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REVIEW ARTICLE

Application of remote sensing methods in agriculture

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ABSTRACT
With advances in satellite, airborne and ground based remote sensing, reflectance data are increasingly being used in agriculture. This paper reviews various remote sensing methods designed to optimize profitability of agricultural crop production and protect the environment. The paper presents examples of the use of remote sensing data in crop yield forecasting, assessing nutritional requirements of plants and nutrient content in soil, determining plant water demand and weed control.

Key Words: *remote sensing; vegetation indices; agronomy; plant protection; crop irrigation.*

INTRODUCTION

Remote sensing is the process of obtaining information about objects without coming into direct contact with the object. The carrier of information in remote sensing is electromagnetic radiation, which travels in vacuum at the speed of light in the form of waves of different lengths. The most useful wavelengths in remote sensing cover visible light (VIS), and extends through the near (NIR) and shortwave (SWIR) infrared, to thermal infrared (TIR) and microwave bands. Passive remote sensing sensors record incident radiation reflected or emitted from the objects while active sensors emit their own radiation, which interacts with the target to be investigated and returns to the measuring instrument.

VEGETATION INDICES

Biophysical features of plants can be characterized spectrally by vegetation indices defined as unitless radiometric measures. They are calculated as ratios or differences of two or more bands in the VIS, NIR and SWIR wavelengths. The usefulness of a vegetation index is determined by its high correlation with biophysical parameters of plants and low sensitivity to factors hampering remote sensing data interpretation, e.g. soil background, relief, nonphotosynthesizing elements of plants, atmosphere, viewing and illumination geometry (Huete and Justice 1999) The most commonly used index is the Normalized Difference Vegetation Index (NDVI), proposed by Rouse et al. (1974) and calculated as a quotient of the difference and sum of the reflectance in NIR and red regions. Green parts of plants reflect intensively in the NIR region due to scattering in the leaf mesophyll and strongly absorb red and blue light via chlorophyll (Ayala-Silva and Beyl 2005).

The NDVI index is used most frequently to determine the condition, developmental stages and biomass of cultivated plants and to forecasts their yields. The NDVI has become the most commonly used vegetation index (Wallace et al. 2004, Calvao and Palmeirim 2004) and many efforts have been made aiming to develop further indices that can reduce the impact of the soil background and atmosphere on the results of spectral measurements.

An example of a vegetation index limiting the influence of soil on remotely sensed vegetation data is SAVI (Soil Adjusted Vegetation Index) proposed by Huete (1988). Another, the VARI index (Visible Atmospheric Resistant Index) (Gitelson et al. 2002), strongly reduces the influence of the atmosphere. Still more have been developed to consider differences in reflectance in the NIR and SWIR ranges indicating the occurrence of lack of water for plants: MSI (Moisture Stress Index) (Rock et al. 1986), LWCI (Leaf Water Content Index) (Hunt et al. 1987), WI (Water Index) (Panuelas et al. 1993), GVMI (Global Vegetation Moisture Index) (Ceccato et al. 2002), and SIWSI (MidIR, G) (Shortwave Infrared Water Stress Index) (Fensholt and Sandholt 2003). In turn, vegetation indices such as CWSI (Crop Water Stress Index) (Jackson et al. 1981), ST (Surface Temperature) (Jackson 1986), WDI (Water Deficit Index) (Moran et al. 1994), and SI (Stress Index) (Vidal et al. 1994) describe the relationship existing between water stress and thermal characteristics of plants. Examples of vegetation indices used in specific agricultural applications reported in the literature are presented in Table 1.

REMOTE SENSING APPLICATION IN AGRICULTURE

Remote sensing can be divided into three categories: ground-based, airborne and satellite. when evaluating a remote sensing platform, spatial and spectral resolution must also be taken into account. The spatial resolution defines the pixel size of satellite or airborne images covering the earth surface and relates to the dimensions of the smallest object that can be recognized on the ground. A sensor's spectral resolution indicates the width of spectral bands in which the sensor can collect reflected radiance.

GROUND-BASED REMOTE SENSING

According to Jackson (1986) handheld remote sensing instruments are very useful for small-scale operational field monitoring of biotic and abiotic stress agents. This technology has better temporal, spectral, and spatial resolutions in comparison to airborne and satellite remote sensing. A limiting factor of handheld remote sensing is one of efficiency and often time reduced to evaluating small areas when compared with aircraft and satellite mounted sensors, which can be used to be used to evaluate much larger areas at a time. Forecasting yield, nutritional requirements of plants, detection of pest damage, water demands and weed control are the most commonly undertaken problems in studies making use of opportunities of field spectrometers in agriculture.

