Remote sensing potential for investigation of maize production: review of literature

A. Ngie[1*]; F. Ahmed[2]; K. Abutaleb[1]

[1] Department of Geography, Environmental Management and Energy Studies, University of Johannesburg, P.O. Box 524 Auckland Park 2006, South Africa

[2] School of Geography, Archaeology and Environmental Studies, University of the Witwatersrand, Johannesburg, South Africa

[*] Corresponding author: email: adelinengie@gmail.com, Tel.: +27 (0)11 559 2270

DOI: http://dx.doi.org/10.4314/sajg.v3i2.4

Abstract

Maize is considered globally as the most important agricultural grain which is staple food for many humans and feed to livestock. There is need to enhance productivity through management tools to meet the demand for growing populations. Farmers are likely to be interested in technologies that are beneficial to their operations. A technology that could assist farmers to produce staple foods e.g. maize more efficiently is remote sensing. The paper focuses on reviewing published research that deals with application of remote sensing in maize farming particularly the spectral characteristics of maize leaves, classification and mapping. It further surveys the application of remote sensing in detecting foliar nitrogen deficiency, water stress and disease infestations in maize. Remote sensing can be considered as a fast, non-destructive and relatively cost-effective method to study biophysical and biochemical parameters of vegetation across vast spatial areas. However, selection of appropriate sensors with special attention on their spatial and spectral resolutions as well as processing techniques will validate a success story for remote sensing application in maize production.

Keywords: Maize · Nutrient monitoring · Remote sensing · Spectral reflectance · Yield predictions

1. Background

Maize has been considered globally as the most important agricultural grain which is staple food in many countries and feed to livestock. It is estimated that by 2050, the demand for maize in developing countries will double, and by 2025 maize will have become the crop with the greatest production globally (FARA, 2009). In 2006 the Abuja Summit on Food Security in Africa identified maize, among other crops, as a strategic commodity for achieving food security and poverty reduction. There was a call to promote maize production on the continent to achieve self-sufficiency by 2015 (AUC, 2006).

Maize production at macro level is limited by climate and soil. The potential areas maize can, therefore, be cultivated are geographically specific to these environmental conditions. At micro level, the determinant or stress factors to maize production would include among other factors water and nutrients deficiencies (nitrogen, phosphorus, potassium, *etc*.), insect pests, and diseases (Zhao *et al.,* 2003). The proper functioning, growth and eventually yield output of the crop is influenced by these factors. Detection of stress levels to which maize production is subjected is therefore essential for assessing the effects on yield, taking action to mitigate these effects and enhancing production.

Precision agriculture is based on intensive sources of information and attempts to address the site-specific needs with spatially variable application. This involves close monitoring and controlling many aspects of crop production that should aid in identifying proper targets and needs of crops for applying locally varying doses of chemicals. For instance, Mondal *et al.* (2011) conducted a research to monitor plant nutrient and moisture needs, soil conditions, and plant health (including identification of disease infestation).

Effective crop planning and management requires informed and sound decisions drawn from knowledge about the crops in the field. In order to improve agricultural management, scientist are applying information technology (IT) and satellite-based technology (*e.g.* global positioning system, remote sensing *etc*.) to identify, analyze, monitor and manage the spatio-temporal variability of agronomic parameters (*e.g.*

nutrients, diseases, water, *etc*.) within crop fields. This aids in timely applications of only the required amount of inputs to optimize profitability, sustainability with a minimal impact on the environment (Mondal *et al.,* 2011). There is therefore the assurance of proper resource utilization and management to enhance crop productivity.

The purpose of this paper was to review published research in maize production using remote sensing as major research tool. The review seeks to investigate the potential of using remotely sensed data and analytical techniques to enhance productivity of maize. This is achieved through an understanding of the spectral characteristics of maize leaves for varietal separation, classification and mapping. The ability of these spectral characteristics can be used to monitor the nutrient status and health condition of the maize leaves. The paper concludes with a summary and some recommendations for the application of remote sensing in the production of maize.

2. Spectral characteristics of maize leaves, classification and mapping

When energy strikes on a surface material, it is either absorbed or reflected back through the electromagnetic spectrum. The visible (400-700nm wavelength) and near infrared (NIR) (700-2500nm wavelength) region of the electromagnetic spectrum is the region at which most agricultural studies carry out measurements. This is because the spectral region includes wavelengths which are sensitive to physiological and biological functions of crops (Lillesand *et al.,* 2008). The spectral characteristics of healthy vegetation are distinctive with low reflectance in blue, high in green, very low in red and very high in the NIR (Chen *et al.,* 2010; Genc *et al.,* 2013).

There is a large difference in the spectral characteristics between soil and crop, especially at the ‘red edge’ which is the point where the electromagnetic spectrum changes from visible to NIR (wavelength of approximately 700nm) (**Figure 1**). This region is used to detect biochemical and biophysical parameters in crops thereby being useful in vegetation studies. The principle is that the majority of the red light is absorbed by the chlorophyll in the canopy while a high proportion of the NIR light is reflected

(Ramoelo *et al.*, 2012). The canopy greenness increases, either due to increasing crop density or chlorophyll content. Canopy greenness is therefore related to the percentage of red reflectance absorbed and the percentage NIR reflectance reflected (Lillesand *et al.*, 2008). Therefore, the reflectance spectral techniques are very suitable for providing relevant information on both crop foliar and canopy which could be related to nutrient status and stress factors on the crops (Scotford & Miller, 2005; Ramoelo *et al.*, 2012).

Measurements at the red-edge bands has made possible the estimation of foliar nutrients and chlorophyll concentrations in differing vegetation types at varying growth stages (Huang *et al*., 2004; Cho and Skidmore, 2006; Darvishzadeh *et al*., 2008; Mokhele & Ahmed, 2010). Therefore, remote sensing (both multispectral and hyperspectral) can therefore provide an effective means for fast and non-destructive estimation of leaf nitrogen and water status in crop plants through complimentary tools such as regression models (Yao *et al.*, 2010).

