

# Outdoor Applications of Hyperspectral Imaging Technology for Monitoring Agricultural Crops: A Review

Mohammad Raju Ahmed<sup>1</sup>, Jannat Yasmin<sup>1</sup>, Changyeun Mo<sup>2</sup>, Hoonsoo Lee<sup>3</sup>, Moon S. Kim<sup>3</sup>,  
Soon-Jung Hong<sup>4</sup>, Byoung-Kwan Cho<sup>1\*</sup>

<sup>1</sup>Department of Biosystems Machinery Engineering, College of Agricultural and Life Science, Chungnam National University, 99 Daehak-ro, Yuseong-gu, Daejeon 34134, Korea

<sup>2</sup>National Academy of Agricultural Science, Rural Development Administration, 310 Nongsaengmyeong-ro, Wansan-gu, Jeonju, Jeollabuk-do 54875, Korea

<sup>3</sup>Environmental Microbiology and Food Safety Laboratory, BARC-East, Agricultural Research Service, US Department of Agriculture, 10300 Baltimore Avenue, Beltsville, MD 20705, USA

<sup>4</sup>Rural Human Resource Development Center, 420 Nongsaengmyeong-ro, Wansan-gu, Jeonju, Jeollabuk-do 54874, Korea

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## Abstract

**Background:** Although hyperspectral imaging was originally introduced for military, remote sensing, and astrophysics applications, the use of analytical hyperspectral imaging techniques has been expanded to include monitoring of agricultural crops and commodities due to the broad range and highly specific and sensitive spectral information that can be acquired. Combining hyperspectral imaging with remote sensing expands the range of targets that can be analyzed. **Results:** Hyperspectral imaging technology can rapidly provide data suitable for monitoring a wide range of plant conditions such as plant stress, nitrogen status, infections, maturity index, and weed discrimination very rapidly, and its use in remote sensing allows for fast spatial coverage. **Conclusions:** This paper reviews current research on and potential applications of hyperspectral imaging and remote sensing for outdoor field monitoring of agricultural crops. The instrumentation and the fundamental concepts and approaches of hyperspectral imaging and remote sensing for agriculture are presented, along with more recent developments in agricultural monitoring applications. Also discussed are the challenges and limitations of outdoor applications of hyperspectral imaging technology such as illumination conditions and variations due to leaf and plant orientation.

**Keywords:** Hyperspectral imaging, Outdoor monitoring, Remote sensing, Plant stress, Nitrogen status

## Introduction

The world population is increasing steadily. Increasing agricultural production to meet the increasing demand has become one of the most challenging tasks for achieving global food security (Senthilnath et al., 2016). Agricultural resources, such as land for planting and water for irrigation, are quite limited, which makes the problem even more challenging. By 2050, production needs to be increased by ~60%, compared with the yield in the 2005-2007 period

(Alexandratos and Bruinsma, 2012). Therefore, significant attention has been devoted to developing new technologies to increase agricultural production.

Spectral imaging was introduced nearly 40 years ago. In the early 1990's, this technology was limited to terrestrial military applications, remote sensing, and astrophysics (Rencz and Ryerson, 1999). Spectral imaging combines digital imaging and spectroscopy; therefore, the resulting image provides more detailed information about the scene than the image acquired using a conventional color camera. In multispectral imaging (MSI), the same image is acquired in several wavelength regions, using only a very limited number of spectral bands. Hyperspectral imaging

\*Corresponding author: Byoung-Kwan Cho

Tel: +82-42-821-6715; Fax: +82-42-823-6246

E-mail: chobk@cnu.ac.kr

(HSI), on the other hand, divides the spectrum into many bands (Yang et al., 2014), each with a very narrow bandwidth. In the term hyperspectral, “hyper” refers to using many light sensors, each with a very narrow range of sensitivity (Ahmadi et al., 2013). HSI is a very powerful technique for measuring, analyzing, and interpreting spectra acquired from a given object or scene. The technique can be used in applications involving very short and very long distances, by employing airborne or satellite-based sensors (Goetz et al., 1985). Owing to their high information content, hyperspectral images are well-suited for automated image processing, which can be used for monitoring agricultural crops, both indoors and outdoors.

The application of HSI with remote sensing in agriculture will allow for real-time gathering of crop condition data, monitoring of the field environment, and precise irrigation and supply of fertilizers to the crops, which will increase production while decreasing cost and labor. This imaging method also allows for disease detection and weed mapping in agricultural crops, and will yield information on vegetation characteristics, estimated yield, maturity stages, and seed viability, all of which play vital roles in increasing production. HSI with remote sensing is a rapid, easy, and non-destructive technique that has been used by many researchers in agricultural fields (Thenkabail et al., 2000; Apan et al., 2004; Jay et al., 2010; Yang et al., 2014; Nansen et al., 2015; Senthilnath et al., 2016), making it a promising analytical tool for agricultural applications.

In this paper, we summarize the current research and potential applications of HSI and remote sensing for outdoor agricultural crop monitoring. To facilitate a better understanding of HSI, the foundations and instrumentation of the method are also presented here, along with brief explanations of the uses of HSI and remote sensing in agriculture. We review papers published during the last few decades, in order to demonstrate the various outdoor applications of this method. Limitations of the outdoor use of spectral imaging technology are also discussed.

### HSI foundations and instrumentation

When light is focused on an object or material, the object instantly reacts; this light-matter interaction is the basis of spectral imaging. Visible light and other types of electromagnetic radiation are normally defined in terms of their wavelengths. The light-matter interaction is wavelength-dependent, and the outcomes of different interactions are often manifested in reflectance, transmittance,

absorbance, phosphorescence, fluorescence, or radioactive decay. These manifestations provide a detailed fingerprint of a sample in terms of its physical characteristics (Figure 1) (ElMasry and Sun, 2010). Electromagnetic radiation is divided into several types depending on the wavelength: gamma rays, X-rays, ultraviolet radiation (UV), visible light (VIS, 0.4-0.7  $\mu\text{m}$ ), near-infrared (NIR, 0.7-1.0  $\mu\text{m}$ ), short-wave infrared (SWIR, 1.0-2.5  $\mu\text{m}$ ), mid-infrared (MWIR, 2.5-15  $\mu\text{m}$ ), far-infrared, microwaves, and radio waves (FM and AM) (Fischer and Kakoulli, 2006; ElMasry and Sun, 2010). Each region is correlated to distinctive atomic or molecular transitions, according to the radiation energy. For HSI, NIR to MWIR range radiation is most commonly used for monitoring and quality inspection of agricultural products (ElMasrya et al., 2012; Kandpal et al., 2015).