Table 1. Vegetation indices compiled from the literature

Index	Formula	Spectral bands or wavelenghts [nm]	Level/Sensor	Application	References
Advanced Normalised Vegetation Index	$ANVI = \frac{NIR - BLUE}{NIR + BLUE}$	*BLUE*: 400 – 500 *NIR*: 700 – 900	Airborne (RMK TOP 15 camera)	Mapping Ridolfia segetum patches in sunflower crop	Peña-Barragan et al. (2006)
Aphid Index	$AI = \frac{NIR1 - NIR2}{RED1 + RED2}$	*RED*1: 712 *RED*2: 719 *NIR*1: 761 *NIR*2: 908	Ground-based (ASD FieldSpec3 spectrometer)	Identification of aphid infestation in mustard	Kumar et al. (2010)
Chlorophyll Index	$CI = \frac{NIR}{GREEN} - 1$	*GREEN*: 520 - 600 *NIR*: 760 - 900	Ground-based (Exotech radiometr) Satellite (QuickBird)	Plant nitrogen status estimates	Bausch and Khosla (2010)
Continuum Removed (CR) Spectral Index	$A_{CR(1200)} = \int_{\lambda_{1116}}^{\lambda_{1284}} (1 - \frac{NIR}{NIR_{CR}})$ $A_{CR(1200)} = \frac{(NIR1 - NIR2)(1 - \frac{NIR3}{NIR3_{CR}})}{2}$	*NIR*: 1116 – 1284 *NIR*1: 1267 *NIR*2: 1156 *NIR*3: 1210	Laboratory (ASD FieldSpec Spectrora-diometer) Airborne (MIVIS)	Estimation of the water content at leaf and landscape level	Colombo et al. (2008)
Damage Sensitive Spectral Index	$DSSI = \frac{RED - NIR - BLUE - GREEN}{(RED - NIR) + (BLUE - GREEN)}$	*BLUE*: 509 *GREEN*: 537 *RED*: 719 *NIR*: 873	Ground-based (ASD FieldSpec Handheld Spectroradio meter)	Determine the sunn pest damage on wheat	Genc et al. (2008)
Effective Leaf Area Index	$ELAI = -0.441 + 0.285 \frac{NIR}{RED}$	*RED:* 610 – 680 *NIR:* 780 – 890	Ground-based (CIMEL 313 radiometer)	Winter oilseed rape yield prediction	Wójtowicz et al. (2005)
Green Normalized Difference Vegetation Index	$GNDVI = \frac{NIR - GREEN}{NIR + GREEN}$	*GREEN*: 557–582 *NIR*: 720 – 920 and/or *GREEN*: 520 – 600 *NIR*: 760 – 900	Airborne (Multispectral Digital Camera) Satellite (IKONOS)	Corn yield predictions	Chang et al. (2003)
Green Red Vegetation Index	$GRVI = \frac{GREEN - RED}{GREEN + RED}$	*GREEN*: 520 - 590 *RED*: 620 - 680	Ground-based (GER 1500 Spectroradio-meter)	Estimation of damage caused by thrips	Ranjitha et al. (2014)
Healthy-Index	$HI = \frac{GREEN - RED1}{GREEN + RED1} 0.5 RED2$	*GREEN*: 534 *RED*1: 698 *RED*2: 704	Airborne (MCA-6 and Micro-Hyperspec Tetracam)	Early detection of Verticillium wilt of olive	Calderón et al. (2013)
Leaf Rust Disease Severity Index 1 Leaf Rust Disease Severity Index 2	$LRDSI\_1 = 6.9 \frac{RED1}{BLUE} - 1.2$ $LRDSI\_2 = 4.2 \frac{RED2}{BLUE} - 0.38$	*BLUE*: 455 *RED*: 605 *RED*: 695	Ground-based (ASD FieldSpec spectrometer)	Detection of Wheat Leaf Rust	Ashourloo et al. (2014)

