MAKERERE UNIVERSITY

COLLEGE OF ENGINEERING DESIGN ART & TECHNOLOGY
SCHOOL OF THE BUILT ENVIRONMENT
DEPARTMENT OF GEOMATICS & LAND MANAGEMENT

TOPIC:
COMPARISON OF PERFORMANCE OF HYPERSPECTRAL AND MULTISPECTRAL IMAGES FOR CROP DISCRIMINATION AT SPECIES LEVEL

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Contents

Declaration

I, **MUNIIRAH SALEH ALSHAKSI** declare that this report is a result of my own research and has never been submitted for any academic qualification. This work does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any university, and to the best of my knowledge and belief it does not contain any material previously published or written by another person, except when due reference is made in the text.

Signature: ....

Student Name: **Muniirah Saleh Alshaksi**

Date: 10th May 2022

Supervisor: Professor Gidudu Anthony

Signature: ....

Date: 10th May 2022

Dedication

This report is dedicated to my entire family, friends and all the people who have guided and supported me for the last four academic years.
I dedicate this literature to my lovely mother Mrs. Mariam Saleh

I also dedicate this report to Latifa Namugarura for being there for me throughout the entire program. You have been my best cheerleader.
Above all, I dedicate this report to God Almighty my creator who has provided for me and strengthened me in the course of my program. I will always live to praise you O Lord my God.

Acknowledgements.

First of all, I am grateful to the Almighty God who graces us and without the blessings from Him, we cannot think of breathing to learn.

Special gratitude goes to My Supervisor Prof Anthony Gidudu who has guided me throughout the entire project and providing any assistance requested from the proposal writing stage up to the report writing stage.

Furthermore, I extend my appreciation to the lecturers at the department of geomatics and land management for everything they have taught me that has made the accomplishment of this project a success.

Finally, all the members of year 4 land surveying class 2020/21for the advice and support they have showed and given me during my research.

Abstract.

Crop discrimination is the basis for vegetation mapping; one of the first steps to crop monitoring and mapping efforts. More specifically, this is used to; characterize, model, classify and map crops, species composition, crop type, biophysical & biochemical properties, disease and stress, nutrient, moisture, crop productivity etc. These changes affect crop reflectance which such that the reflected spectra has differences. Hyperspectral sensors, a new development offers to solve the crude spectral categorization; narrow contiguous bands (1-10nm) sensitive to subtle differences in spectral behavior to attain a higher accuracy. Despite the many studies and comparisons on crop discrimination using hyperspectral imagery for crop discrimination, few studies have been done in Africa, hence this study. Additionally, a selection of bands is needed to solve dimensionality as well as provide optimal data for discrimination. This study offers a comparative study of the performance of hyperspectral (Hyperion) and multispectral (Landsat ETM+ and EO-1 ALI to determine crop discrimination. Crop discrimination was determined using Stepwise Discriminant Analysis, Principal Component Analysis and a correlation study between Hyperion bands to determine redundant bands. From stepwise discriminant analysis, a subset of wavebands is selected to discriminate crops with their variability scores of 61%, 48 and 45% for Hyperion, ALI and Landsat respectively. Principal component analysis generated principal components for wavebands with most lying the 1200-1600nm region. Correlation analysis produces lambda vs lambda plots to all from which bands redundant bands are selected. Classification accuracy is done using Discriminant analysis to using a selection of bands that generate 95% accuracy for Hyperion, 87% for ALI and 85% for ETM+.

1 INTRODUCTION

1.1 Background

MAPPING the geographical, environmental, or ecological properties of natural features is essential for monitoring spatiotemporal dynamics of Earth surface processes and understanding their internal mechanisms e.g., crop mapping (Jensen, 2006). Critical and a basis for crop mapping discrimination of crops, which enables identification, characterization, modelling, classification and monitoring efforts (Thenkabail *et al.*, 2013a).