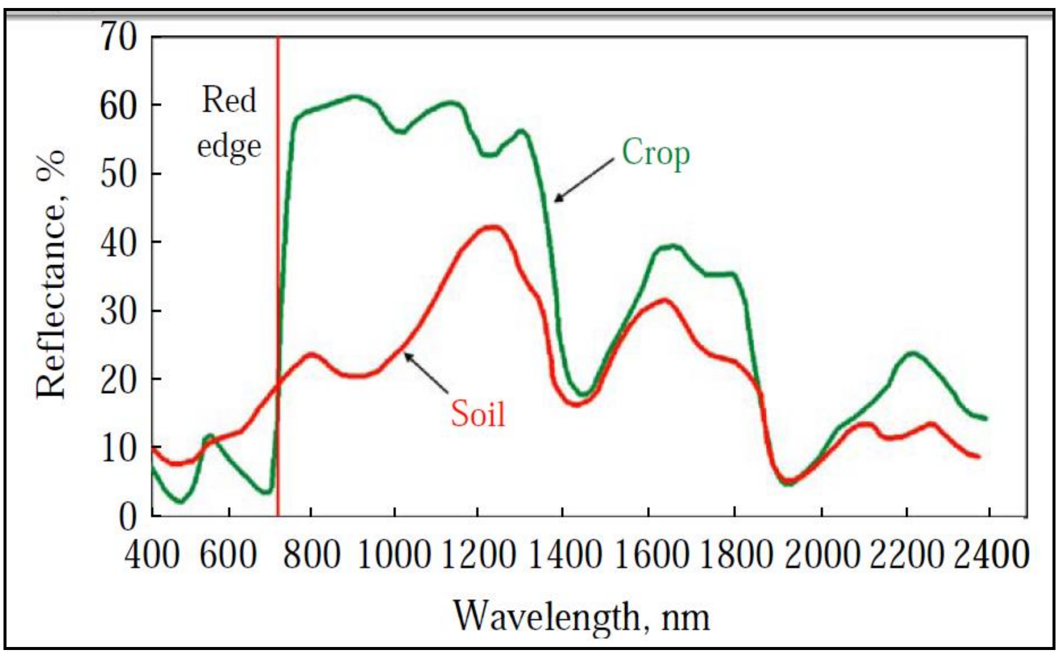

Figure 1: Spectral reflectance curves for soil and crop (green vegetation) according to Scotford & Miller, 2005.

Spectral unmixing techniques can be used to quantify crop canopy cover within each pixel of an image and have the potential for mapping the variation in crop yield. Each image pixel contains a spectrum of reflectance values for all the wavebands measured. These spectra can be regarded as the signatures of surface components such as plants or soil, provided that components, referred to as endmembers, covers the whole pixel. Spectra from mixed pixels can be analyzed with linear spectral unmixing, which models each spectrum in a pixel as a linear combination of a finite number of spectrally pure spectra of the endmembers in the image, weighted by their fractional abundances (Yang *et al.*, 2007; 2010). Spectral unmixing is an alternative to soft classification for sub-pixel analysis (Lu and Weng, 2004). This is usually very essential in crop identification and classification studies. The classification is performed under either supervised techniques which include maximum likelihood, minimum distance, parallelepiped etc or unsupervised technique.

Adding to traditional unsupervised and supervised classification methods are advanced techniques such as artificial neural networks (ANN), support vector machines (SVM), decision trees (DT) and image segmentation which have been used to classify remote sensing data (Lu & Weng, 2007; Mathur & Foody, 2008). However, these classifiers remain to be evaluated using different types of remote sensing data from diverse crop growing environments. There is also the field-based crop identification which entails field boundary information and results in higher classification accuracy (De Wit & Clevers, 2004).

Remote sensing has played a significant role in crop classification for various purposes. Effective crop classification requires an understanding of the spectral characteristic (foliar and canopy levels) of the particular crop. In order to understand for instance the maize canopy spectral characteristics, a field investigation is targeted when the plant canopy is covered which is usually during six to eight weeks after planting. The light reflectances acquired during such growth stages could apply in differentiation of varieties; classification and mapping of maize varieties. For instance, Yang *et al.* (2011) used maximum likelihood and SVM classification techniques on SPOT 5 imagery to identify crop types and to estimate crop areas. Different band ratios of multispectral or hyperspectral data and classifications schemes have been applied, depending on geographic area, crop diversity, field size, crop phenology and soil condition (Nellis *et al.,* 2009).

To extract vegetation species from hyperspectral imagery, a set of signature libraries of vegetation are usually required (Xavier *et al.,* 2006). For certain applications, the vegetation libraries for particular vegetation species might be already available. However, for most cases, the spectral signature library is established from data collected with a spectrometer. As such, vegetation mapping using hyperspectral imagery must be well designed to collect synchronous field data for creating imagery signatures (Melgani, 2004).

In most agricultural studies, spectral reflectance values of at least two wavelength bands (on either sides of the 'red edge') are measured to enable the calculation of a ratio. These ratios are known as vegetation indices and many have been developed over the years. These indices are usually correlated against field observations of nutrient stress measured at foliar or canopy level. The number of wavelength bands measured will determine the complexity of the data analysis; wherein a small number of bands will translate to a simple data analysis. This could be illustrated in a scenario where *in situ* measured reflectance values of the red and NIR wavelengths are used to calculate normalized difference vegetation index (NDVI).

However this only holds true until canopy closure when the crop has a leaf area index (LAI) of up to three where LAI is defined as the ratio between total leaf area, one side only, per unit area of ground (Scotford & Miller, 2005). Mirik *et al.* (2012) also described spectral vegetation indices as mathematical expressions that involve reflectance values from different parts of the electromagnetic spectrum. These expressions are aimed at optimizing information and normalizing measurements made across different environmental conditions.

Shanahan *et al.* (2003) proposed a study evaluating the use of two indices (NDVI and green NDVI (GNDVI)) on a large plot scale. The experiment was conducted on four varieties of irrigated corn treated with five differing levels of nitrogen. Remote measurements were taken with active sensors emitting light in four bands: blue (460nm), green (555nm), red (680nm), and NIR (800nm). The authors concluded that differences in NDVI was significantly impacted by nitrogen and sampling date. Also, increased nitrogen was correlated to increased chlorophyll content but not on a large scale. However, Strachan *et al.* (2002) recommended that canopy reflectance at red edge position can explain 81% of maize leaf nitrogen variability.