Table 1 continued on next page

Table 1 continued

Modified Soil-adjusted Vegetation Index	$MSAVI2 = 0.5[2NIR + 1 - \sqrt{(2NIR+1)^2 - 8(NIR - RED)}]$	*RED*: 630 – 690 *NIR*: 760 – 860	Satellite (Terra ASTER)	Prediction of corn canopy nitrogen content	Bagheri et al. (2012)
Normalized Difference Infrared Index	$NDII = \frac{NIR - SWIR}{NIR + SWIR}$	*NIR*1: 845 – 885 *NIR*2: 1650–1700	Airborne (MASTER)	Detection of diurnal orchard canopy water content variation	Cheng et al. (2013)
Normalized Difference Water Index	$NDWI = \frac{NIR1 - NIR2}{NIR1 + NIR2}$	*NIR*1: 841 - 876 *NIR*2: 1230–1250	Satellite (MODIS)	Estimation of plant water content	Zarco-Tejada et al. (2003)
Normalized Pigment Chlorophyll Ratio Index	$NPCI = \frac{RED1 - BLUE1}{RED2 + BLUE2}$	*BLUE*: 460 *RED*: 660	Ground-based (Exotech and CropScan radio-meters)	Estimation of leaf chlorophyll content	Hatfield and Prueger (2010)
Optimized Soil-Adjusted Vegetation Index	$OSAVI = \frac{NIR - RED}{NIR + RED + 0.16}$	*RED:* 640 – 720 *NIR:* 770 - 880	Satellite (IKONOS)	Nitrogen status estimation of winter wheat	Jia et al. (2011)
Ratio Vegetation Index	$RVI = \frac{NIR}{RED}$	*RED:* 630 – 690 *NIR:* 760 - 900	Ground-based (ASD FieldSpec Handheld Spectroradio meter)	Estimating nitrogen status of winter wheat	Li et al. (2008a)
Relative Reflectance Index	$RRI = \frac{NIR_a / VIS_a}{NIR_r / VIS_r}$	*VIS:* 400 – 700 *NIR*: 740 - 820	Ground-based (quantum sensor LI-190s and LI-220S)	Indication of drought of field grown oilseed rape	Mogensen et al. (1996)
Shortwave Infrared Water Stress Index	$SIWSI(6,2) = \frac{SWIR - NIR1}{SWIR + NIR1}$ $SIWSI(6,2) = \frac{SWIR - NIR2}{SWIR + NIR2}$	*NIR*1: 841 - 876 *NIR*2: 1230 - 1250 *SWIR*: 1628 - 1652	Satellite (MODIS)	Indication of canopy water content	Fensholt and Sandholt (2003)
Simple Ratio	$SR = \frac{RED}{NIR}$	*RED:* 648 *NIR:* 747	Airborne (Hyperspectra l camera)	Detection of pest infestation in regional scale	Glaser et al. (2009)
Structure Insensitive Pigment Index	$SIPI = \frac{NIR - BLUE}{NIR - RED}$	*BLUE*: 445 *RED*: 680 *NIR*: 800	Ground-based (ASD FieldSpec Handheld Spectroradio meter)	Determine the sunn pest damage on wheat	Genc et al. (2008)
Transformed Soil-Adjusted Vegetation Index	$TSAVI = \frac{a(\mathrm{NIR} - aRED - b)}{a\mathrm{NIR} + RED - ab + X(1 + a^2)}$	*RED*: 610 – 720 *NIR*: 760 – 950	Airborne (Pushbroom camera) Satellite (SPOT HRV)	Assimilation of remote sensing data into sugar beet yield predicttion model	Launay and Guerif (2005)
Triangular greenness index	$TGI = -0.5[(RED - BLUE)(RED - GREEN) - (RED - GREEN)(RED - BLUE]$	*BLUE*: 450 – 520 *GREEN*: 520 - 600 *RED*: 630 - 690	Ground-based (ASD FieldSpec spectrome-ter), Airborne (AVIRIS), Satellite (Landsat TM)	Crop nitrogen requirements detection	Hunt et al. (2013)

AIRBORNE REMOTE SENSING

Up to date, airborne remote sensing is mainly realized with the use of piloted aircrafts, however, in recent years they are more often replaced by Unmanned Aerial Vehicles (UAVs), which are aircraft remotely piloted from a ground station. UAVs are typically low cost, light weight and low airspeed aircrafts that are well suited for remotely sensed data gathering. Currently, there are two broad platforms for UAVs, namely the 'Fixed Wing' and 'Rotary Wing' types. Fixed wing UAVs have the advantage of being able to fly at high speeds for long durations with simpler aerodynamic features. Some of them do not even require a runway or launcher for takeoff and landing. The rotary wing UAVs have the advantage of being able to take off and land vertically and hover over a target. However, because of mechanical complexity and shortened battery power, they have a short flight range

UAVs have several advantages; they can be deployed quickly and repeatedly, they are flexible in terms of flying height and timing of missions and they can obtain very high resolution imagery. This imagery allows for observation of individual plants, patches, gaps and patterns over the landscapes that have not previously been possible (Franklin et al. 2006, Laliberte et al. 2006). According to Nebiker et al. (2008) UAVs with a typical spatial resolution of 1–20 cm could fill the resolution gap between piloted aircraft (resolution of 0.2–2 m) and ground-based platforms (< 1 cm). Providing a swath width of 50–500 m and a spatial resolution of 1- 20 cm, UAV platforms may be able to provide high resolution inputs necessary for site-specific crop management. UAVs with a very high resolution might be used also in agronomical research, management of specialty crops and studies of the within-field variability. Various ultra light imaging systems, weighing about 100 g, have been developed to be used with UAVs in recent years. One of the lightest available multispectral camera is ADC Micro (Tetracam, Chatsworth, CA, USA), which weights 90 g and produces images in three channels: green (520-600 nm), red (630-690 nm) and NIR (760-920 nm).

SATELLITE IMAGERY

Historically, satellite imagery has been used for crop type mapping, general crop condition assessment, and crop acreage estimation. Typically, these applications were used over large areas due to the limited spatial resolution of sensors. Finer resolutions of more recent satellite sensors, however, are now enabling within field assessment of problems such as drought stress, flooding and hail damage.

A growing number of satellite remote sensing applications does not mean that this technology is free from limitations. Stafford (2000) stressed that satellite images can be affected by variable weather conditions. Lamb and Brown (2001) indicated that the low-resolution satellite images beneficial only for large-scale studies and may not be appropriate for the small-scale farms. Additionally, satellites providing higher-resolution images, e.g., QuickBird (2.4 m in VNIR) and ASTER (15 m), have long revisit times (1-3.5 and 16 days respectively), making them of limited utility for any application that might require frequent images. To reduce the revisit time, satellites are often deployed in constellations consisting of a few synchronized satellites, which are coordinated and overlap in ground coverage.