Crop discrimination as one of the first steps to support crop monitoring and mapping efforts; enables estimating of vegetation properties of ecologically or economically important species and invasions (Lu, He and Dao, 2019; Asner G., R.E, Ford, Metcalfe, & Liddell, 2009; Somers & Asner, 2013). Remote sensing has replaced traditional means that involved exhaustive, expensive and time-consuming field work to offer feasible, cost-effective, timely and accurate data that can be manipulated to various forms over large scales (Harris, 2010; Thenkabail *et al.*, 2004). Among others, the discriminating ability at species level largely depends on spectral variability/ separability enhanced by the sensor resolution. Nevertheless, different vegetation species show subtle variations (low inter-species spectral variability) especially during particular phenological stages and at typical spectral resolution and band width of multispectral sensors (Sobhan, 2007; Esch, Metz, Marconcini, & Keil, 2014; Galvão, Epiphanio, Breunig, & Formaggio, 2012). These traditional multispectral sensors data have known limitations in discriminating subtle variations due to crude spectral categorization and spectral overlap between crop species (Govender *et al.*, 2008, Asner *et al.*, 2000; Pieterse, 2016).

With the advent of hyperspectral sensors, new possibilities and parameters for spectrally discriminating crops have been realized. A number of recent studies have highlighted the importance of optimal narrowband data from specific portions of the spectrum to target and obtain the most sensitive/ detailed information (e.g., Blackburn, 1999; Carter, 1998; Elvidge & Chen, 1995; Thenkabail, 2002) and dramatically improve discrimination capabilities and accuracies. However, hyperspectral images are characterized by high dimensionality such that many bands contain redundant information.

Previous studies have evaluated and compared the performance of both sensors at crop discrimination and many suggest hyperspectral sensors provide better accuracies (e.g., Sluiter & Pebesma, 2010; Lu, He and Dao, 2019; Thenkabail *et al.*, 2004; Mariotto *et al.*, 2013) with exception of few studies that provide comparable accuracies (e.g., Yang & Everitt, 2010; Koppe *et al.*, 2010) which is attributed to data in the optimal regions. These studies suggest that hyperspectral imagery does not always perform better than multispectral at discrimination thus the need to evaluate their performance further. The need to evaluate potential of using hyperspectral data against multispectral with different conditions that influence crop characteristics to influence reflectance changes is critical. With a few such research studies extended in Africa, this proposal intends to compare the performance of hyperspectral and multispectral images for crop discrimination in Uganda.

1.2 Problem

Different crop species reflect differently at different wavelengths due to the molecular composition of the plants material that changes with area such that it absorbs, reflects and emits electromagnetic energy with distinct patterns (Mariotto *et al.*, 2013). Given that multispectral sensors have many limitations with respect to their suitability to studying crop discrimination, hyperspectral sensors were introduced to offer amongst others better analytical methods and spectral resolution i.e., narrow bands which target and highlight even subtle variations in spectral behavior (Lu, He and Dao, 2019; Lu *et al.*, 2020; Thenkabail *et al.*, 2004; Thenkabail *et al.*, 2013b).

Due to limitations such as limited area and repeat coverage, data costs and excessive need for sufficient field samples, a few studies have investigated the performance of hyperspectral data for vegetation mapping in Africa hence being replaced with multispectral data (Pieterse, 2016; Rocchini, 2010; Thenkabail et.al,2004; Dhumal *et al.*, 2015). With distinction in development stages to factors such as phenology, climate and soils changes , a comparison of the performance of sensor data for crop discrimination is critical for determining spectral variation as a basis for crop mapping and acreage estimation (Dhumal *et al.*, 2015). Additionally, the use of hyperspectral imagery introduces issues with Hughes phenomenon, which necessitate selection of optimal bands to solve redundancy and dimensionality. This research compares the performance of hyperspectral against multispectral images for crop discrimination as well as select optimal narrow-bands for the task at species level for farms along Jinja-Lugazi.