3. Monitoring nutrient stress in maize

3.1. Nitrogen deficiencies in maize

Nitrogen (N) is a biochemical nutrient essential for plant growth. It forms part of many structural, metabolic and genetic compounds. Nitrogen is a critical building block of Chlorophyll which is essential for the process of photosynthesis. Availability of N in the soil usually related to plant growth, photosynthetic capacity and stress (Ustin *et al.,* 1998; Yao *et al.,* 2010). Nitrogen deficiency in a plant will have symptoms on the lower, older leaves first before progressing upward to younger leaves if the condition is not corrected (Sawyer, 2004).

Nitrogen deficiencies interfere with protein synthesis and growth in crops such as maize (Bruns and Abel 2005). Numerous studies have been conducted to proof the direct effect of N to yield levels of maize (Lindquist *et al.*, (2007); Shapiro and Wortmann, 2006; Singh *et al.,* 2003; Abouziena *et al.*, 2007; Savabi *et al.,* 2013). Nitrogen deficiency-induced effects on kernel number could be related to photosynthesis or plant growth at flowering (Andrade *et al.,* 2002). Gitelson *et al.* (2005) developed a model, based upon field measurements made by means of a hyperspectral radiometer, for non-destructive estimation of chlorophyll in maize and soybean canopies.

Nitrogen deficiency could be detected earlier in crops when visual symptoms of deficiency are less evident with the use of remote sensors (Jackson *et al.,* 1981). This is achieved through its various compounds providing an effective means for monitoring growth status and physiological parameters in crop plants. Its presence in chlorophyll and other cellular structures influences information on spectral reflectance (Yao *et al.,* 2010).

The measurement of chlorophyll content is also important with regard to N management. Hence, a number of studies have utilised remote sensing techniques to determine the status of nitrogen and other essential nutrients in field crops such a maize and wheat as illustrated through this review.

Zhao *et al.* (2003) induced differing levels of nitrogen stress on corn and measured growth parameters, chlorophyll concentration, photosynthetic rates, and reflectance. The study demonstrated that reductions in leaf nitrogen concentrations are greater in plants suffering from inadequate soil N availability. Reduced nitrogen concentrations were correlated with lower rates of stem elongation and leaf area. The authors in 42 days after crop emergence noticed a 60% reduction in chlorophyll *a*, which caused an increased reflectance near 550 and 710nm. Therefore, reduced chlorophyll concentrations as a result of stress translate in decreased light absorbency and increased reflectance in these wavelength regions.

Remotely sensed imagery can provide valuable information about in-field N variability in maize as well as variability at canopy level still using the relationship with N content. Maize leaf reflectance (near 550nm wavelength) has a good relationship with leaf N content (Osborne *et al.,* 2002). Martin et al. (2007) found that NDVI increased with maize growth stage during the crop life cycle and a linear relationship with grain yield is best at the V7–V9 maize growth stages.

Solari *et al.* (2008) investigated the potential use of active sensors at a field scale in determining N status in corn. Irrigated plots with uniform soils and fertilization, excluding N, were established at the initial stage and later differing rates and timing of nitrogen applications were administered in order to induce variable growth patterns. The authors discovered that the NDVI was sensitive to differences in N, hybrid, and growth stage. There exist a strong linear relationship between leaf chlorophyll concentration and leaf N concentration, where the greater leaf area and green plant biomass levels result in higher reflectance and higher subsequent NDVI values (Inman *et al.,* 2007). This implies that these variables (leaf area and plant biomass) are directly related to the N content of the plant; hence higher NDVI values indicate higher plant N content (Shaver *et al.*, 2011).

3.2. Water stress in maize

The saying that ‘water is life’ denotes for both flora and fauna. Water is a key determinant in the production of crops with maize inclusive. Accurate water content estimation is required to make decisions on irrigation and also crop yield estimations in agricultural studies (Peñuelas *et al.,* 1993). The water content/status of a plant can be measured from root, stem and leaf material or the whole canopy. Leaf analyses are however, the most important organ for evaluating nutrient and water status of plants in comparison to other tissue types (Suo *et al.,* 2010). The leaf is also mostly responsible for photosynthesis, an essential physiological process in plants. Hence, the health and nutrient status with water status inclusive of the plants can be evaluated from the leaves.

Considerable technological developments have taken place over the years to determine water stress using remote sensing. The basis of detecting water stress relates to the differences in reflectance properties of plants under different water stress levels at certain wavelengths in the NIR portion of the electromagnetic spectrum (Genc *et al.,* 2013). Two spectral regions have been found useful for detecting water status in plants; one characterised by high reflectance caused by reflections and scattering of light in the spongy mesophyll layer (NIR 0.7 – 1.3µm) and the other characterised by strong water absorption (mid infrared (MIR) 1.3 – 3.0µm). The first one is based on the turgor pressure in the leaf tissues while the second is directly related to leaf water content. The reflectance spectra of water stressed plants absorb less light in the visible and more light in the NIR regions of the spectrum than plants not experiencing water stress.

As a result of the absorption by oxygen-hydrogen (O–H) bonds in water, its absorption features could be found at approximately 760nm, 970nm, 1200nm, 1450nm, and 1950nm (Li, 2006). The first derivatives of reflectance associated with the slopes of the lines near water-absorption wavelength bands 900nm and 970nm correlates well with leaf water content (Danson *et al.,* 1992). Studies have shown that reflectance spectra of green vegetation in the 900-2500nm region are associated with liquid water absorption and are also weakly affected by other biochemical components absorption. It is possible to investigate the effect of water on nutrient stress (nitrogen) through discrimination based on the visible and NIR reflectance of maize leaves (Christensen *et al.,* 2005). Prior knowledge of water status of plants can increase the ability to discriminate nutrient stress significantly.