When photons are incident on the surface of a medium or an object, light-matter interaction takes place immediately. Depending on the energy of the incident photons, the atoms in the irradiated sample will transition into lower or higher molecular energy levels, indicating a change in the vibrational mode of the bonds between the atoms. Consequently, the extent to which light is emitted or absorbed defines the properties of the material. A detector reacts to the irradiation and records the amount of light that is emitted or absorbed. The two main types of detectors are thermal and photonic. In HSI of agricultural crops, photonic detectors are commonly used for monitoring. Different types of detectors have been proposed; in particular, charge-coupled devices (CCDs) that are made from low-cost lead

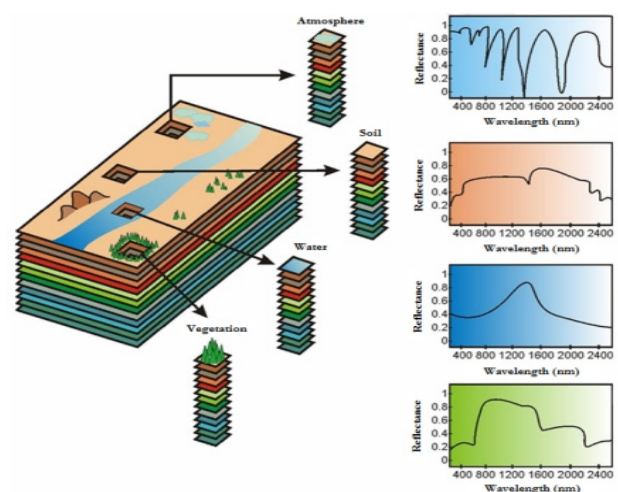


Figure 1. Concept of HSI illustrated using NASA's AVIRIS (Plaza et al., 2009).

**Table 1.** Characteristics of HSI systems used in agricultural applications

Detectors	Spectral range	Application in agriculture	Reference
CCD	400-1000 nm	detecting bruises on apple	Xing et al., 2005
MCT	900-1700 nm	detecting aflatoxin on corn kernels	Kandpal et al., 2015
CCD	398-1010 nm	detecting blueberry fruit maturity	Yang et al., 2014
CCD	550-800 nm	detecting fungal diseases	Moshou et al., 2011
CCD	400-720 nm	detecting external insect infestations	Wang et al., 2011
CCD	385-1000 nm	detecting water stress	Kim et al., 2011
CCD	650-1100 nm	measuring soluble solids	Martinsen and Schaare, 1998
CCD	400-1000 nm	bruise damage detection on mushrooms	Gowen et al., 2008
CCD	400-1000 nm	quality attributes for strawberry	EIMasry et al., 2007
CCD	600-1000 nm	detection of apple fruit firmness	Lu and Peng, 2007
CCD	400-1000 nm	evaluation of the shelf-life of mushrooms	Taghizadeh et al., 2010
CCD	400-1000 nm	defect and surface color of whole pickles	Ariana and Lu, 2010
CCD	430-900 nm	poultry inspection	Lu and Chen, 1999
CCD	400-1000 nm	maturity stages of banana	Rajkumar et al., 2012
CCD	500-1000 nm	peach fruit firmness	Lu and Peng, 2006
CCD	400-1000 nm	wheat and weed discrimination	Hadoux et al., 2014

oxide-lead sulfide (PbO-PbS), indium gallium arsenide (InGaAs), or mercury cadmium telluride (HgCdTe or MCT) have been commonly applied to determine the amount of light emission or absorption at particular peaks throughout the spectrum (Casini et al., 1999; D'Souza et al., 1999; Sizov, 2000; Gat, 2000; John et al., 2003; Tran, 2003; Bajwa et al., 2004; Rogalski, 2004; Xenics, 2016). In this technique, it is important to identify a distinct spectral range and obtain particular peaks from the spectrum. For a more detailed explanation, see (Xing et al., 2005).

During the last two decades, various types of detectors and spectral ranges have been used for agricultural applications. Some examples are summarized in Table 1.

### Remote sensing in agriculture

The situation in which there is no contact between the sensor and the analyzed object or area is referred to as remote sensing. Monitoring of the biochemical and biophysical attributes of crops is very important for improving plant productivity as well as for investigating water-stress, pigment and moisture content, and nutrient availability. These data can be obtained using direct field techniques; however, this approach is both time-consuming and laborious. On the other hand, remote sensing requires less time, is non-destructive, and provides spatial estimates for quantifying and monitoring these attributes. Satellite or airborne remote sensing is used for monitoring management

in agricultural fields. Lamb and Brown (2001) used airborne remote sensing to identify weeds in the monitored crops. They made two important notes regarding remote sensing: (i) sufficient differences in spectral reflectance or texture exist between weeds and their background soil or plant canopy, and (ii) remote sensing offers an appropriate spatial and spectral resolution for detecting the presence of weed plants. Application of remote sensing for monitoring crop stress, resulting from, e.g., weeds, disease, insects, water, frost, and soil temperature changes, was described by Hatfield and Pinter in 1993. In 1997, Moran et al. reviewed the potential and the limitations of remote sensing for monitoring crops in precision agriculture. They listed the potential of remote sensing for detecting the soil moisture content, crop phenologic stage, crop nutrient deficiencies, crop disease, weed infestation, and insect infestation. In contrast, instrument calibration, atmospheric correction, and cloud screening were identified as the limitations of remote sensing.

### HSI in agriculture

Spectral imaging is defined as a serial acquisition of many digital images, with distinct and well-defined optical wavelengths. There are two main categories-MSI and HSI. MSI refers to the situation in which the number of wavelength bands is 10 or fewer (GIS Geography, 2016; eXtension, 2016); this method has been used in

many areas, including agriculture (Muir et al., 1982; Kim et al., 2002; Lu, 2004; Park et al., 2004). HSI refers to the situation in which the number of wavelength bands is larger than 10.

The major limitation of MSI is its low spectral resolution. This sometimes causes a loss of some critical information, as MSI averages spectral information over broadband widths (Blackburn, 1998; Thenkabail et al., 2000). In contrast, HSI with remote sensing examines many contiguous, narrow spectral channels (Campbell, 1996); thus, it is able to provide additional information, and no critical data are lost. HSI with remote sensing is better than MSI and demonstrates versatility for a variety of crop monitoring applications (Hunt et al., 1989; Blackburn, 1998; Champagne et al., 2003; Zhu et al., 2006; Wang et al., 2008; Prabhakar et al., 2011; Ranjan et al., 2012; Pradhan et al., 2014; Mahajan et al., 2014; Prasannakumar et al., 2014). HSI has already proven to be very effective in defense, agricultural research, and environmental applications (Lu and Chen, 1999; Ustin et al., 2004; Farley et al., 2007).

To identify subtle spectral features corresponding to the chemical and physical properties of an object, HSI spectrometers acquire data in high spectral resolution domains. This has a powerful capability for use in agricultural crop monitoring, vegetation monitoring, and water quality assessment (Thenkabail et al., 2000; Kim et al., 2011). In the last decade, HSI technology has been used for detecting bruises and bitter pits on apples and mushrooms (Nicolai et al., 2006; Gowen et al., 2008), for measuring fruit maturity, firmness and soluble solid content (ElMasry et al., 2007; Lu and Peng, 2007; Noh et al., 2007), for detecting deterioration in mushrooms (Taghizadeh et al., 2010), and for detecting chilling injuries and internal defects in cucumbers (Cheng et al., 2004; Ariana and Lu, 2010).