1.3 Objectives

Main objective

- Comparison of hyperspectral and multispectral image data to study the performance of crop discrimination of the crops on Jinja-Lugazi farms.

Specific objectives

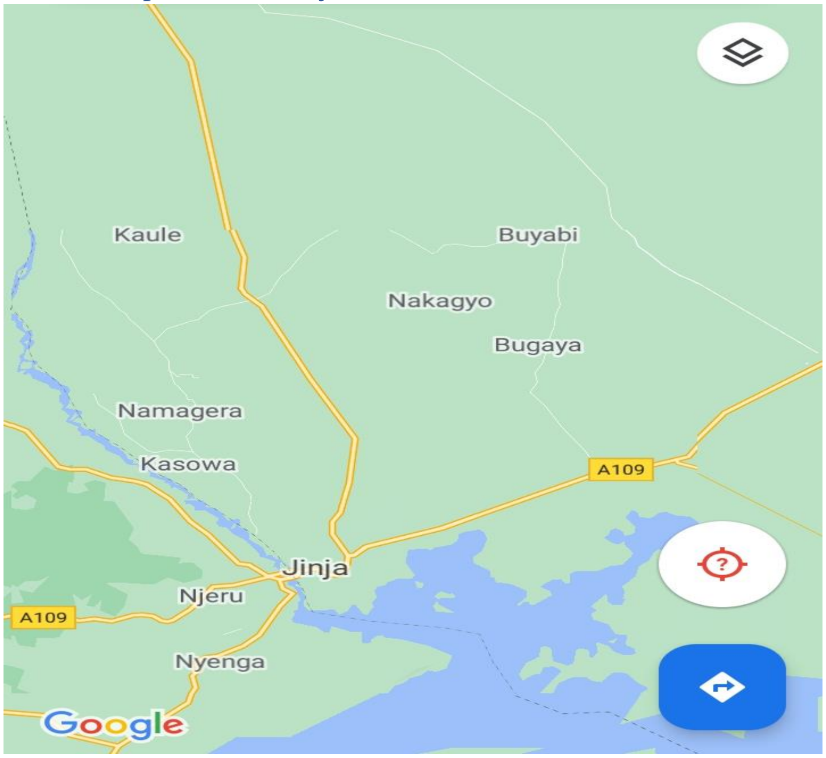
- Determine the most sensitive/ optimal Hyperion wavebands for characterizing maize, cotton, sugarcane and a mix of crops on farms along Jinja-Lugazi.
- Comparison of the separability of maize, cotton, sugarcane and a mix of crops at species level using E0-1 ALI, Landsat ETM+ and Hyperion.

1.4 Justification

Discrimination of crops is basis for crop mapping to include characterization, identification, modelling, monitoring and acreage estimation efforts. Due to the scale required to map and monitor crops, fast, generalizable and objective methods that provide results that can be quickly and analyzed are required and Hyperspectral imagery and data can fulfill these requirements at improved capabilities and accuracies (Hennessy, Clarke and Lewis, 2020). A comparison of sensors with respect to their performance is needed to establish and validate the capabilities and accuracies of these sensors in the presence of the distinct development stages that influence spectral variation in the crops. With computational processing and dimensionality of hyperspectral data still being a challenge (Varshney & Arora, 2004), more insight on the optimal wavebands is essential in reducing the number of redundant bands which are often more than the useful bands (Thenkabail et.al., 2011) hence studies to firmly establish optimal narrow wavebands in crop discrimination to foster crop type mapping (Mariotto *et al.*, 2013; Thenkabail *et al.*, 2013a). With no single best approach available, the optimal bands that best describe the vegetation characteristics and discriminate crops are determined using comprehensive analysis to provide complimentary and supplementary information i.e., i) principal component analysis (PCA), (ii) lambda–lambda R2 models (LL R2M), (iii) stepwise discriminant analysis (SDA) (Thenkabail, Enclona, Ashton, Legg, *et al.*, 2004; Jain *et al.*, 2007). The LL R2M helps to eliminate redundant bands and indicates those that best model the characteristics of the vegetation; PCA provides insight into the variation in the data and in effect reduces the dimensionality of the data; and SDA tests the strength of data in separating while discriminating species types(Jain *et al.*, 2007).