The water band index is derived from the ratio of reflectance measured at 900nm and 970nm (Peñuelas *et al.,* 1993). This spectral index has been correlated with ground-based measurements of plant water content at both the leaf and canopy scales. It is, however, more sensitive to leaf water content than the water content of the whole plant. This is advantageous in agricultural applications where leaf water content changes more noticeably in response to drought conditions than the water content of the entire plant foliage (Champagne *et al.,* 2003). Leaf water content can be measured with the spectrometer to determine available water to the plants.

Genc *et al.* (2013) conducted an experiment on corn plants where reflectance measurements were made at the red and NIR portions before and after irrigation application. The results confirmed a decrease and increase in reflectance spectral at respective regions as the water level at field capacity increases. However, when the authors compared results at all four water levels, the reflectance spectra indicated that water stressed corn plants absorbed less light in the visible and more light in the NIR regions of the spectrum than unstressed plants.

A recent significant breakthrough in passive optical remote sensing has been the development of hyperspectral sensors on satellite platforms (such as EO-1 Hyperion) that provide continuous narrow bands and high resolution in the visible and infrared spectral region. Compared with multispectral imagery that only has a dozen of spectral bands, hyperspectral imagery includes hundreds of spectral bands. Hyperspectral sensors are well suited for vegetation studies as reflectance/absorption spectral signatures from individual species as well as more complex mixed-pixel communities can be better differentiated from the much wider spectral bands of its imagery (Yang *et al.,* 2010). However, the interpretation of this hyperspectral data can be complicated by the interrelationships between wavelength variables but many statistical techniques have been utilised to analyse such data. For example, neural networks; partial least-squares analysis; fuzzy logic; principle component analysis and stepwise multiple linear regression have all been used (Xie *et al.,* 2008).

Maize growth rate can be used as a good predictor of kernel number when nitrogen and water supply are considered as variables. This relationship was proven by modifying maize growth rate by N and/or water supply to that similarly obtained when plant growth was changed by variations in plant density and incident radiation. The effect of reducing N availability was similar to the effect of reducing water availability (Andrade *et al.,* 2002).

Thus, the effect of water deficiencies, nitrogen stress, plant density, and incident radiation on maize kernel set can be predicted through a relationship between growth rate and kernel number. This is explained by two aspects: the correlation between growth rate at flowering to growth of reproductive structures, and also that early seed development and kernel set in maize is dependent on a continued supply of assimilates from concurrent photosynthesis (Zinselmeier *et al.*, 2000).

A few water indices have been developed to study crop stress which include the water band index (WBI) (Peñuelas *et al.,* 1993), shortwave infrared water stress index (SIWSI) (Fensholt & Sandholt, 2003) and normalized difference water index (NDWI) (Gao, 1995; Serrano *et al.*, 2000). Recent studies have focused on combining the blue, green, red with blue and the NIR wavelengths in indices to estimate vegetation water content (**Table 1**) (Genc *et al.,* 2013). Therefore, the use of remote sensing is particularly and practically suitable for assessing water stress and implementing appropriate management strategies because it presents unique advantages of repeatability, accuracy and cost-effectiveness over ground-based survey methodologies for water stress detection.

Table 1: Spectral indices and some wavelength bands used to detect water stress in maize

Index	Abbreviation and formula	Reference
Normalized difference vegetation index	NDVI = (NIR − R) / (NIR + R)	Rouse *et al.*, 1973
Green NDVI	GNDVI = (NIR − G) / (NIR + G)	Gitelson & Merzlyak, 1996
Simple ratio	SR = R / NIR	Jordan, 1969
Normalized difference water index	NDWI = (G – NIR)/(G + NIR)	Gao, 1995; Mcfeeters, 1996; Serrano *et al.*, 2000
Water band index,	WBI = 970nm/ 900nm	Peñuelas *et al.*, 1993
Shortwave infrared water stress index	SIWSI(6,2)= (r6 -r2)/((r6+r2) (10) or SIWSI(5,2)= (r5 -r2)/((r5+r2) (band 6 and 5 respectively of MODIS); SIWSI = SWIR−R(R_d) and SWIR+ R(R_s).	Fensholt & Sandholt, 2003; Haixia *et al.*, 2013
Ratio of blue and NIR	BN = B / NIR	Genc *et al.*, 2013
Ratio of green and NIR	GN = G / NIR	Genc *et al.*, 2013
Ratio of red + green and NIR	RGN = (R + G) / NIR	Genc *et al.*, 2013

SWIR (short wave infrared); NIR (near infrared); R (red); G (green); B (Blue)

3.3. Disease detection

Detection and identification of plant diseases and planning effective control measures are important to sustain crop production. Maize production is challenged by disease attacks ranging from insect to fungi. Plant diseases do not only affect yields but also increase the cost of production through treatment procedures on the crops. Some of the common diseases on the maize crop include but are not limited to grey leaf spot, common rust, northern corn leaf blight, phaeosphaeria leaf spot, maize streak disease, stem rot diseases and others.

When crops are infested by a disease, the biochemical constituent of the plant changes and so would be the spectral signatures. This is the reason why remote sensing could be used to monitor the infestation of diseases in field crops. Applications of remote sensing in field crops, for rapid detection of pest damage or disease, also include the use of handheld optical devices (Sudbrink *et al.*, 2003; Moshou *et al.*, 2004; Xu *et al.*, 2007; Mirik *et al.*, 2007) and airborne sensors (Sudbrink *et al.*, 2003).

The health of the leaf can also be monitored wherein changes in leaf chlorophyll content provide an indicator of maximum photosynthetic capacity, leaf development and/or stress (Si *et al.*, 2012). Assessment of photosynthetic functioning is one of the most important bases for the diagnosis and prediction of plant growth and subsequent yield estimation.

Williams *et al.* (2012) used the potential of the hyperspectral NIR imaging to evaluate fungal contamination in maize kernels. Using the principal component analysis (PCA), bad pixels as well as shading of acquired absorbance images were removed before further analysis. They concluded that the methodologies used were able to detect infection, the degree of infection and increase of infection over time. Therefore, remote sensing could assist in early detection of disease infestation in maize.

4. Crop yield predictions

Crop yield prediction is production estimates that are made a couple of months before the actual harvest. This is frequently done through computer programmes that utilize agro-meteorological data soil data, remotely sensed and agricultural statistics to describe quantitatively the plant-environment interactions (Dixon *et al.*, 1994; Zere *et al.*, 2004). In some instances, meteorological data is included to run some of the yield models (Unganai & Kogan, 1998). The meteorological data is usually generated from weather stations and cover a given area.