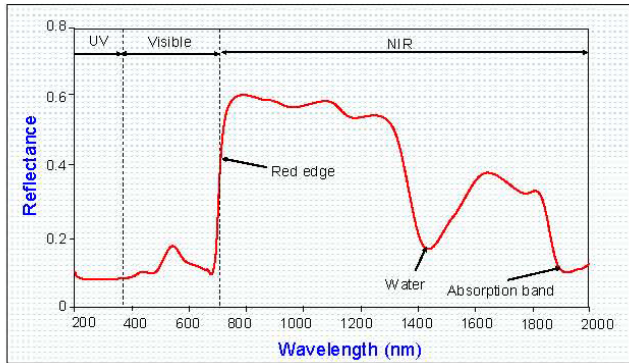
### **Outdoor applications of HSI with remote sensing in agriculture**

HSI is a powerful tool for monitoring agricultural crops. However, the potential outdoor applications of HSI have not been fully explored, owing to some limitations such as variations in the light intensity, background noise, and leaf orientations. Some techniques for overcoming these limitations are discussed below. These barriers are expected to be completely overcome in the near future as HSI technology is improving rapidly.

### ***Chlorophyll pigments and nitrogen status of crop plants***

Wheat is one of the most important food crops worldwide. Monitoring is essential for increasing the production of wheat, and much research has been done on applying HSI with remote sensing to real wheat fields. In wheat monitoring, the key monitored quantities are water stress, nitrogen status, and fungal diseases. Lawlor (2001), Haboudane et al. (2002), and Rodriguez et al. (2005) determined that the presence of chlorophyll pigments in leaf tissues strongly affects the electromagnetic spectrum in the visible region, especially in the blue (450 nm) and red (670 nm) bands. In addition, a relationship between the concentrations of leaf nitrogen and chlorophyll pigments was established; strong absorption of these two wavelengths increased the concentration of chlorophyll pigments, indicating that the leaves of the crop contain high amount of nitrogen. Thus, spectral analysis can provide a measure of nitrogen content.

Plant leaves contain spongy mesophyll cells that strongly reflect infrared wavelengths in the NIR region. In 2000, Barnes et al. have studied reflectance in the NIR region, especially in the red limit. In the visible region, red wavelength reflectance is very low, owing to absorption by chlorophyll for photosynthesis. By contrast, reflectance is dominant in the NIR region, owing to the cellular structure of the leaves. The location of the inflection point (the point of maximal gradient), also termed the "red edge," correlates with the plant chlorophyll amount (Figure 2). Therefore, electromagnetic energy reflected from plant leaves and canopies can be used for estimating the chlorophyll concentration, providing an estimate of the nitrogen content (Haboudane et al., 2002). Lee et al. (2000) found that combining red edge wavelengths with NIR wavelengths yielded good precision and accuracy in predicting cotton leaf nitrogen concentration. Tilling et al. (2006) conducted an experiment on wheat fields using HSI with remote sensing to determine the nitrogen stress. They used a portable spectro-radiometer (FieldSpec® Pro, Analytical Spectral Devices, Boulder, CO, USA) to collect spectral reflectance in the 390-2500 nm range. The experiment was conducted in both 2004 and 2005 over 48 plots (18 m × 12 m), using four rates of nitrogen fertilization (0, 16, 39, and 163 kg N/ha) and two rates of nitrogen fertilization (0 and 39 kg N/ha), respectively. HSI data were collected at a canopy level using a light aircraft. After developing the nitrogen stress index, the researchers found that the amount of nitrogen decreases

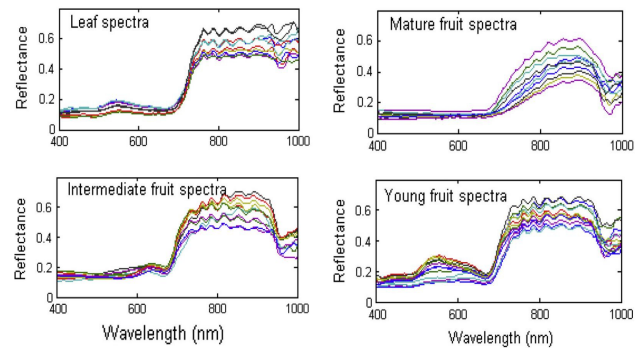


**Figure 2.** Typical reflectance spectrum of a green leaf. Variations in the reflectance at the 'red edge' (in the 650–800 nm range) can be used to discriminate between different plants (Sahba et al., 2006).

through the season owing to depletion of available nitrogen during crop growth. In 2008, Feng et al. determined the relationships between leaf nitrogen concentration and leaf dry weight (LNC), and between leaf nitrogen accumulation per unit soil area (LNA) and ground-based canopy hyperspectral reflectance, in order to establish quantitative models for real-time monitoring of leaf nitrogen in wheat, with particular hyperspectral bands, to reduce the amount of data and to expedite the computation, which is most important for real-time monitoring. In numerous studies, both HSI and MSI have proved their efficiency in assessing physiological parameters and nutrient levels in crop plants. Hinzman et al. (1986), Takebe et al. (1990), McMurtrey et al. (1994), and Diker and Bausch (2003) studied the nitrogen effect on wheat, rice, and corn, respectively, using spectral reflectance. In addition, Casanova et al. (1998) and Hansen and Schjoerring (2003) conducted experiments to determine vegetation indices for rice and wheat fields using HSI.

### *Maturity identification*

Fruits from the same cluster normally mature at different times. A cluster may contain all growth stages, including young fruit, intermediate fruit, and mature fruit. In 2014, Yang et al. reported a method for detecting different blueberry fruit maturity stages using field HSI. They investigated the feasibility of HSI for classifying blueberry growth stages. They also determined useful spectral bands suitable for an MSI system since an MSI system has a higher processing speed and lower cost. The spectral range was 398–1010 nm with a spatial resolution of 1 mm. The original image contained 776 bands with a spectral resolution of 0.79 nm; thus, the images had a



**Figure 3.** Spectra of ten pixels for each class: background (leaf), mature fruit, intermediate fruit, and young fruit (Yang et al., 2014).

very large size. Therefore, binning was used to reduce the spectral resolution by half, i.e., to 388 bands with a spectral resolution of 1.59 nm. The data for the different fruit growth stages are shown in Figure 3. Leaf pixels were used for showing the background spectrum because most of the background was occupied by leaves.

In the NIR region, leaves exhibited high reflectance, because they contained the largest amount of chlorophyll pigments. By contrast, the mature fruits were very dark, thus exhibiting a comparatively low reflectance. The intermediate fruits were red and the young fruits were green; thus, these exhibited higher values in the red and green bands, respectively.

In addition, many investigations of fruit maturity using HSI, based on laboratory measured spectral data, have been performed (Nagata et al., 2004, Carley, 2006; Lu and Peng, 2006; Rajkumar et al., 2012; Yang et al., 2012).