With spectral variation being most profound at interspecies in comparison to intraspecies, this proposal intends to discriminate crops at crop type level (Sobhan, 2007). To characterize, identify and model at interspecies or crop parameters, additional data is collected and analyzed.

1.5 Description of Study area



Jinja -Lugazi is located in Southern part of Uganda bordering Lake Victoria and are among the fastest growing and populated districts in Uganda. These two are well endowed with high amounts of rainfall ranging from 780-1200mm and average precipitation of 999.9mm with rainy months through months of January, March, April, May, October, November and December occurring in two seasons. Major crops grown in Jinja include beans, cassava, groundnuts, cotton, sugarcane, maize, millet and yams with cash crops being coffee and tea among others. For Lugazi, main crops grown is sugarcane covering a large area as its for commercial produce. The high rainfall amounts in the region also lead to increased floods during this season. Rainwater harvesting is defined as the method of collection, concentration and storage of rainwater that runs off a natural or man-made catchment surface for future use (Rahman 2017). Available water resources in include lakes Victoria, river Nile and groundwater but due to the competing demand for water uses, these sources have an increasing water stress and yet the groundwater aquifers dry out during the dry spells (Michael 2012).

2 Literature review

2.1 Vegetation mapping

Vegetation mapping is an important task for managing and monitoring of vegetation properties to provide insight into the plant physiological status and vegetation community features and further support ecosystem conservation and management as well a understand biodiversity pattern (Fourty et.al., 1996; Blackburn, 2007, Committee on Global Change Research, National Research Council, 1999).

Crop mapping includes the quantification for classification, modelling and identification of biochemical and biophysical of plant characteristics to determine the plant structure, physiology and water content (Strachan et al. 2002), detect stress (Carter, 1998), identify crops and invasions and determine acreage to crop productivity (McGwire et al. 2000; Galvão et.al., 2018; Mariotto *et al.*, 2013) as in precise agriculture. The characteristics include biomass, leaf area index (LAI), pigment content (e.g., chlorophyll, carotenoid, anthocyanin), stress (e.g., due to drought or disease or metal), management properties (e.g., nitrogen application, tillage, weed identification and crop typing), and other biochemical properties (e.g., lignin, cellulose, plant residue) (Thenkabail et.al., 2011; Ullah et.al., 2012; Technology *et al.*, 2003; Aboelghar, Arafat and Farag, 2013).

Crop mapping is only possible with a distinction/discrimination of crops or characteristics being mapped such as to show their distribution.

2.2 Crop discrimination

Discrimination is the building block of all mapping, classification, modelling and characterization of physical/chemical features. Crop discrimination with starting level at species allows (a) modeling biophysical and yield characteristics of agricultural crops (Thenkabail et al., 2000; Thenkabail, Smith, & De-Pauw, 2002), (b) measuring chlorophyll content of plants (Blackburn & Ferwerda, 2008), (c) sensing subtle variations in leaf pigment concentrations (Blackburn & Ferwerda, 2008), (d) extracting biochemical variables such as nitrogen and lignin (Houborg & Boegh, 2008), (e) detecting crop moisture variations (Colombo, *et.al.*, 2011), (f) assessing absolute water content in plant leaves (Jollineau & Howarth, 2008), (g) identifying small differences in percent green vegetation cover (Chen, *et.al.*, 2008), (h) detecting plant stress (Thenkabail *et al.*, 2004), and (i) discriminating land-cover types (Thenkabail et al., 2004). These studies have made significant advances in understanding, modeling, and mapping various biophysical and biochemical quantities of agricultural crops.

