yatkin M, Ottosen CO, Rosenqvist E. 2011. Automatic identification of crop and weed species with chlorophyll fluorescence induction curves. *Precision Agric* **12**: 546-563.

Valantin-Morison M, Meynard JM, Dore T. 2007. Effects of crop management and surrounding field environment on insect incidence in organic winter oilseed rape (*B. napus* L.). *Crop Protec* **26**: 1108-1120.

Van Hezewijk BH, De Clerck-Floate RA, Moyer JR. 2008. Effect of nitrogen on the preference and performance of a biological control agent for an invasive plant. *Biol Control* **46**: 332-340.

Velioglu HM, Boyaci IH, Kurultay S. 2011. Determination of visual quality of tomato paste using computerized inspection system and artificial neural networks. *Comp Electr Agric* **77**: 147-154.

Venette J. 1998. Sclerotinia spore formation, transport and infection. In: Proceedings of Xth International Sclerotinia Workshop, 21 January, 1998, Fargo, North Dakota, USA, pp. 5-9.

Vigneau N, Ecarnot M, Rabatel G, Roumet P. 2011. Potential of field hyperspectral imaging as a non destructive method to assess leaf nitrogen content in wheat. *Field Crops Res* **122**: 25-31.

Wang X, Zhang M, Zhu J, Geng S. 2008. Spectral prediction of Phytophthorainfestans infection on tomatoes using artificial neural networks (ANN). *Int J Remote Sens* **29**: 1693-1706.

West JS, Bravo C, Oberti R, Lemaire D, Moshou D, Mccartney HA. 2003. The potential of optical canopy measurement for targeted control of field crop diseases. *Ann Rev Phytopath* **41**: 593-614.

Wilson RC, Overton TR, Clark JH. 1998. Effects of Yucca shidigera extract and soluble protein on performance of cows and concentrations of urea nitrogen in plasma and milk. *J Dairy Sci* **81**: 1022-1027.

Wolf FJP, Verreet AJ. 2002. An integrated pest management system in Germany for the control of fungal leaf diseases in sugar beet: The IPM sugar beet model. *Plant Dis* **86**: 336-344.

Wu D, Shi H, Wang S, He Y, Bao Y, Liu K. 2012a. Rapid prediction of moisture content of dehydrated prawns using online hyperspectral imaging system. *Anal Chim Acta* **726**: 57-66.

Zhang X, Liu F, He Y, Gong X. 2013. Detecting macronutrients content and distribution in oilseed rape leaves based on hyperspectral imaging. *Biosys Eng* **115**: 56-65.

Xu HR, Ying YB, Fu XP, Zhu SP. 2007. Near-infrared spectroscopy in detecting leaf miner damage on tomato leaf. *Biosys Eng* **96**: 447-454.

Yang Z. 2005. Detecting Greenbug Infestation on Wheat Using Ground-based Multi-spectral Radiometry. Ph.D. Dissertation, Oklahoma State University.

Yang Z. Rao MN, Elliott NC. 2005. Using ground-based multispectral radiometry to detect stress in wheat caused by greenbug (Homoptera: Aphididae) infestation. *Comp Electron Agric* **47**: 121-135.

Yang Z, Rao MN, Elliott NC, Kindler SD, Popham TW. 2009. Differentiating stress induced by greenbugs and Russian wheat aphids in wheat using remote sensing. *Comp Electron Agric* **67**: 64-70.

Yao X, Zhu Y, Tian YC, Feng W, Cao WX. 2010. Exploring hyperspectral bands and estimation indices for leaf nitrogen accumulation in wheat. *Int J Appl Earth Obs Geoinfo* **12**: 89–100.

Zeng JM, Zhang L, Li YQ, Wang Y, Wang MC, Duan X, He ZG. 2010. Over-producing soluble protein complex and validating protein-protein interaction through a new bacterial co-expression system. *Protein Expres Purif* **69**: 47-53.

Zhang M, Qin Z. 2004. Spectral analysis of tomato late blight infections for remote sensing of tomato disease in California. In: Proceedings of ecoscience and Remote Sensing Symposium, IGARSS **6**: 4091-4094.

Zhang NQ, Wang MH, Wang N. 2002. Precision agriculture-A world wide overview. *Comput Electron Agric* **36**: 113-132.

Zhang X, He Y. 2013. Rapid estimation of seed yield using hyperspectral images of oilseed rape leaves. *Industrial Crops and Products* **42**: 416-420

Zhao Y, Xu X, Liu F, He Y. 2011. A novel hyperspectral waveband selection algorithm for insect attack detection. *Trans ASABE* **55**: 281-291.

Zheng WS, Fei YH, Huang Y. 2009. Soluble protein and acid phosphatase exuded by ectomycorrhizal fungi and seedlings in response to excessive Cu and Cd. *J Environ Sci* **21**: 1667-1672.

Zou XB, Shi JY, Hao LM, Zhao JW, Mao HP, Chen ZW, Li YX, Holmes M. 2011. *In vivo* non-invasive detection of chlorophyll distribution in cucumber (*Cucumis sativus*) leaves by indices based on hyperspectral imaging. *Anal Chim Acta* **706**: 105-112.