### *Detection of disease or infections*

Typically, healthy plants interact (absorb, reflect, emit, transmit, or fluoresce) with electromagnetic radiation differently from infected plants. Using this hypothesis, Moshou et al. (2011) investigated arable crops for which hyperspectral reflectance and MSI techniques were developed for simultaneous acquisition in the canopy. Lee et al. (2010) reported that fluorescence spectroscopy is the most appropriate technique for detecting fungal disease. When a leaf or stem is infected with fungi, it loses pigmentation, so that photosynthetic processes cannot run properly. As a result, the cell walls collapse and the infection patterns become visible. According to Lee et al. (2010), pathogen propagation and chlorophyll degradation can be detected in the visible region (400–700 nm) and at the red edge (related to chlorophyll), while short wave NIR



(680-800 nm) and NIR (1400-1600 nm and 1900-2100 nm) are suitable for detecting browning and dryness, respectively. In wheat, rye, barley, and oat production, *Fusarium* infections often cause serious problems by reducing yield and grade and may also contaminate the grain with fungal toxins. Bauriegel et al. (2011) studied wheat using HSI for early detection of *Fusarium* infections. *Fusarium* infections cause head blight disease in the wheat plants, which can be detected by performing spectral analysis (400-1000 nm). The group began with laboratory experiments with the plants under controlled conditions in a greenhouse. The plants were artificially inoculated with a mixture of pathogens of the strain *F. culmorum* on three successive days from the beginning of flowering, and then, data were acquired. After that, the experiment was moved to the field (Julius-Kuehn-Institute, Braunschweig, Germany). According to the published report, head blight could successfully be recognized during its development. The use of HSI for detecting various diseases in crop plants is currently under extensive investigation. Pozdnyakova et al. (2002), Williams et al. (2010), and Bauriegel et al. (2010) studied, respectively, the phytophthora root rot, *Fusarium verticillioides* in maize and *Fusarium* head blight detection on wheat using HSI. In addition, Sankaran et al. (2010) reviewed the use of HSI techniques for detecting plant diseases. In many studies, it was also found that the spectral signatures of the crop plants were changed by the fungi and bacterial damage at molecular, cellular and/or tissue levels (Zhensheng and Buchenauer, 2000; West et al., 2003).

### *Plant stress detection*

Plant stress owing to biotic or abiotic factors is expressed in the plant canopy by a variety of symptoms. Productivity is significantly reduced when a plant becomes stressed. Therefore, early detection of plant stress is critical for minimizing the loss of productivity. Machine vision algorithms and infrared imagery have already been applied for estimating plant water stress in tomato canopies, olive orchards, and deciduous trees by Kurata and Yan (1996), Kacira et al. (2002), Sepulcre-Canto et al. (2006), and Naor (2008), respectively. However, plant stress can be a compound result of the effects of water and nutrient levels, disease, and insects, which makes accurate stress detection very challenging. Recent studies indicate that HSI can be used for efficiently detecting plant stress. Using a hyperspectral camera, the

spectral signature of plant leaves was analyzed to identify the onset and intensity of plant water stress. Kim et al. (2011) studied young apple trees inside of a greenhouse with five different levels of water treatment. A hyperspectral camera, along with an active-illuminated spectral vegetation sensor and a digital color camera, was used to monitor the plants within a spectral range of 385-1000 nm. Chlorophyll and xanthophylls in plant leaves absorb most of the radiance in the visible region; in contrast, reflectance occurs in the NIR region. When a plant becomes stressed, the reflectance pattern changes owing to a reduction in photosynthetic absorbance. As a result, reflectance increases in the visible region and decreases in the NIR region. Thus, plant stress can be estimated by combining data from these different spectral bands. Zygielbaum et al. (2009) observed drought stress in maize plants inside a greenhouse. They investigated the reflectance at two wavelengths related to relative water content and reported optimal results for  $R_{520} / R_{720}$  with an  $R^2 = 0.99$ . Vegetation indices (VIs) correspond to a mathematical combination or transformation of spectral regions that accentuates the spectral properties of green plants such that they appear distinct from other image features. Curran et al. (2001) and Sanches et al. (2013) successfully applied VIs in photogrammetry and remote sensing for plant-related research, especially for identifying stressed plants.

### *Crop plant and weed discrimination*

The use of spectral properties to differentiate plant species was reviewed by Zwiggelaar (1998). That review included a discussion on different modeling approaches to estimate reflection from crops using optical and chemical information. The identification of weeds in an agricultural field via remote sensing was reviewed by Thorp and Tian (2004). The researchers discussed the use of different canopy spectral responses of weeds and crops for discriminating between weeds and crops using remote sensing technology. Hadoux et al. (2014) reported a method for discriminating weeds and wheat using spectra acquired in the real field, where lighting and leaf orientations were uncontrolled. The vegetation spectra of weeds and wheat are highly similar; thus, large spectral variability was required for differentiating weeds from wheat. Several pre-treatment methods, such as centering, linear de-trending, normalization, logarithmic transformation, first and second derivation, and smoothing, combined

with partial least squares linear discriminant analysis (PLS-LDA), and Gaussian support vector machine (SVM) were applied to remove nuisance variability such as soil and leaf orientation differences. The best discrimination was obtained using a combination of the logarithmic transformation and PLS-LDA method (Hadoux et al., 2014). Borregaard et al. (2000) and Piron et al. (2008) estimated the effective wavelengths for discriminating carrots from weeds, and potatoes from various weed leaves, under artificial lighting.

### *Other applications*

Xiao and Xu (2010) investigated the impact of heavy metals on wheat leaves, which is relevant when the irrigation water is supplied from sewage. Hyperspectral remote sensing technology was used, and the spectral region was 350-1050 nm with a resolution of 3 nm. The researchers used an atomic absorption flame spectrophotometer for detecting the copper and zinc content, and used graphite furnace atomic absorption spectrometry for detecting the lead content. Differences between reflectance characteristics of wheat leaves irrigated by clear ground water and by sewage were evaluated, revealing that high amounts of copper, zinc, and lead affect the chlorophyll content of vegetation.

Spectral variation among four grape varieties (Cabernet Sauvignon, Merlot, Semillon, and Shiraz) was examined by Lacar et al. (2001). The objective of that study was to evaluate the potential of airborne visible-NIR hyperspectral imagery for discrimination and mapping of grape vine varieties, namely Shiraz and Cabernet Sauvignon. The experiment was conducted at the Koonunga Hill vineyard in the Barossa Valley, South Australia. The spectral region was 400-900 nm, and 80 spectral samples were randomly selected for each variety. The images were statistically analyzed to determine whether there were any differences between the two varieties, and if so, to identify the spectral regions in which the differences were the most significant. Nine bands in the visible region (400-700 nm) of the spectrum were identified, while the infrared band at 711 nm showed only a slight difference.