Crops are very distinct in their development stages and show different phenological characteristics and timings according to their nature (Dhumal *et al.*, 2015). Even for the same crop and growing season, the duration and magnitude of stage can differ between varieties owing to environmental factors hence introducing variability inter and intra-species (Galvao, 2011;

Prospere, Mclaren and Wilson, 2014). These variations are more pronounced and visible at inter-species level than at intraspecies level which occurs due to changes in molecular structure (Sobhan, 2007). Inter-species variability is a result of differences in phenological patterns, growth stages and plant color, size, etc., while intra-species variability is as a result of stress, age differences, precipitation, micro-climate, soil characteristics, phenology, topography, stress etc. (Smith et al., 2004; Carter, 1993; Carter, 1994; Portigal et al., 1997; Roberts et al., 1998; Gracia and Ustin, 2001)

Species discrimination proves advantageous to reveal species composition (invasive, commercially valuable and type), monitor changes in species richness, compositions and distribution / acreage among others making it viable to recognize the succession process of the eco-system (Lu, He and Dao, 2019; Asner G., R.E, Ford, Metcalfe, & Liddell, 2009; Somers & Asner, 2013; Sobhan, 2007; Dhumal *et al.*, 2015). To discriminate crops at intra-species level i.e., crop type mapping and characterization, additional data is required (Sobhan, 2007).

2.2.1 Factors affecting crop discrimination

Factor affecting crop discrimination are grouped into 5 categories; biophysical, crop development, management, crop calendar and regional aspects.

Biophysical; Each crop belongs to a family, species etc. in the lowest scale, each crop belongs toa cultivar and plants are expected to be homogeneous at this stage concerning heir genotypes and phenotypes. At species level, its expected plants depart from homogeneity. In terms of remote sensing, the differences are related to aspects such as leaf pigment, leaf structure, duration of life cycle, plant structure, height and physiology such as to affect reflectance (Gausman,1995).

Crop development; at different phenological stages, crops are distinct and this is classified by their life cycle into annual, perennial and semi-perennial crops. Annual Crops are planted once or 3 times a year, perennial crops can stay in field for many years while semi-perennial remain in field for few years e.g, sugarcane is a semi-perennial crop. These impacts on growth changes e.g., flowering, germination etc. ()

Crop management; farmers use distinct management practices depending on cultivated crop e.g., type of pruning for coffee, technological use in harvesting, tree spacing. These are used to distinguish between crops ()

Regional; with regards to soil type, topology, precipitation, etc., crops grow different such as to have distinctions. These can be used to discriminate amongst crops ()

Comparison of select crops based on factors above

Crop species	Phenological type	Cropping patterns	
sugarcane	Semi-perennial	Single cropping	Thick (less planophile canopy), 1-2m height,

Maize	Annual	Single cropping Multiple cropping	Long leaves, 1-2m height,
cotton	Annual	Single cropping intercropping	
Beans	Annual	Multiple cropping intercropping	Leguminous -broad leaves, planophile canopy,

Table 1; A table showing crop species and their characteristics.

2.3 Remote sensing as a tool for Crop Discrimination at species level

Traditionally, species discrimination involved exhaustive and time-consuming field work which is dependent on taxonomic information and visual estimation of plant cover which proves to be costly and difficult over large areas (Sobhan, 2007).

Remote sensing, however offers a quick , practical , economic and efficient means to spectrally distinguish crops over a larger area with improved capabilities using enhanced processing techniques that are robust, accurate and fast (Miglani *et al.*, 2008; Verrelst *et al.*, 2015; Pieterse, 2016) thus improving crop discrimination. These methods are based on spectral differences between crops which occur as a result of photosynthetic activity, age differences, stress, environmental factors, phenology, soil, climate, topology, precipitation recorded from leaf reflectance, field reflectance or remotely sensed imagery (Begue *et al*., 2007; Thenkabail *et.al*., 2004; Smith *et.al*., 2004) for intra-species and phenology, cell structure, moisture content, nutrient, biochemical and biophysical properties (Gausman, 1985; Smith *et.al.*,2004; Gracia and Ustin, 2001; Thenkabail *et al.*, 2015; Thenkabail *et al.*, 2013; Marshall and Thenkabail (2015, 2014) at interspecies level. Discrimination at inter-species level is the basis for all.