FORECASTING OF YIELD

Remote sensing has been used to forecast crop yields based primarily upon statistical–empirical relationships between yield and vegetation indices (Thenkabail et al. 2002, Casa and Jones 2005). Information on expected yield is very important for government agencies, commodity traders and producers in planning harvest, storage, transportation and marketing activities. The sooner this information is available, the lower the economic risk, translating into greater efficiency and increased return on investments.

GROUND-BASED REMOTE SENSING

Walsh et al. (2012), conducting research on winter wheat, using ground based spectra to forecast yield at the beginning of shooting stage. Many authors draw attention to the development phase of plants, as a critical component of yield forecasting (Basnyat and McConkey 2001, Wójtowicz et al. 2005, Piekarczyk 2011a). For instance, the most accurate yield forecasts of winter oilseed rape were achieved when the spectral measurements were performed in the phase of full budding of the crop (Wójtowicz et al. 2005). However, Piekarczyk et al. (2011a) showed that the strongest relationship between the spectral data and the winter rape yield was obtained at the beginning of the flowering stage, while wheat yields were most accurately predicted when the plants were in the shooting phase. Many studies have shown the usefulness of the NDVI index for yields forecasting (Basnyat and McConkey 2001, Piekarczyk et al. 2004, Wójtowicz et al. 2005, Walsh et al. 2012), but good correlations with predicted yield were also obtained for RVI (Ratio Vegetation Index) and ELAI (Estimated Leaf Area Index) indices (Wójtowicz et al. 2005). According to Piekarczyk et al. (2011b), before oilseed rape flowering the strongest correlation with yield was best when indices were calculated on the basis of reflectance in green and NIR wavelengths (550 and 775 nm, respectively). For yield forecasting, at the time of rape flowering, indices calculated on the basis of reflectance in NIR wavelengths and their logarithmic transformation were better than non-transformed spectral data (Piekarczyk 2011a).

AIRBORNE REMOTE SENSING

The usefulness of aerial photographs for forecasting maize yield, using portions of the VIS and NIR ranges several times during the growing season, has been studied as well (Chang et al. 2003). Airborne remote sensing data can substantially improve crop yield forecasting models. Launay and Guerif (2005) developed such a model that assimilates information obtained from images taken throughout the growing season. Yield estimates were improved decreasing the root mean square error (RMSE) from 20% to about 10%. The robustness of the model depended on the number and timing of images which defines the number and the type of plant biophysical parameters that can be assessed. When yield estimations were compiled for areas for which the soil was poorly characterized the forecasts generated by the model were improved (the RMSE decreased from 21% to 15%) if late in the season remote sensing data were assimilated. The authors also found that the crop model was considerably less reliable in severe drought conditions.

Yield predictions can be also derived on the basis of data recorded from an UAV platform. An unmanned helicopter was used by Swain and Zaman (2013) to obtain multispectral images to estimate rice (*Oryza sativa* L.) yield. With the use of a linear regression model the authors proved a high relationship between spectral data and rice yield (R^2=0.76) existed.

SATELLITE REMOTE SENSING

On a regional scale, crop yield estimation was carried out based on vegetation indices derived from AVHRR/NOAA satellite image data (Prasad et al. 2006). The model developed by the authors, describing relationships between satellite spectral data and crop yield in Iowa gave high R^2 values for corn (0.78) and soybean (0.86). Dąbrowska-Zielińska et al. (2008) used the method to monitor the growth and yield of cereals on the basis of AVHRR/NOAA images in Polish conditions. The authors developed a model which estimated wheat yield (with an error RMSE=13%) on the basis of LAI and evapotranspiration indices calculated from AVHRR images.

Galvão et al. (2009) studied the possibility of using satellite Hyperion hyperspectral images to estimate the yield of soybean obtaining a high correlation (r = 0.74) between vegetation indices and weight of harvested seed. The model developed by Li et al. (2008b) used an artificial neural network structure and enabled the prediction of yields of maize and soybean using MODIS sensor at a regional scale. Model results produce an accuracy of 85%. Doraiswamy et al. (2004) also studied the possibility of using MODIS satellite data for forecasting yields using a calibrated form of the model developed by Li et al. (2008b). Model calibration was accomplished using ground reflectance measurements. Simulated yield resultss were in good agreement with yields reported by USDA–National Agricultural Statistics Service (NASS) for corn and soybean with -3.12 and 6.62 percent difference, respectively.