### **Limitations**

While the spectral properties of agricultural crops have been analyzed in a laboratory, they cannot be directly compared to outdoor measurements owing to the different measurement conditions. Light sources are controlled and

stable in the laboratory setting. In addition, the samples are well prepared with little background noise, which makes the environment ideal for collecting spectral data. In contrast, field measurement uses sunlight as its illumination source, and the background contains various types of plant leaves, stems, soil, sky, and man-made objects such as polyvinyl chloride (PVC) irrigation pipes. Owing to the inconsistency of sunlight and the increased background noise, acquisition of spatial and spectral data becomes more critical (Yang et al., 2014). Leaf orientation is also a major factor in discriminating between different plant species when HSI is used outdoors. Franz et al. (1991) reported that accurate spectral discrimination is possible for controlled leaf orientations, but discrimination accuracy significantly decreases as soon as leaf orientation changes. Vigneau et al. (2011) explored the effect of leaf orientation for building a predictive model for nitrogen content using HSI. Identifying weeds in the crop rows is a much more difficult problem, which requires more advanced processing of spectral data (Brown et al., 2005; Slaughter et al., 2008; Hadoux et al., 2012). However, some studies have attempted to overcome these limitations. For example, to reduce the soil background noise, Rondeaux et al. (1996) proposed a soil-adjusted vegetation index (SOAVI), and Gitelson et al. (2002) proposed a visible atmospherically resistant index (VARI) to revise atmospheric effects on spectra. Demetriades-shah et al. (1990) reported that derivative spectral indices minimized background noise and resolved mixed spectra in comparison with the conventional broad-band spectral indices.

## **Conclusion**

HSI is a growing technology that has already proved its potential in the laboratory setting. However, with regard to outdoor applications, much remains to be solved. In this paper, many different outdoor applications of HSI with remote sensing have been reviewed. The monitoring of plant stress, determination of nitrogen status and fruit maturity, early detection of infections, and weed discrimination are important tasks that are vital for increasing the crop production. HSI has been shown to enable fast data acquisition on all of these attributes, and remote sensing enables one to cover a vast area. Variable illumination, background noise, and leaf orientation are the primary limitations precluding the use of HSI outdoors; further

research is required for developing acquisition and processing techniques that will allow to overcome these limitations.

## Conflict of Interest

The authors have no conflicting financial or other interests.

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## References

- Ahmadi, S. B. B., Y. A. Nanehkaran and S. Layazali. 2013. Review on hyper-spectral imaging system. *International Journal of Scientific & Engineering Research* 4(5):253-258.
- Alexandratos, N. and J. Bruinsma. 2012. World agriculture towards 2030/2050: The 2012 revision. *ESA Work. Pap* 3.
- Apan, A., A. Held, S. Phinn and J. Markley. 2004. Detecting sugarcane 'orange rust' disease using EO-1 Hyperion hyperspectral imagery. *International Journal of Remote Sensing* 25(2):489-498.
- Ariana, D. P. and R. F. Lu. 2010. Evaluation of internal defect and surface color of whole pickles using hyperspectral imaging. *Journal of Food Engineering* 96(4): 583-590.
- Bajwa, S. G., P. Bajcsy, P. Groves and L. F. Tian. 2004. Hyperspectral image data mining for band selection in agricultural applications. *Transactions of the ASAE* 47(3): 895-907.
- Barnes E. M., T. R. Clarke and S. E Richards. 2000. Coincident detection of crop water stress, nitrogen status and canopy density using ground based Multispectral data. In: *Proceedings of the 5th International Conference on Precision Agriculture*, Madison, WI: ASA-CSSA-SSSA.
- Bauriegel, E., A. Giebel and W. B. Herppich. 2010. Rapid Fusarium head blight detection on winter wheat ears using chlorophyll fluorescence imaging. *Journal of Applied Botany and Food Quality* 83(2):196-203.
- Bauriegel, E., A. Giebel, M. Geyer, U. Schmidt and W. B. Herppich. 2011. Early detection of Fusarium infection in wheat using hyper-spectral imaging. *Computers and Electronics in Agriculture* 75(2):304-312.
- Blackburn, G. A. 1998. Quantifying chlorophylls and carotenoids at leaf and canopy scales: an evaluation of some hyperspectral approaches. *Remote Sensing of Environment* 66(3):273-285.
- Brown, R. B. and S. D. Noble. 2005. Site-specific weed management: sensing requirements-what do we need to see?. *Weed Science* 53(2):252-258.
- Campbell, J. B. 1996. *Introduction to Remote Sensing*. 2nd ed. Taylor and Francis, London.
- Carley, S. D. 2006. *Potential Use of Hyperspectral and Multispectral Remote Sensing Imagery to Enhance Management of Peanut (Arachis hypogaea L.)*. Unpublished Ph.D. diss. Raleigh, North Carolina: North Carolina State University, Department of Crop Science and Plant Pathology.
- Casanova, D., G. F. Epema and J. Goudriaan. 1998. Monitoring rice reflectance at field level for estimating biomass and LAI. *Field Crops Res* 55(1-2): 83-92.
- Casini, A., F. Lotti, M. Picollo, L. Stefani and E. Buzzegoli. 1999. Image spectroscopy mapping technique for non-invasive analysis of paintings. *Studies in Conservation* 44(1):39-48.
- Champagne, C. M., K. Staenz, A. Bannari, H. Mcnairn and J. C. Deguise. 2003. Validation of a hyperspectral curve-fitting model for the estimation of plant water content of agricultural canopies. *Remote Sensing of Environment* 87(2-3): 148-160.
- Cheng, X., Y. R. Chen, Y. Tao, C. Y. Wang, M. S. Kim and A.M. Lefcourt. 2004. A novel integrated PCA and FLD method on hyperspectral image feature extraction for cucumber chilling damage inspection. *Transactions of the ASAE* 47(4):1313-1320.
- Curran, P. J., J. L. Dungan and D. L. Peterson. 2001. Estimating the foliar biochemical concentration of leaves with reflectance spectrometry: testing the kokaly and clark methodologies. *Remote Sensing of Environment. Environ* 76(3):349-359.
- D'Souza, A. I., L. C. Dawson, D. Berger, S. Clark, P. S. Wijewarnasuriya, J. Bajaj, J. A. Arias, W. E. Tennant, L. Kozlowski and K. Vural. 1999. HgCdTe detectors and FPAs for remote sensing applications. In: *Infrared Technology and Applications XXV*, Proceedings of SPIE-3698, ed. B.F. Andresen and M. Strojnik Scholl 538-544, Orlando, FL.
- Demetriades-shah, T. H., M. D. Steven and J. A. Clark. 1990. High resolution derivative spectra in remote sensing. *Remote Sensing of Environment* 33(1):55-64.
- Diker, K. and W. C. Bausch. 2003. Potential use of nitrogen reflectance index to estimate plant parameters and yield