2.3.1 Factors influencing crop discrimination using remote sensing

Influencing the discrimination of crops using remote sensing are factors to include spatial, temporal and spectral resolution.

The spatial resolution influences spatial heterogeneity and accurate location i.e., variability increases with spatial resolution however causes a reduction in classification performance due to reduced averaging of pixels (Sobhan, 2007; Begue *et al.*, 2017 ; Mariotto *et al.*, 2013; Dhumal *et al.*, 2015; Verrelst *et al.*, 2015; Lu, He and Dao, 2019). This is particularly important when considering the spatial arrangement of crops (crop patterns) and texture (Begue et.al., 2017; Gao, 2009).

Spectral resolution determines data /detail at a point data. Recent research has demonstrated that optimal information required to quantify crop characteristics is present in a few specific narrow bands at parts of the spectrum(Chan & Paelinckx, 2008; Thenkabail, Enclona, Ashton, & Van Der Meer, 2004), and can dramatically improve discrimination capabilities and classification accuracies for various agricultural crops, relative to broadbands such as Landsat Thematic Mapper (TM) and Système Pour l'Observation de la Terre (SPOT) High Resolution Visible (HRV) (Lee, Cohen, Kennedy, Maiersperger, & Gower, 2004; Thenkabail, Enclona, Ashton, Legg, et al., 2004).

Temporal resolution determines the phenological differences in crops. Phenology has a well-defined temporal pattern, which can be used to characterize an individual species and discriminate it from others (Turner et al., 2003; Underwood, Ustin, and DiPietro, 2003). Timing in image acquisition for stages to allow optimal crop i.e. ,information about crops is time sensitive (Mariotto *et al.*, 2013). Crop cycle affects chances to acquiring optimal window with cloud free images (higher for perennial crops) (Dhumal *et al.*, 2015). Two species can have different discriminatory probability at different times of the year largely to the change of phenological stages of plant species (Sobhan, 2007).

Additionally, the performance of sensor at spectral variation in reflectance spectra is enhanced by its signal to noise ratio.

2.4 Sensors used for crop discrimination using remote sensing

2.4.1 Multispectral imagery;

These offer broadband data at comparable spatial resolutions. Landsat ETM+, is the most commonly used multispectral sensor with advantage of older imagery archive. Images are characterized with 30*30m spatial resolution, 16-day temporal resolution, 6 multispectral bands (10 total) provided at 16bit. These images are distributed at different levels of correction with level1T provided in units top-of atmospheric radiance i.e., geometric, and radiometric corrected (USGS; Xie, Sha and Yu, 2008). Particularly noteworthy are the high signal to noise ratio and signal to noise ratio comparable to EO-1 sensors as well as the geometric fidelity and calibration levels for images provided by OLI. Prior to use, non-multispectral bands are dropped ((Peña and Brenning, 2015).

EO-1 ALI is a multispectral sensor similar on-board the Earth Observing One (EO-1) satellite with spectral bands similar to Landsat OLI. Data is provided at different levels of correction e.g., geometric and radiometric correction for Level 1T in units of top-of atmosphere radiance. It is important to note that thermal bands are dropped when using EO-1 ALI.