NUTRITIONAL REQUIREMENTS OF PLANTS

GROUND-BASED REMOTE SENSING

Ground level remote sensing methods are also used to determine the nutritional requirements of plants. Li et al. (2008a) using a handheld radiometer capable of measuring in the 325–1075 nm range, demonstrated a positive linear relationship between RVI and nitrogen uptake in winter wheat (R^2=0.60 and RMSE=30.5%). In the study conducted by Stroppiana et al. (2009) a spectral range from 350 to 2500 nm was applied to estimate plant nitrogen concentration in paddy rice, by means of normalized difference indices derived via a the combination of all possible wavelengths within that range. The best correlation (R^2=0.65) between plant nitrogen concentration and a normalized difference index was obtained in that study by using reflectance data in the visible part of the spectrum (503 and 480 nm). A good correlation between canopy reflectance and leaf nitrogen accumulation was also obtained by Zhu et al. (2008) in a study of rice (*Oryza sativa* L.) and wheat (*Triticum aestivum* L.). The best results were achieved when a ratio of reflectance in 810 nm to reflectance in 660 nm and a ratio of reflectance in 870 nm to reflectance in 660 nm were used in the calculations (R^2=0.84 and 0.85, respectively). Another way developed to assess nitrogen status in a crop field is measuring the reflectance with active sensors like GreenSeeker (NTech Industries, Inc, Ukiach, CA, USA) and CropCircle (Holland Scientific Inc., Lincoln, Nebrasca, USA). Which, unlike passive sensors have their own light source. Active sensors usually generate only two or three wavelengths. The GreenSeeker has a red (660 nm) and a NIR (770 nm) whereas the CropCircle model ACS-470 has three measurements spectral channels and a set of interchangeable filters (450 nm, 550 nm, 650 nm, 670 nm, 730 nm, 760 nm) which the user can select depending on the application. More sophisticated than GreenSeeker and CropCircle sensors is the Yara N-sensor (Yara International ASA, Germany) capable of recording spectral information in five single wavebands. This sensor has been successfully used in nitrogen fertilization for wheat (Heege et al. 2008), barley (Soderstron et al. 2010), triticale (Zillmann et al. 2006), corn (Tremblay et al. 2009), sugarcane (Singh et al. 2006, Portz et al. 2012) and potato (Zebarth et al. 2003).

AIRBORNE REMOTE SENSING

An interesting example of using airborne hyperspectral images for plant nutritional stress detection is presented by Quemada et al. (2014) who compared reliability of ground level and airborne sensing methods to distinguish between nitrogen-deficient and nitrogen-sufficient maize plots. Readings at ground level were taken with SPAD (Minolta Camera Co., Osaka, Japan), Dualex and Multiplex (FORCE-A, Orsay, France) sensors, and airborne data were acquired by the hyperspectral sensors Micro-Hyperspec VNIR imager (Headwall Photonics, Fitchburg, MA, USA). This camera acquired radiance imagery in 260 bands in the 400-885 nm region, 300 m over the experimental site. The study showed that vegetation indices based on airborne measurements were as reliable as measurements taken with ground-level equipment used for assessing crop nitrogen status.

The use of airborne remote sensing in agriculture is also well documented by Goel et al. (2003) who validated the potential of that technology to detect nitrogen deficiency and weed infestation in corn. The objective of the study was to determine the relationship between the reflectance obtained in the 72 VIS and NIR wavebands (from 409 to 947 nm) and spectral differences resulting from the presence of weeds in the crop and various rates of fertilizer. Results indicate that the reflectance of corn is significantly influenced by the presence of weeds and nitrogen deficiencies in plants. Differences in spectral response due to nitrogen stress were most evident at 498 and 671 nm at all growth stages, and the presence of weeds had no interactive effect. Differences in other spectral regions, whether related to nitrogen, weeds or the combination of the two, appeared to be dependent on the growth stage. Airborne images were taken three times during the season, the first image was acquired 30 days after planting a second 66 days after planting at the tasseling stage, and the last 86 days after planting at the full-grown stage. Weeds were easiest to detect when corn was in the tasseling stage. Agüera et al. (2011) compared the efficiency of the nitrogen status assessments obtained from multispectral images taken from UAV and data recorded with a ground-based platform. NDVI calculated from both platforms proved to be good indicator of leaf nitrogen content, however a higher correlation coefficient ($R=0.80$) was found when using the UAV platform than for ground-based measurements ($R=0.71$).

SATELLITE REMOTE SENSING

There are also numerous examples of the use of the satellite images for the estimation of nitrogen status of crops. For example, Bausch and Khosla (2010) demonstrated that the QuickBird satellite multi-spectral data could be used for an accurate assessment of the within field spatial variability of nitrogen status of maize for in-season nitrogen management. Similar results were presented by Jia et al. (2011) who showed that single band reflectance in NIR (770 – 880 nm, red (640 – 720 nm) and green (520 – 610 nm) wavelengths as well as vegetation indices of NDVI, GNDVI, RVI and OSAVI (Table 1) were well correlated with wheat nitrogen status parameters and that high resolution satellite images were useful tools in nitrogen fertilization management.

DETECTION OF DISEASE AND PEST DAMAGE

GROUND-BASED REMOTE SENSING

Variability in the reflectance spectra of plants resulting from the occurrence and severity of pests and disease allows their identification using remote sensing data. Spectral characteristics of healthy and infested plants are significantly different. In the VIS range a healthy leaf reflects radiation in a small amount due to strong absorption by photosynthetic pigments, while the spectral reflectance in NIR bands is relatively high and is determined mostly by leaf internal structure and dry matter.