Crop phenology is fundamental to crop management, where timing of management practices is increasingly based on stages of crop development. The development of maize is subdivided into ten growth stages which summarily fall between the vegetative and reproductive phases. Plant development (phenology) is influenced by a variety of factors such as available soil moisture, date of planting, air temperature, day length, soil condition and nutrients. These factors therefore also influence the plant's condition and productivity (Nellis *et al.*, 2009). In order to achieve maximum production, vegetative stage three (four to six weeks after emerging) is more vital. This because at growth stage three there are eight to twelve leaves of the new maize plant that are fully unfolded. This is the stage of applying sprays and fertilizers. The yield potential of the plants is determined at this stage depending on the moisture and nutritional conditions at the time (Andrade *et al.*, 2002).

Maize yield is usually associated with the kernel number at harvest and is a function of the physiological condition of the maize crop during the reproductive phases - bracketing, flowering or silking (Otegui & Andrade, 2000). Andrade *et al*., 2002 also determined that Kernel number can be related to photosynthetic activity via chlorophyll content.

Remote sensing techniques can be used to extract information about biophysical and biochemical parameters of vegetation such as LAI, chlorophyll, phosphorus, fibre, lignin, N (Darvishzadeh *et al*., 2008; Ramoelo *et al*., 2011) and silicon (Mokhele & Ahmed, 2010) which are essential for the plant growth. Statistical regression techniques are used to derive specific vegetation parameters and indices (Darvishzadeh *et al*., 2008; Si *et al*.,

2012) that could be utilised in estimating crop productivity. For instance, the LAI is used to quantify canopy structure, crop growth and hence predict primary productivity.

High correlations are found between vegetation indices and green biomass in studies done at field level (Groten, 1993). This is related to the crop type and yields but requires ground truthing and actual yield measurements in selected fields (pixels) that cover the full range of observed vegetation indices such as NDVI values. Viña *et al.* (2004) using visible atmospherically resistant spectral indices documented a capability for detecting changes in corn due to biomass accumulation, changes induced by the appearance and development of reproductive structures, and the onset of senescence.

Shanahan *et al.* (2001) used remotely sensed imagery to compare different vegetation indices as a means of assessing canopy variation and its resultant impact on corn (*Zea mays* L.) grain yield. Results showed that green normalized difference vegetation index (GNDVI), developed by Gitelson *et al.* (1996), derived from images acquired during midgrain filling were the most highly correlated with grain yield (**Table 1**). Therefore GNDVI could be used to produce relative yield maps depicting spatial variability in fields, offering a potentially attractive alternative to use of a combine yield monitor.

While most studies on yield prediction with remotely sensed data apply multispectral data due to its availability, hyperspectral images could also be utilised. For instance, Uno *et al.* (2005) statistically analysed hyperspectral images with an artificial neural network (ANN) and vegetation indices to develop models to predict yields for maize in Canada. After using the PCA to reduce the number of input variables for analysis, a greater prediction accuracy (20% validation) was obtained with an ANN model than with either of the three conventional empirical models based on NDVI, SR or photochemical reflectance index (PRI).

The use of remote sensing to estimate biological crop yields is being explored in many countries such as the United States, China and India, and likely will become the keystone of agricultural statistics in the future (Zhao *et al.*, 2007). The fact that crop productivity vary greatly across climatic regions since it depends on agroclimatic conditions, the application of remote sensing in this field would be necessary. The variability of these conditions warrants models to be developed based on the conditions of different areas where the crops are planted. Moreover, there is room to improve on methodologies and principles already developed in the creation of new models.

5. Summary and recommendations

According to this review there is great potential for remote sensing to be used in investigating maize growth process in order to enhance production of this global crop. This is backed by the availability of products with higher spatial, spectral and temporal resolution becoming more efficient, affordable and cost-effective. Its success in biophysical vegetation parameters identification and monitoring through the various growth stages of maize has been studied even though not uniformly across the globe.

Spectral reflectance measurements can provide a basis for variable biophysical vegetation parameters. There is a good relationship between these parameters when the spectral reflectance is measured at the leaf scale. Research in the past has been undertaken to estimate foliar nitrogen concentrations in experimental fields using portable spectrometers, with promising results. However when measured at the canopy level the relationship is further complicated for various parameters (LAI, wet and dry biomass *etc*.) and therefore further research are needed.

Sensor readings were also found to be more associated with chlorophyll content during vegetative growth phases than during reproductive phases (Solari *et al.,* 2008). Taking advantage of improvements in sensor characteristics and processing techniques, the use of remotely sensed data for yield predictions for maize is gaining grounds. This is contributing substantially in a more accurate description of within-field crop yield variability which is a great concern in precision agriculture. However, it is still a challenge to develop accurate operational maize yield-estimating models.

The challenge of water deficiency monitoring over a large spatial area has been overcome through the use of remote sensing. It is practically suitable for assessing water stress and implementing appropriate management strategies because it presents unique advantages of repeatability, accuracy, and cost-effectiveness over the ground-based surveys for water stress detection.

One of the potential applications of remote sensing technique in agriculture is the detection of plant disease on extensive areas before the symptoms clearly appear on the plant leaves. This is advantageous because remote sensing detects biophysical changes before physiological changes are visible. The challenge of disease infestation on maize production warrants more investigation as not much was found during this literature survey. Early detection and delineation of maize infested areas especially in some of the high productive areas that are prone to diseases (*e.g.* grey leaf spot) using hyperspectral remotely sensed data could be attempted. Therefore, spectroscopy analysis could be considered as an efficient technique for non-destructive, rapid, and accurate measurement which is widely applied in agricultural fields for crop discrimination, monitoring of nutritional status as well as diseases (Sankaran *et al.*, 2010).

Acknowledgement

The funding for this research was provided through the University of Johannesburg bursary schemes. The authors also appreciate the inputs from the anonymous reviewers to this paper.