2.4.2 Hyperspectral imagery

Most commonly used is the EO-1 Hyperion, a spaceborne sensor onboard the Earth Observing One (E0-1) satellite, set up for experimental comparison with Landsat and provides a spectrum of 350-2500nm of the electromagnetic spectrum a with 1-10nm sampling rate spanning over 242 spectral bands and provided at level 1 calibration. It provides comparable spatial and temporal resolution to Landsat (30*30 m and 16 days respectively). It’s the only spaceborne hyperspectral sensor that spans over Uganda and provided at zero cost and provides images until 2017 to allows study of specific characteristics of crops (Thenkabail *et.al*., 2013).

From the 242 bands, uncalibrated bands are dropped as well as wavebands in atmospheric windows and water bands as they have high noise (Galvao et.al, 2018; Begue et.al, 2018; Thenkabail, Enclona, Ashton, Legg, *et al.*, 2004; Miglani *et al.*, 2008; Thenkabail *et al.*, 2013a; Marshall and Thenkabail, 2015).

- Uncalibrated bands-band 1-7, band 58-76, band 223-242
- Atmospheric /water bands- band 121-126, band167-bnad180, band 220-22

The radiance values are converted to sensor reflectance prior to data analysis using FLAASH algorithm (Mariotto *et al.*, 2013; Thenkabail *et al.*, 2013a; Hennessy, Clarke and Lewis, 2020; Lu *et al.*, 2020).In regards to atmospheric corrections, the original at-sensor reflectance data is considered the best option in comparison with other atmospheric corrections (Thenkabail *et al.*, 2013a).

A comparison of hyperspectral and multispectral sensors

parameters			
sensor	Hyperion	EO-1 ALI	Landsat ETM+
Spatial resolution	30x30 m	30x30m	30x30m
Swath	7.7 km	37 km	185 km
Number of bands (multipspectral)	220 bands	10 bands	7 bands
Temporal resolution	16 days	16 days	16 days
Spectral resolution	1-10nm		
Radiometric resolution		12 bits	8bits
Spectral coverage	Contiguous bands	Discrete bands	Discrete bands

Table 2; A comparsion of the characteristics of the different sensors.

Dimensionality: Are all bands important?

The high dimensionality of hyperspectral data also known as Hughes Phenomenon is known to cause imprecise class estimation in the spectral feature space and can lower classification accuracy and requires more training samples in order to maintain minimum statistical confidence and functionality. (Clark *et.al.*, 2005). Studies by Thenkabail *et al*., (2004) Thenkabail (2019) and Mariotto *et al.*(2013) highlight the importance of optimal/most sensitive wabands from contigous/ collinear bands in capturing and discriminating the subtle differences in targets and that alone can produce accuracy such as other bands are redundant ((Miglani *et al.*, 2008; Thenkabail *et al.*, 2013a; Hennessy, Clarke and Lewis, 2020; Mariotto *et.al.*, 2013; Thenkabail *et.al*., 2009; Thenkabail *et.al*., 2013b; Dhumal *et.al.,* 2015; Hennessy *et.al*., 2020). Band selection solves redundancy while highlighlighting optimal bands for discrimination.

A comparison of bands selected frm previos studies to use for crop discrimination using Hyperion

Vaiphasa et al., (2005)	720, 1277, 1415, and 1644 nm
Thenkabail et al., (2004)	495, 555, 655, 675, 705, 735, 885, 915, 985, 1085, 1135, 1215, 1245, 1285, 1445, 1675, 1725, 2005, 2035, 2235, 2295 and 2345 nm
Thenkabail et.al., (2014)	
Thenkabail et al., (2002)	490, 520, 550, 575, 660, 675, 700, 720, 845, 905, 920, 975
Schmidt and Skidmore, (2003)	404, 628, 771, 1398, 1803, and 2183 nm

Table 3; a coparison of select band centers from crop characterization by different researchers.