- of maize. *Biosystems Engineering*. 85(4):437-447.
- ElMasry, G., and D.W. Sun. 2010. *Hyperspectral Imaging for Food Quality Analysis and Control*. 1st ed. London, UK: Elsevier Inc.
- ElMasry, G., N. Wang, A. ElSayed and M. Ngadi. 2007. Hyperspectral imaging for nondestructive determination of some quality attributes for strawberry. *Journal of Food Engineering* 81(1):98-107.
- ElMasry, G., D. W. Sun and P. Allenb. 2012. Near-infrared hyperspectral imaging for predicting colour, pH and tenderness of fresh beef. *Journal of Food Engineering* 110(1):127-140.
- eXtension. 2016. Available at: <http://articles.extension.org/pages/40073/what-is-the-difference-between-multispectral-and-hyperspectral-imagery>
- Farley, V., A. Vallières, A. Villemaire, M. Chamberland, P. Lagueux and J. Giroux. 2007. Chemical agent detection and identification with a hyperspectral imaging infrared sensor. In: *Electro-Optical Remote Sensing, Detection, and Photonic Technologies and Their Applications*, Proceedings of SPIE-6739, Florence, Italy.
- Feng, W., X. Yao, Y. Zhu Y. C. Tian and W. X. Cao. 2008. Monitoring leaf nitrogen status with hyperspectral reflectance in wheat. *European Journal of Agronomy* 28(3):394-404.
- Fischer, C. and I. Kakoulli. 2006. Multispectral and hyperspectral imaging technologies in conservation: current research and potential applications. *Studies in Conservation* 51(1):3-16.
- Franz, E., M. R. Gebhardt and K. B. Unklesbay. 1991. The use of local spectral properties of leaves as an aid for identifying weed seedlings in digital images. *Transactions of the ASAE*. 34(2):0682-0687.
- Gat, N. 2000. Imaging spectroscopy using tunable filters: a review. In: *Wavelet Applications VII*, Proceedings of SPIE-4056, ed. H. H. Szu, M. Vetterli, W. J. Campbell and J. R. Buss 50-64, Orlando, FL.
- GIS Geography. 2016. Available at: <http://gisgeography.com/multispectral-vs-hyperspectral-imagery-explained/>
- Gitelson, A. A., Y. J. Kaufman, R. Stark and D. Rundquist. 2002. Novel algorithms for remote estimation of vegetation fraction. *Remote Sensing of Environment* 80(1):76-87.
- Goetz, A. F. H., Vane, G., Solomon, J. E. and B. N. Rock. 1985. *Imaging spectrometry for Earth remote sensing*. Science 228:1147-1153.
- Gowen, A. A., C. P. O'Donnell, M. Taghizadeh, P. J. Cullen, J. M. Frias and G. Downey. 2008. Hyperspectral imaging combined with principal component analysis for bruise damage detection on white mushrooms (*Agaricus bisporus*). *Journal of Chemometrics* 22(3-4):259-267.
- Haboudane D, J. R. Miller, N. Tremblay, P. J. Zarco-Tejada, and L. Dextraze. 2002. Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application in precision agriculture. *Remote Sensing of Environment* 81(2-3):416-426.
- Hadoux, X., N. Gorretta and G. Rabatel. 2012. Weeds-wheat discrimination using hyperspectral imagery. In: *CIGR-Ageng 2012, International Conference on Agricultural Engineering*. Valencia, Spain.
- Hadoux, X., N. Gorretta, J. M. Roger, R. Bendoula and G. Rabatel. 2014. Comparison of the efficacy of spectral pre-treatments for wheat and weed discrimination in outdoor conditions. *Computers and Electronics in Agriculture* 108:242-249.
- Hansen, P. M. and J. K. Schjoerring. 2003. Reflectance measurement of canopy biomass and nitrogen status in wheat crops using normalized difference vegetation indices and partial least squares regression. *Remote Sensing of Environment* 86(4):542-553.
- Hatfield, P. L. and P. J. Pinter Jr. 1993. Remote sensing for crop protection. *Crop Protection* 12(6):403-414.
- Hinzman, L. D., M. E. Bauer and C. S. T. Daughtry. 1986. Effects of nitrogen fertilization on growth and reflectance characteristics of winter wheat. *Remote Sens. Environ* 19(1):47-61.
- Hadoux, X., N. Gorretta, J. M. Roger, R. Bendoula and G. Rabatel. 2014. Comparison of the efficacy of spectral pre-treatments for wheat and weed discrimination in outdoor conditions. *Computers and Electronics in Agriculture* 108:242-249.
- Hunt, J., E. Ramond and B. N. Rock. 1989. Detection in changes in leaf water content using near and mid-infrared reflectance. *Remote Sensing of Environment* 30(1):45-54.
- Jay, S. C., R. L. Lawrence, K. S. Repasky and L. J. Rew. 2010. Detection of leafy spurge using hyper-spectral-spatial-temporal imagery. *Geoscience and Remote Sensing Symposium (IGARSS)* 4374-4376, Honolulu, IEEE International.
- John, J., L. Zimmermann, P. Merken, S. D. Groote, G. Borghs, C. V. Hoof, S. Nemeth and T. Colin. 2003. Extended wavelength InGaAs on GaAs hybrid image sensors. In: *Infrared Spaceborne Remote Sensing XI*, Proceedings of SPIE- 5152, ed. M. Strojnik 263-270, San Diego, California, USA.
- Kacira, M., P. P. Ling and T. H. Short. 2002. Machine vision