References

Abouziena, H. F., M. F. El-Karmany, M. Singh and S. D. Sharma, 2007: Effect of Nitrogen Rates and Weed Control Treatments on Maize Yield and Associated Weeds in Sandy Soils. *Weed Technology 21(4),* 1049-1053.

Andrade, F.H., L. Echarte, R. Rizzalli, A.D. Maggiora and M. Casanovas, 2002: Kernel Number Prediction in Maize under Nitrogen or Water Stress. *Crop Science 42,* 1173-1179.

AUC (African Union Commission), 2006: Resolution of the Abuja Food Security Summit. Addis Ababa, Ethiopia. http://www.fara-africa.org/media/uploads/library/docs/policy_briefs/patterns_of_change_in_maize_production_in_africa.pdf Accessed 2/09/2013

Bruns, H.A. and C.A. Abel, 2005: Nitrogen fertility effects on bt -endotoxin and nitrogen concentrations of maize during early growth. *Agronomy Journal 95,* 207-211.

Champagne, C.M., K. Staenz, A. Bannari, H. Mcnairin 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,* 148-160.

Chen, P., D. Haboudane, N. Tremblay, J. Wang, P. Vigneault and B. Li, 2010: New spectral indicator assessing the efficiency of crop nitrogen treatment in corn and wheat. *Remote Sensing of Environment 114,* 1987-1997.

Cho, M.A. and A.K.. Skidmore, 2006: A new technique for extracting the red edge position from hyperspectral data: the linear extrapolation method. *Remote Sensing of Environment 101(2)*, 181-193.

Christensen, L. K., S.K. Upadhyaya, B. Jahn, D.C. Slaughter, E. Tan and D. Hills, 2005: Determining the Influence of Water Deficiency on NPK Stress Discrimination in Maize using Spectral and Spatial Information. *Precision Agriculture 6(6)*, 539-550.

Danson, F., M. Steven, T. Malthus and J. Clark, 1992: High-spectral resolution data for determining leaf water content. *International Journal of Remote Sensing 13,* 461-470.

Darvishzadeh, R., A. Skidmore, M. Schlerf, C. Atzberger, F. Corsi and M. Cho, 2008: LAI and chlorophyll estimation for a heterogeneous grassland using hyperspectral measurements. *ISPRS Journal of Photogrammetry and Remote Sensing, 63,* 409-426.

De Wit, A.J.W. and J.G.P.W. Clevers, 2004: Efficiency and accuracy of per-field classification for operational crop mapping. *International Journal of Remote Sensing 25(20),* 4091-4112.

Dixon, B.L., S.E. Hollinger, P. Garcia and V. Tirupattur, 1994: Estimating Corn Yield Response Models to Predict Impacts of Climate Change. *Journal of Agricultural and Resource Economics 19(1),* 58-68.

Forum for Agricultural Research in Africa (FARA), 2009: Networking Support Function 3: Regional Policies & Markets. Patterns of Change in Maize Production in Africa: Implications for Maize Policy Development. Ministerial Policy Brief Series (Number 3). 8pages.

Fensholt, R. and I. Sandholt, 2003: Derivation of a shortwave infrared water stress index from MODIS near- and shortwave infrared data in a semiarid environment. *Remote Sensing of Environment 87,* 111-121.

Gao, B.C., 1995: NDWI – a normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment 58,* 257-266.

Genc, L., M. Inalpulat, U. Kizil, M. Mirik, S.E. Smith and M. Mendes, 2013: Determination of water stress with spectral reflectance on sweet corn (*Zea mays L*.) using classification tree (CT) analysis. *Zemdirbyste-Agriculture 100(1),* 81-90.

Gitelson, A. A. and N. Merzlyak, 1996: Signature analysis of leaf reflectance spectra: algorithm development for remote sensing of chlorophyll. *Journal of Plant Physiology 148,* 494-500.

Gitelson, A., A. Vina, V. Ciganda, D. Rundquist and T. Arkebauer, 2005: Remote estimation of canopy chlorophyll content in crops. *Geophysical Research Letters* 32 pp. L08403 doi: 10.1029/2005GL022688.

Gitelson, A., Y. Kaufman, and M. Merzlyak, 1996: Use of a green channel in remote sensing of global vegetation from EOSMODIS. *Remote Sensing and Environment 58,* 289-298.

Groten, S.M.E., 1993: NDVI–crop monitoring and early yield assessment of Burkina Faso. *International Journal of Remote Sensing 14(8),* 1495-1515.

Haixia, F., C. Chen, H. Dong, J. Wang and Q. Meng, 2013: Modified Shortwave Infrared Perpendicular Water Stress Index: A farmland water stress monitoring method. *Journal of Applied Meteorology and Climatology 52(9),* 2024-2032.

Huang, Z., B.J. Turner, S.J. Dury, I.R.Wallis and W.J. Foley, 2004: Estimating foliage nitrogen concentration from HYMAP data using continuum removal analysis. *Remote Sensing of Environment 93(1-2),* 18-29.

Inman, D., R. Khosla, R.M. Reich and D.G. Westfall, 2007: Active remote sensing and grain yield in irrigated maize. *Precision Agriculture 8,* 241-252.

Jackson, R.D., C.A. Jones, G. Uehara and L.T. Santo, 1981: Remote detection of nutrient and water deficiencies in sugarcane under variable cloudiness. *Remote Sensing of Environment 11,* 327-337.

Jordan, C. F., 1969: Derivation of leaf area index from quality of light on the forest floor. *Ecology 50,* 663-666.

Li, M. Z., 2006: *Spectroscopy Analysis Technology and Application*. Beijing: Science Press.

Lillesand, T.M., R.W. Kiefer, and J.W. Chipman, 2008: Remote sensing and image interpretation. 6th edition. NJ: Wiley.

Lindquist, J.L., D.C. Barker, S.Z. Knezevic, A.R. Martin and D.T. Walters, 2007: Comparative nitrogen uptake and distribution in corn and velvetleaf (Abutilon theophrasti). *Weed Science 55,* 102-110.

Lu, D. and Q. Weng, 2004: Spectral mixture analysis of the urban landscape in Indianapolis with Landsat ETM+ imagery. *Photogrammetric Engineering and Remote Sensing 70(9),* 1053-1062.