Ground based spectral reflectance proved to be very helpful in detection of pest damage in crops. Genc et al. (2008), using a handheld radiometer reliably assessed the sunn pest (*Eurygaster integriceps*) damage to wheat, with the help of NDVI and structure insensitive pigment index (SIPI – Table 1). The study conducted by Ranjitha et al. (2014) also showed differences in reflectance between healthy and pest damaged plants. Out of three vegetation indices (RVI, NDVI, GRVI – Table 1) tested in the study, GRVI appeared to be the most sensitive to thrips (*Thrips tabaci* Lind) damage of cotton.

In a study of aphid infestation, Kumar et al. (2010) compared the spectral reflectance from healthy and infested canopies of mustard using field as well as laboratory spectroscopy. Results showed that spectral indices NDVI, RVI, AI and SIPI (Table 1) were significantly correlated with aphid infestation and these indices could be used for identifying aphid infestation in mustard. Yang et al. (2005) conducted a greenhouse study to characterized greenbug (*Schizaphis graminum* Rondani) stress in wheat. They found that a waveband centered at 694 nm and spectral vegetation indices derived from wavelengths centered at 800 nm and 694 nm were most sensitive to greenbug-damaged wheat. Riedell and Blackmer (1999) used a handheld radiometer in greenhouse to characterize leaf reflectance spectra of wheat stressed by Russian wheat aphid (*Diuraphis noxia* Mordvilko). They concluded that leaf reflectance in the 625–635 nm and 680–695 nm ranges, as well as the normalized total pigment to chlorophyll *a* ratio index (NPCI - Table 1) were good indicators of chlorophyll loss caused by aphid feeding. Russian wheat aphid was taken into account in the study conducted by Mirik et al. (2007), who tested the relationship between four vegetation indices (AI, NDVI, SIPI, DSSI) and aphid abundance. In that study the only consistent and statistically significant relationships were found between Russian wheat aphid abundance and AI for all fields (Mirik et al. 2007) . The superiority of AI over NDVI, SIPI, DSSI in detection of aphid abundance indicate that invention of new spectral indices may create the potential to improve pest detection with the use of remote sensing. However one should be aware that detection of pest abundance with remote sensing methods should be supported by field inspection.

An example of the use of spectral measurements for identification of a plant disease is presented by Ashourloo et al. (2014), who investigated the use of vegetation indices derived from data obtained with a hyperspectral radiometer for detecting infections of wheat leaf Rust (*Pucciniatriticina*). The authors developed two indices: Leaf Rust Disease Severity Index 1 and 2 (LRDSI1 and LRDSI2 - Table 1) based on the reflectance in the 605, 695 and 455 nm wavelengths and both indices had high R^2 with the disease severity (0.94 and 0.95, respectively).

Zhang et al. (2003), detected the presence of *Phytophthora infestans* in tomatoes using reflectance. The study showed that the near infrared (NIR) region, especially 700 – 1300 nm, was much more useful than the VIS range to detect disease symptoms caused by *P. infestans*. The difference of spectral reflectance in VIS range between healthy and infected plants was only 1.19%, while the difference in the NIR region was higher then 10%. Similar results were obtained by Baranowski et al. (2015) who elaborated a hyperspectral method of early detection of biotic stresses caused by Alternaria alternate, a pathogen of oilseed rape (*Brassica napus* L.). The greatest spectral differences between the infected and uninfected parts of oilseed rape leaves were observed in the SWIR region between the water absorption bands (1470 and 1900 nm).

AIRBORNE REMOTE SENSING

When using airborne imagery to detect infested plants in agricultural crops it is important to select a sensor with appropriate spectral and spatial resolution. Mewes (2010) compared the effectiveness of the identification of wheat plants infected with brown rust??? (*Puccinia recondita f. sp. tritici*) with two hyperspectral cameras, one of which (AISA-DUAL, Specim LTD, Oulu, Finland) recorded the reflected radiation in the 498 channels in the range of 400 - 2500 nm with a spectral resolution of 2.5 - 5.8 nm and the second (ROSIS, German Space Agency, DLR) in the 115 channels in the range of 383 - 839 nm with a spectral resolution of 5 nm. The accuracy with which healthy and infested plants were identified in the AISA-DUAL images was higher than in the ROSIS images (respectively 84.32% and 80.33%), and was associated with stronger correlations at longer NIR wavelengths. AISA images were recorded from a lower altitude than ROSIS images (2300 m and 2880 m, respectively) what resulted in higher spatial resolution (1.5 m and 2.0 m, respectively) and stronger AISA signal intensity due to lower atmospheric absorption and scattering of the signal reflected from the field surface. Both sensors had the same Signal to Noise Ratio (>500:1) and images were taken almost at the same time, thus obtained imagery data could be directly compared