- extracted plant movement for early detection of plant water stress. *Transactions of the ASAB* 45(4):1147-1153.
- Kandpal, L. M., S. Lee, M. S. Kim, H. Bae and B. K. Cho. 2015. Short wave infrared (SWIR) hyperspectral imaging technique for examination of aflatoxin B1 (AFB1) on corn kernels. *Food Control* 51:171-176.
- Kang, Z. and H. Buchenauer. 2000. Cytology and ultrastructure of the infection of wheat spikes by *Fusarium culmorum*. *Mycological Research* 104(09): 1083-1093.
- Kim, M. S., A. M. Lefcourt, K. Chao, Y. R. Chen, I. Kim and D. E. Cha. 2002. Multispectral detection of fecal contamination on apples based on hyperspectral imagery: part 1. Application of visible and near-infrared reflectance imaging. *Transactions of the ASAE* 45(6):2027-2037.
- Kim, Y., D. M. Glenn, J. Park, H. K. Ngugi and B. L. Lehman. 2011. Hyperspectral image analysis for water stress detection of apple trees. *Computers and Electronics in Agriculture* 77:155-160.
- Kurata, K. and J. Yan. 1996. Water stress estimation of tomato canopy based on machine vision. *Acta Horticulturae (ISHS)* 440:389-394.
- Lacar, F. M., M. M. Lewis and I. T. Grierson. 2001. Use of Hyperspectral Reflectance for Discrimination between Grape Varieties. In: *Transactions International Geoscience and Remote Sensing Symposium 2878-2880*, Sydney, IEEE.
- Lamba, D. W. and R. B. Brown. 2001. PA-Precision Agriculture: Remote-Sensing and Mapping of Weeds in Crops. *Journal of Agricultural Engineering Research* 78(2):117-125
- Lawlor, D. W. 2001. *Photosynthesis*. 3rd ed. BIOS Scientific, Oxford, U. K.
- Lee, T., K. R. Reddy and G. F. Sassenrath-Cole. 2000. Reflectance indices with precision and accuracy in predicting cotton leaf nitrogen concentration. *Crop Science*. 40(6):1814-1819.
- Leea, W. S., V. Alchanatisb, C. Yangc, M. Hirafujid, D. Moshoue and C. Lif. 2010. Sensing technologies for precision specialty crop production. *Computers and Electronics in Agriculture* 74(1): 2-33.
- Lu, R. 2004. Multispectral imaging for predicting firmness and soluble solids content of apple fruit. *Postharvest Biology and Technology* 31(2):147-157.
- Lu, R. and Y. Peng. 2006. Hyperspectral scattering for assessing peach fruit firmness. *Biosystems Engineering* 93(2):161-171.
- Lu, R. and Y. Peng. 2007. Development of a multispectral imaging prototype for real-time detection of apple fruit firmness. *Optical Engineering* 46(12):123201.
- Lu, R. and Y. R. Chen. 1999. Hyperspectral imaging for safety inspection of food and agricultural products. In: *Pathogen Detection and Remediation for Safe Eating*, Proceedings of SPIE-3544, ed. Y.R. Chen 121, Boston, MA.
- Mahajan, G. R., R. N. Sahoo, R. N. Pandey, V. K. Gupta and D. Kumar. 2014. Using hyperspectral remote sensing techniques to monitor nitrogen, phosphorus, sulphur and potassium in wheat (*Triticum aestivum* L.). *Precision Agriculture* 15(2):227-240.
- Martinsena, P. and P. Schaareb. 1998. Measuring soluble solids distribution in kiwifruit using near-infrared imaging spectroscopy. *Postharvest Biology and Technology* 14(3):271-281.
- McMurtrey III, J. E., E. W. Chappelle, M. S. Kim, J. J. Meisinger and L. A. Corp. 1994. Distinguishing nitrogen fertilization levels in field corn (*Zea mays* L.) with active induced fluorescing and passive reflectance measurements. *Remote Sensing of Environment* 47(1):36-44.
- Moran, M. S., Y. Inoue and E. M. Barnes. 1997. Opportunities and limitations for image-based remote sensing in precision crop management. *Remote Sensing of Environment* 61(3):319-346.
- Moshou, D., C. Bravo, R. Oberti, J. S. West, H. Ramon, S. Vougioukas and D. Bocti. 2011. Intelligent multi-sensor system for the detection and treatment of fungal diseases in arable crops. *Biosystems Engineering* 108:311-321.
- Moshou, D., C. Bravo, R. Oberti, J. S. West, H. Ramon, S. Vougioukas and D. Boctis. 2011. Intelligent multi-sensor system for the detection and treatment of fungal diseases in arable crops. *Biosystems Engineering* 108(4):311-321.
- Muir, A. Y., R. L. Porteous and R. L. Wastie. 1982. Experiments in the detection of incipient diseases in potato tubers by optical methods. *J. Agric. Eng. Res* 27:131-138.
- Nagata, M., J. G. Tallada, T. Kobayashi, Y. Cui and Y. Gejima. 2004. Predicting maturity quality parameters of strawberries using hyperspectral imaging. In: *ASAE/CSAE Annual International Meeting*, Ottawa, Ontario, Canada, Paper No. 043033.
- Nansen, C., G. Zhao, N. Dakin, C. Zhao and S. R. Turner. 2015. Using hyperspectral imaging to determine germination of native Australian plant seeds. *J. Photochem. and Photobiol. B: Biology* 145:19-24
- Naor, A. 2008. Water stress assessment for irrigation scheduling of deciduous trees. *Acta Horticulturae (ISHS)* 792:467-481.
- Nicolai, B. M., K. Beullens, E. Bobelyn, M. L. Hertog, A. Schenk, S. Vermeir and J. Lammertyn. 2006. Systems to characterize internal quality of fruit and vegetables. *Acta Horticulturae*

- (ISHS) 712: 59-66.
- Noh, H. K., Y. Peng and R. Lu. 2007. Integration of hyperspectral reflectance and fluorescence imaging for assessing apple maturity. *Transactions of the ASAE* 50(3):963-971.
- Park, B., K. C. Lawrence, W. R. Windham and D. P. Smith. 2004. Multispectral imaging system for fecal and ingesta detection on poultry carcasses. *Journal of Food Process Engineering* 27(5):311-327.
- Piron, A., V. Leemans, O. Kleynen, F. Lebeau and M. F. Destain. 2008. Selection of the most efficient wavelength bands for discriminating weeds from crop. *Computers and Electronics in Agriculture* 62(2):141-148.
- Plaza, J., A. J. Plaza and C. Barra. 2009. Multi-Channel Morphological Profiles for Classification of Hyperspectral Images Using Support Vector Machines. *Sensors* 9(1):196-218.
- Pozdnyakova, L., P. V. Oudemans, M. G. Hughes and D. Giménez. 2002. Estimation of spatial and spectral properties of phytophthora root rot and its effects on cranberry yield. *Computers and Electronics in Agriculture* 37(1-3):57-70.
- Prabhakar, M., Y. G. Prasad, M. Thirupathi, G. Sreedevi, B. Dharajothi and B. Venkateswarlu. 2011. Use of ground based hyperspectral remote sensing for detection of stress in cotton caused by leafhopper (Hemiptera: Cicadellidae). *Computers and Electronics in Agriculture* 79(2):189-198.
- Pradhan, S., K. K. Bandyopadhyay, R. N. Sahoo, V. K. Sehgal, R. Singh, V. K. Gupta and D. K. Joshi. 2014. Predicting wheat grain and biomass yield using canopy reflectance of booting stage. *J. Indian Soc. Remote Sensing* 42(4):711-718.
- Prasannakumar, N. R., S. Chander and R. N. Sahoo. 2014. Characterization of brown plant hopper damage on rice crops through hyperspectral remote sensing under field conditions. *Phytoparasitica* 42(3):387-395.
- Rajkumar, P., N. Wang, G. Elmasry, G. S. V. Raghavan and Y. Garipey. 2012. Studies on banana fruit quality and maturity stages using hyperspectral imaging. *Journal of Food Engineering* 108(1):194-200.
- Ranjan, R., U. K. Chopra, R. N. Sahoo, A. K. Singh and S. Pradhan. 2012. Assessment of plant nitrogen stress through hyperspectral indices. *Int. J. Remote Sensing* 22(20):6342-6360.
- Rencz, A. N. and R. A. Ryerson. 1999. Remote sensing for the earth sciences: manual of remote sensing Volume 3. New York: Wiley & Sons.
- Rodriguez D, G. L. Fitzgerald, R. Belford and L. Christensen. 2005. Detection of nitrogen deficiency in wheat from spectral reflectance indices and basic crop eco-bio physiological concepts. *Australian Journal of Agricultural Research* 57(7):781-789.
- Rogalski, A. 2004. Optical detectors for focal plane arrays. *Opto-Electronics Review* 12(2):221-245.
- Rondeaux, G., M. Steven, and F. Baret. 1996. Optimization of soil-adjusted vegetation indices. *Remote Sensing of Environment* 55(2):95-107.
- Sahba, K., S. Askraha, and K. E. Alameh. 2006. Non-contact laser spectroscopy for plant discrimination in terrestrial crop spraying. *Optics Express* 14(25):12485-12493.
- Sanches, I. D., C. R. S. Filho, L. A. Magalhães, G. C. M. Quitério, M. N. Alves and W. J. Oliveira. 2013. Assessing the impact of hydrocarbon leakages on vegetation using reflectance spectroscopy. *ISPRS J. Photogramm. Remote Sens.* 78:85-101.
- Sankaran, S., A. Mishra, R. Ehsani and C. Davis. 2010. A review of advanced techniques for detecting plant diseases. *Computers and Electronics in Agriculture* 72(1): 1-13.
- Senthilnath, J., A. Dokania, M. Kandukuri, K. N. Ramesh, G. Anand and S. N. Omkar. 2016. Detection of tomatoes using spectral-spatial methods in remotely sensed RGB images captured by UAV. *Biosystems Engineering* 146:16-32.
- Sepulcre-Canto, G., P. J. Zarco-Tejada, J. C. Jiménez-Muñoz, J. A. Sobrino, E. de Miguel and F.J. Villalobos. 2006. Detection of water stress in an olive orchard with thermal remote sensing imagery. *Agricultural and Forest Meteorology* 136(1-2):31-44.
- Sizov, F. F. 2000. Infrared detectors: outlook and means. *Semiconductors Physics, Quantum Electronics & Optoelectronics* 3(1):52-58.
- Slaughter, D. C., D. K. Giles and D. Downey. 2008. Autonomous robotic weed control systems: a review. *Computers and Electronics in Agriculture* 61(1):63-78.
- T. Borregaard, H. Nielsen, L. Norgaard and H. Have. 2000. Crop-weed discrimination by line imaging spectroscopy. *J. Agric. Eng. Res* 75(4):389-400.
- Taghizadeh, M., A. Gowen, P. Ward and C. P. O'Donnell. 2010. Use of hyperspectral imaging for evaluation of the shelf-life of fresh white button mushrooms (*Agaricus bisporus*) stored in different packaging films. *Innovative Food Science & Emerging Technologies* 11(3):423-431.
- Takebe, M., T. Yoneyama, K. Inada and T. Murakami. 1990. Spectral reflectance ratio of rice canopy for estimating crop nitrogen status. *Plant. Soil* 122(2):295-297.