Lu, D. and Q. Weng, 2007: A survey of image classification methods and techniques for improving classification performance. *International Journal of Remote Sensing 28 (5),* 823-870.

Martin, K. L. Martin, K. Girma, K. W. Freeman, R. K. Teal, B. Tubańa, D. B. Arnall, B. Chung, O. Walsh, J. B. Solie, M. L. Stone and W. R. Raun , 2007: Expression of variability in corn as influenced by growth stage using optical sensor measurements. *Agronomy Journal 99,* 384-389.

Mathur, A. and G.M. Foody, 2008: Crop classification by support vector machine with intelligently selected training data for an operational application. *International Journal of Remote Sensing 29(8),* 2227-2240.

McFeeters, S.K., 1996: The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing 17(7),* 1425-1432.

Melgani, F., 2004: Classification of hyperspectral remote sensing images with Support Vector Machines. *IEEE Transactions on Geoscience and Remote Sensing 42(8),* 1778-1790.

Mirik M., R.J. Ansley, G.J. Michels Jr. and N.C. Elliott, 2012: Spectral vegetation indices selected for quantifying Russian wheat aphid (Diuraphis noxia) feeding damage in wheat (Triticum aestivum L.). *Precision Agriculture 13,* 501-516.

Mokhele, T.A. and F.B. Ahmed, 2010: Estimation of leaf nitrogen and silicon using hyperspectral remote sensing. *Journal of Applied Remote Sensing 4(043560),* 1-18.

Mondal, P., M. Basu and P.B.S. Bhadoria, 2011: Critical review of precision agriculture technologies and its scope of adoption in India. *American Journal of Experimental Agriculture 1(3)*, 49-68.

Moshou, D., C. Bravo, J. West, S. Wahlen, A. McCartney and H. Ramon, 2004: Automatic detection of 'yellow rust' in wheat using reflectance measurements and neural networks. *Computers and Electronics in Agriculture 44(3)*, 173-188.

Nellis, M., P. Price and D. Rundquist, 2009: Remote sensing of cropland agriculture. *Papers in Natural Resources.* Paper 217. *The SAGE Handbook of Remote Sensing* 26pp. http://www.sage-ereference.com/hdbk_remotesense/Article_n26.html . Chapter DOI: 10.4135/978-1-8570-2105-9.n26.

Osborne, S.L., J.S. Schepers, D. Francis and M.R. Schlemmer, 2002: Detection of phosphorus and nitrogen deficiencies in corn using spectral radiance measurements. *Agronomy Journal 94(6)*, 1215-1221.

Otegui, M.E. and F.H. Andrade, 2000: New relationships between light interception, ear growth and kernel set in maize. p. 89-102. In M. Westgate and K. Boote (ed.) *Physiology and modeling kernel set in maize.* CSSA Spec. Publ. 29. CSSA, Madison, WI.

Pannar Seed, Know the Maize Plant. http://www.pannarseed.co.za/uploads/documents/40/Know%20The%20Maize%20Plant.pdf Accessed Nov 20 2012.

Peñuelas, J., I. Filella, C. Biel, L. Serrano and R. Save, 1993: The reflectance at the 950-970 region as an indicator of plant water status. *International Journal of Remote Sensing 14 (10)*, 1887-1905.

Ramoelo, A., A.K. Skidmore, M.A. Cho, M. Schlerf, R. Mathieu and I.M.A. Heitkönig, 2012: Regional estimation of savanna grass nitrogen using the red-edge band of the spaceborne RapidEye sensor. *International Journal of Applied Earth Observation and Geoinformation 19*, 151-162.

Ramoelo, A., M.A. Cho, R. Mathieu, A.K. Skidmore, M. Schlerf, I.M.A. Heitkönig and H.H.T. Prins, 2011: Integrating environmental and in situ hyperspectral remote sensing variables for grass nitrogen estimation in savanna ecosystems, 34th International Symposium on the Remote Sensing of Environment (ISRSE). The GEOSS Era: Towards Operational Environmental Monitoring, Sydney, Australia, http://www.isprs.org/proceedings/2011/ISRSE-34/index.html Accessed November26 2012.

Rouse, J.W., Haas R.H., Schell J.A. and D.W. Deering, 1973: Monitoring vegetation systems in the Great Plains with ERTS: 3rd ERTS symposium. *NASA, SP-351 (1)*, 309-317.

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.

Savabi, M.R., B.T. Scully, T.C. Strickland, D.G. Sullivan, and R.K. Hubbard, 2013: Use of statistical and conceptual path models to predict corn yields across management-zones on the Southeast Coastal Plain. *Journal of Agricultural Science 1(2)*, 32-51.

Sawyer, J., 2004: Integrated pest management, nutrient deficiencies and application injuries in field crops. Unpublished report IPM 42 revised July 2004, Department of Agronomy, Iowa State University.

Scotford, I.M. and P.C.H. Miller, 2005: Applications of Spectral Reflectance Techniques in Northern European Cereal Production: A Review. *Biosystems Engineering 90(3),* 235-250.

Serrano L., I. Fillella and J. Peñuelas, 2000: Remote sensing of biomass and yield of winter wheat under different nitrogen supplies. *Crop Science 40,* 723-731.

Shanahan, J.F., J.S. Schepers, D.D. Francis, G.E. Varvel, W.W. Wilhelm, J.M. Tringe, M.R. Schlemmer and D.J. Major, 2001: Use of remote-sensing imagery to estimate corn grain yield. *Agronomy Journal 93,* 583-589.

Shanahan, J.F., K. Holland, J.S. Schepers, D.D. Francis, M.R. Schlemmer, and R. Caldwell. 2003. Use of crop reflectance sensors to assess corn leaf chlorophyll content. In VanToai, T., D.Major, M. McDonald, J. Schepers, L.Tarpley, (Eds.) *Digital imaging and spectral techniques: Applications to precision agriculture and crop physiology.* Proceedings of a symposium sponsored by Division C-2 of the Crop Science Society of America, the USDA-ARS, and the Rockefeller Foundation in Minneapolis, MN, November 2001. ASA Special Publication. 66. ASA, Madison, WI. 135-150.