Glaser et al. (2009) accurately identified maize plots infested by corn rootworm (*Diabrotica virgifera*) using hyperspectral images acquired with spatial resolutions from 0.5 to 2.0 meters. The classification accuracies for identification of insect infested plots were up to 99% and were greater in the case of images recorded later in the season. The maximum separability between infested and un-infested maize, was derived using SR index (Table 1) calculated as ratio of two bands in VIS (648 nm) and NIR (747 nm) wavelengths. Spatial resolution of the image data is a key factor in the detection of the plant diseases and pest. Better results can be achieved using UAV, which provides higher resolution images compared to piloted aircraft platforms. Garcia-Ruiz et al. (2013) compared the effectiveness of citrus greening disease (caused by motile bacteria *Candidatus* Liberibacter spp) detection using an UAV-based sensor with a similar imaging system mounted on a piloted aircraft with spatial resolutions of 5.45 cm/pixel and 0.5 m/pixel, respectively. Classification accuracy of 67–85% achieved based on UAV-based datasets did not differ very much from the results obtained based on aircraft-based datasets of 61–74%. However, comparison of false negatives results achieved based on data acquired with the use of UAV and aircraft, that is, 7-32 and 28-45 respectively, indicated superiority of the first method over the latter.

SATELLITE REMOTE SENSING

The occurrence of plant diseases and pests in agricultural crops can also be observed using satellite images. Apan et al. (2004) demonstrated that Hyperion satellite hyperspectral imagery could be used to detect orange rust (*Puccinia kuehnii*) disease in sugarcane. Chen et al. (2007) used Landsat multispectral imagery to successfully detect severe infestations of the take-all disease (*Gaeumannomyces graminis*) in wheat. Franke and Menz (2007) evaluated high resolution QuickBird satellite multispectral imagery for detecting powdery mildew (*Blumeria graminis*) and leaf rust (*Puccinia recondita*) in winter wheat. Results demonstrated that multispectral images are generally suitable to detect infield heterogeneities in wheat vigor, particularly for later stages of fungal infections, but only moderately appropriate for distinguishing early infection levels in wheat.

ASSESSMENT OF WATER DEMANDS OF PLANTS

GROUND-BASED REMOTE SENSING

Another example illustrating the possibilities of spectral measurements carried out at the ground level is the development of spectral indices for determining the water demands of plants. For this purpose TIR remote sensing can be used (Taghvaeian et al. 2013). Since the temperature of a plant canopy depends on the degree of heat stress and water supply, it is possible to determine the current status of plant water supply using thermal data. Depending on water availability, plants showing symptoms of wilting emit more longwave infrared radiation. In order to compare the thermal data in time and space, the CWSI index was developed. It was obtained by normalizing the canopy temperature using the minimum and maximum differences between the plant canopy temperatures and air temperatures. Remotely sensed data can also be applied to determine the start date of crop irrigation as demonstrated by Mogensen et al. (1996), who used spectral measurements for the control of oilseed rape plantation. The study showed a strong relationship between the Relative Reflectance Index (RRI – Table 1) and water content in the soil. RRI index calculated as the ratio of the reflectance index of the withered crops to that of the fully irrigated reference crop allows to determine the optimal start date of irrigation.

AIRBORNE REMOTE SENSING

From airborne data Champagne et al., (2003) directly estimated the canopy equivalent water thickness (EWT), which is the weight of water per unit area of leaf. There is a close relationship between EWT and biomass of plants and their LAI, which are important variables in many agriculture applications. The model built by the authors, describing the relationship between EWT and hyperspectral airborne imagery data, proved to be a good predictor for broadleaf crops like beans, corn, canola and peas while for wheat provided poor predictions.

Another measure of plant water content, which can be estimated on the basis of airborne images, is canopy water content (CWC) determined as the total amount of foliage water per unit ground area. Plant water potential and relative water content are closely related to CWC but the latter measure is easier to estimate through optical remote sensing (Hunt et al., 2013). Various methods have been developed to estimate CWC from remotely sensed data, such as the NDWI and the NDII indices (Table -1) (Cheng et al., 2013; Colombo et al., 2008). Cheng et al. (2014) studied the daily and seasonal variation of CWC in nut tree orchards applying continuous wavelet analysis to the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data acquired in 224 bands from 365 to 2500 nm at a spectral resolution of 10 nm. The authors found that CWC is strongly correlated to three wavelet features at 1100 nm, 167 nm and 2180 nm wavelengths and their combination provided the best wavelet model and predicted CWC with a R^2 of 0.84.

UAV platforms have proved to be very useful for water irrigation management. The possibility of flight at low altitude allows for acquiring thermal images with high spatial resolution and thus eliminating the soil background effect. Gago et al. (2013) using thermal image pixel resolution of 2.5 cm obtained R^2=0.86 for the relationship between CWSI index (Table 1) and plant water status in vineyards a significant improvement in water stress assessment published compared to previous papers (Baluja et al. 2012).

Satellite remote sensing

Many studies have shown that accurate estimates of water content in plants can also be obtained from the satellite level. Gao (1996) estimated plant liquid water using the NDWI (Table 1) calculated from a combination of two water absorption bands from the MODIS satellite sensor centered at 860 nm and 1240 nm. Another index, SIWSI using water absorption features at 858 nm and 1640 nm was applied by Fensholt and Sandholt (2003) to monitor spatial and temporal changes in vegetative water content in rice paddy fields (*Oryza sativa* L.) in China.