- Thenkabail, P. S., R. B. Smith and E. D. Pauw. 2000. Hyperspectral vegetation indices and their relationships with agricultural crop characteristics. *Remote Sensing of Environment* 71(2):158-182.
- Thenkabail, P. S., R. B. Smith and E. De Pauw. 2000. Hyperspectral vegetation indices and their relationships with agricultural crop characteristics. *Remote Sensing of Environment* 71(2):158-182.
- Thorp, K. R. and L. F. Tian. 2004. A review on remote sensing of weeds in agriculture. *Precision Agriculture* 5(5): 477-508.
- Tilling, A. K., G. O'Leary, J. G Ferwerda, S. D Jones, G. Fitzgerald and R. Belford. 2006. Remote Sensing to Detect Nitrogen and Water Stress in Wheat. In: Australian Agronomy Conference, 13th AAC, Perth, Western Australia.
- Tran, C.D. 2003. Infrared multispectral imaging: principles and instrumentation. *Applied Spectroscopy Reviews* 38(2):133-153.
- Ustin, S. L., D. A. Roberts, J. A. Gamon, G. P. Asner and R. O. Green. 2004. Using Imaging Spectroscopy to Study Ecosystem Processes and Properties. *BioScience* 54(6):523-534.
- Vigneau, N., M. Ecartotb, G. Rabatela and P. Roumet. 2011. Potential of field hyperspectral imaging as a non-destructive method to assess leaf nitrogen content in Wheat. *Field Crops Research* 122(1):25-31.
- Wang J., K. Nakano, S. Ohashi, Y. Kubota, K. Takizawa and Y. Sasaki. 2011. Detection of external insect infestations in jujube fruit using hyperspectral reflectance imaging. *Biosystems Engineering* 108:345-351.
- Wang, F. M., J. F. Huang and X. Z. Wang. 2008. Identification of optimal hyperspectral bands for estimation of rice biophysical parameters. *J. Integr. Plant Biol.* 50(3):291-299.
- West, J. S., C. Bravo, R. Oberti, D. Lemaire, D. Moshou and H. A. McCartney. 2003. The potential of optical canopy measurement for targeted control of field crop diseases. *Annual Review of Phytopathology* 41:593-614.
- Williams, P., M. Manley, G. Fox and P. Geladi. 2010. Indirect detection of *Fusarium verticillioides* in maize (*Zea mays* L.) kernels by near infrared hyperspectral imaging. *Journal of Near Infrared Spectroscopy* 18(1):49-58.
- Xenics. 2016. Xenics Infrared Solutions. Available at: [www.xenics.com](http://www.xenics.com)
- Xiao, J. and L. Xu. 2010. Monitoring Impact of Heavy Metal on Wheat Leaves from Sewage Irrigation by Hyperspectral Remote Sensing. In: Geoscience and Remote Sensing (IITA-GRS), 2010 Second IITA International Conference 298-301, Qingdao, IEEE.
- Xing, J., C. Bravo, P. T. Jancsó, H. Ramon and J. D. Baerdemaeker. 2005. Detecting Bruises on 'Golden Delicious' Apples using Hyperspectral Imaging with Multiple Wavebands. *Biosystems Engineering* 90(1): 27-36.
- Yang, C., W. S. Lee and J. G. Williamsonb. 2012. Classification of blueberry fruit and leaves based on spectral signatures. *Biosystems Engineering* 113(4): 351-362.
- Zhensheng, K. and H. Buchenauer. 2000. Cytology and ultrastructure of the infection of wheat spikes by *Fusarium culmorum*. *Mycological Research* 104(09): 1083-1093.
- Zhu, Y., Y. Li, W. Feng, Y. Tian, X. Yao and W. Cao. 2006. Monitoring leaf nitrogen in wheat using canopy reflectance spectra. *Can. J. Plant Sci* 86(4):1037-1046.
- Zwiggelaar, R. 1998. A review of spectral properties of plants and their potential use for crop/weed discrimination in row-crops. *Crop Prot* 17(3):189-206.
- Zygielbaum, A. I., A. A. Gitelson, T. J. Arkebauer and D. C. Rundquist. 2009. Nondestructive detection of water stress and estimation of relative water content in maize. *Geophys. Res. Lett* 36(12):L12403.