Shapiro, C.A. and C.S. Wortmann, 2006: Corn response to nitrogen rate, row spacing, and plant density in Eastern Nebraska. *Agronomy Journal 98*, 529-535.

Shaver, T. M., R. Khosla and D. G. Westfall, 2011: Evaluation of two crop canopy sensors for nitrogen variability determination in irrigated maize. *Precision Agriculture*. DOI 10.1007/s11119-011-9229-2.

Si, Y., M. Schlerf, R. Zurita-Milla, A. Skidmore and T. Wang, 2012: Mapping spatio-temporal variation of grassland quantity and quality using MERIS data and the PROSAIL model. *Remote Sensing of Environment 121,* 415-425.

Singh, R., R. Sutaliya, R. Ghatak, and S.K. Sarangi, 2003: Effect of higher application of nitrogen and potassium over recommended level on growth, yield, and yield attributes of late sown winter maize (*Zea mays L*.). *Crop Research 26(l),* 71-74.

Solari, F., J. Shanahan, R.B. Ferguson, J.S. Schepers and A.A. Gitelson, 2008: Active sensor reflectance measurements of corn nitrogen status and yield potential. *Agronomy Journal 100,* 571-579.

Strachan, I.B., E. Pattey and J.B. Boisvert, 2002: Impact of nitrogen and environmental conditions on corn as detected by hyperspectral reflectance. *Remote Sensing of Environment 80,* 213-224.

Sudbrink, D.L., F.A. Harris, J.T. Robbins, P.J. English and L.L. Willers, 2003: Evaluation of remote sensing to identify variability of cotton plant growth and correlation with larval densities of beet armyworm and cabbage looper (Lepidoptera: Noctuidae). *Florida Entomologist 86*, 290-294.

Suo, X.M., Y.T. Jiang, M. Yang, S.K. Li, K.R. Wang and C.T. Wang, 2010: Artificial neural network to predict leaf population chlorophyll content from cotton plant images. *Agricultural Sciences in China 9(1),* 38-45.

Unganai, L.S. and F.N. Kogan, 1998: Drought Monitoring and Corn Yield Estimation in Southern Africa from AVHRR Data. *Remote Sensing of Environment 63(3),* 219-232.

Uno, Y., S.O. Prasher, R. Lacroix, P.K. Goel, Y. Karimi, A. Viau and R.M. Patel, 2005: Artificial neural networks to predict corn yield from Compact Airborne Spectrographic Imager data. *Computers and Electronics in Agriculture 47(2),* 149-161.

Ustin, S.L., M.O. Smith, S. Jacquemoud, M.M. Verstraete, and Y. Govaerts, 1998: GeoBotany: Vegetation mapping for Earth sciences, in A.N. Rencz (eds) *Manual of Remote Sensing, vol. 3, Remote Sensing for the Earth Sciences,* 3rd ed., pp. 189-248, Wiley: Hoboken.

Viña, A., A. Gitelson, D. Rundquist, G. Keydan, B. Leavitt and J. Schepers, 2004: Monitoring maize (Zea mays L.) phenology with remote sensing. *Agronomy Journal 96,* 1139-1147.

Williams, P.J., P. Geladi, T.J. Britz and M. Manley, 2012: Investigation of fungal development in maize kernels using NIR hyperspectral imaging and multivariate data analysis. *Journal of Cereal Science 55,* 272-278.

Xavier, A.C., B.F.T. Rudorff, Y.E. Shimabukuro, L.M.S. Berka and M.A. Moreira, 2006: Multi-temporal analysis of MODIS data to classify sugarcane crop. *International Journal of Remote Sensing 27(4),* 755-68.

Xie, Y., Z. Sha and M. Yu, 2008: Remote sensing imagery in vegetation mapping: a review. *Journal of Plant Ecology 1(1),* 9-23.

Xu, H.R., Y.B. Ying, X.P. Fu and S.P. Zhu, 2007: Near-infrared spectroscopy in detecting leaf miner damage on Tomato leaf. *Biosystem Engineering 96,* 447-454.

Yang, C., J. H. Everitt and J. M. Bradford, 2007: Airborne hyperspectral imagery and linear spectral unmixing for mapping variation in crop yield. *Precision Agriculture 8(6),* 279-296.

Yang, C., J. H. Everitt and Q. Du, 2010: Applying linear spectral unmixing to airborne hyperspectral imagery for mapping yield variability in grain sorghum and cotton fields. *Journal of the Application of Remote Sensing 4(1),* 041887, 1-11.

Yang, C., J.H. Everitt and D. Murden, 2011: Evaluating high resolution SPOT 5 satellite imagery for crop identification. *Computers and Electronics in Agriculture 75(2),* 347-354.

Yao, X., Y. Zhu, Y. Tian, W. Feng and W. Cao, 2010: Exploring hyperspectral bands and estimation indices for leaf nitrogen accumulation in wheat. *International Journal of Applied Earth Observation and Geoinformation 12,* 89-100.

Zere, T.B., C.W. van Huyssteen and M. Hensley, 2004: Development of a simple empirical model for predicting maize yields in a semi-arid area. *South African Journal of Plant and Soil 22(1),* 22-27.

Zhao, D., K.R. Reddy, V.G. Kakani, J.J. Read and G.A. Carter, 2003: Corn (*Zea mays L*.) growth, leaf pigment concentration, photosynthesis and leaf hyperspectral reflectance properties as affected by nitrogen supply. *Plant and Soil 257,* 205-217.

Zhao, J., K. Shi, and F. Wei. 2007: Research and Application of Remote Sensing Techniques in Chinese Agricultural Statistics. Paper presented at the Fourth International Conference on Agricultural Statistics, October 22-24, Beijing, China. www.stats.gov.cn/english/icas/papers/P020071017422431720472.pdf.

Zinselmeier, C., J.E. Habben, M.E. Westgate and J.S. Boyer, 2000: Carbohydrate metabolism in setting and aborting maize ovaries. p. 1-13. In M.Westgate and K. Boote (ed.) *Physiology and modeling kernel set in maize.* CSSA Spec. Publ. 29. CSSA, Madison, WI.