Satellite images are particularly useful to estimate vegetation water content over vast agricultural areas and can support effective water management, providing information on the total evaporative water demand for crops. El-Magd and Tanton (2003) directly calculated ET, using Landsat ETM satellite data and a modified sensible heat flux approach. This method is useful for assessing crop water requirements and can be used to determine water use efficiency.

Weed control

Ground-based remote sensing

Intensive studies have been conducted on the use of handheld radiometers in weed control in agricultural crops. Weed control with remote sensing involves identification of the weed species or weed distinction from crop plants. Such distinction of weeds from crops is less complicated than the identification of weed species, but it suffices to apply herbicide precisely on weed plants. For detection of weeds in agricultural crops various vision systems have been used (Slaughter et al. 2007). Systems used in agricultural practice based on optical sensors (photodiodes), such as the Weedseeker (Trimble Navigation Ltd., Westminster, USA), can distinguish the plant from the soil. Nonetheless, distinguishing weeds from crop plants is more difficult. Greater efficiency in distinguishing weeds from crop plants as well as their identification is being evaluated via machine vision, which utilizes optics, electronics, mechanics, computer science and image analysis. In this technology, automatic discriminant analysis is conducted on the basis of information about color and its saturation, shape and texture of plants, allowing one to classify weed and crop plants. Burks et al. (2000, 2002, 2005) demonstrated that the accuracy of this method was very high, varying from 80 to 97%. The combination of the information about the size, shape and color of plants allowed the identification of volunteer potatoes in corn and sugar beet crops (Nieuwenhuizen et al. 2007, Van Evert et al. 2006), as well as the distinction of weeds from corn plants (Shrestha and Steward 2005).

AIRBORNE REMOTE SENSING

Of all applications of airborne remote sensing in pest management, weed detection seems to be the most successful. For example, Lamb et al. (1999), using hyper-spectral radiance data from an airborne sensor demonstrated detection of weeds in a seedling stage of a triticale crop and Deguise et al. (1999) successfully mapped weed patches in a canola (*Brassica napus* L.) field. Interesting information about detecting weed infestations with the help of multi–spectral airborne remote sensors is provided also by Goel et al. (2001) who stated that that the spectral bands centered at 675.98 and 685.17 nm in the red region and NIR bands from 743.93 to 830.43 nm have good potential for discriminating between weed–free and weed–infested areas in corn. Peña et al. (2015) studied the possibility of using UAVs to optimize the application of herbicides on the basis of aerial images. Owing to very low altitudes (40 m) and high spatial resolution aerial imagery weeds were detected with an accuracy of up to 91%, 50 days after sowing.

SATELLITE REMOTE SENSING

Recognition of weed seedlings using high-resolution multispectral satellites such as QuickBird and GeoEye with ground resolutions of 2.44 and 1.64 m, respectively shows promise. Using QuickBird imagery detailed maps of Cirsium arvense distribution in sugar beets during the cotyledon stage were prepared (Backes and Jacobi 2006). However, moderate resolution satellites like SPOT (20 m) or Landsat TM (30 m) and low resolution NOAA-AVHRR (1100 m) have proved to be useful on a broad scale for the detection and mapping of large clusters of weeds due to differences between spectral properties of weeds and their background (Anderson et al. 1993, Ullah et al. 1989, Peters et al.1992).

CONCLUSIONS

The examples described above, in many cases relate to the use of remote sensing in precision agriculture, which has been developing rapidly in recent years. The main purpose of this farm management method is to optimize returns on inputs, while ensuring environmental stewardship. Highly advanced technologies used in precision agriculture require constant access to detailed information characterizing the environmental conditions under which this production takes place. Such information may be obtained from airborne and satellite images at the field scale.

Data collected from satellite, airborne and ground levels facilitate monitoring weed infestations, damages caused by pests and plant pathogens, thereby making it possible to counteract quickly. The ability to use remote sensing data to determine fertilization needs of plants based on the nutrient content of crops and soils helps to increase yields and improve the quality of harvested seeds and fruits, which is important for improving the crop profitability. Accurate determination of the nutritional requirements of plants at critical stages during the field season helps to optimize fertilization as well as reduce potential adverse impacts associated with offsite transport of agrochemicals. Remote sensing has also been used to assess the water needs of plants and determine the date of commencement of irrigation, making it easier to manage crop production under conditions of water stress.

However, two major problems must be solved in order to develop quantitative applications of remote sensing for crop management. The first problem which needs to be dealt with is variation in reflectance caused by solar illumination angles, sensor viewing direction, or plant row orientation. The second problem concerns stress detection algorithms that perform reliably across space and time and capable of discerning water-, nutrient-, and pest-induced stress signals from "noise" introduced by soil and non-photosynthetically active plant material (Pinter et al., 2003). Newer techniques, such as spectral mixing analysis, may be used for these purposes. Recently, Planet Labs company launched into space a fleet of 28 small observing satellites with dimensions of tens of centimeters. The satellites can provide images of agricultural fields at an exceptional combination of resolution and frequency.

Another trend accompanying the development of remote sensing is the integration of remotely sensed parameters with decision support systems. Combining remotely acquired data with existing crop simulation models will improve reliability of decision support systems and will contribute to modernized agricultural production management

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