To reduce redundancy, various band reduction techniques have been developed e.g., through band selection using discriminant analysis, principle components analiysis, partial laest square regressions, least square means, correlation analysis . etc. Various researchers (Cochrane, 2000; Schmidt and Skidmore, 2001; Schmidt and Skidmore, 2003; Thenkabail et al., 2004; Vaiphasa et al., 2005) have used these methods to select informative bands and discriminate vegetaion species/types. Other ways include using feature selection, articicial neural networks , soil electric conductivity and cover canopy characteristics (Bajwa et.al., 2004). While they became successful in discriminating vegetation types or species using their own spectral data, they failed to come up with a comparable list of wavebands.

During optimal band selection, important spectral regions do exist on the different parts of the spectral signature to represent vegetation parameters and can also be used to discriminate, model and characterize different crop characteristics (Sobhan, 2007).

2.5 Crop Spectral reflectance

Reflectance spectra patterns are defined by the reflective amount of light that is absorbed or reflected at different wavelengths by different target material, which depends on their biochemical and structural properties (Gonzalez et al., 2009). Spectra can vary at inter and intra species levels for crops due to factors such as to phenology, nutrient content, biophysical and biochemical properties, disease, light use efficiency, age differences, micro-climate, soil characteristics, precipitation, topography, phenology and a host of other environmental factors including stresses (Gausman, 1985; Smith et.al.,2004; Gracia and Ustin, 2001; Thenkabail et al., 2015; Thenkabail et al., 2013; Marshall and Thenkabail (2015, 2014).

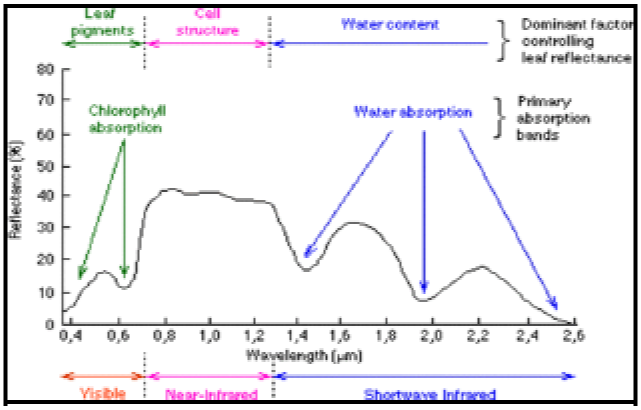
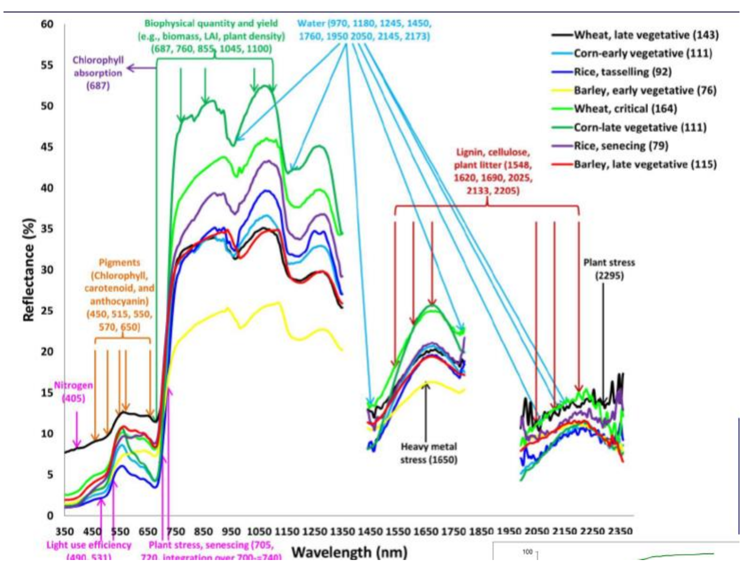


Figure 1: Reflectance Behavior of Vegetation

Researchers have been able to discriminate and classify species based on their reflectance which is correlated to the molecular compositions such as chlorophyll, plant pigments, water and chemical compositions which are represented in various reflectance regions(Sobhan, 2007; Dhumal *et al.*, 2015) all which are caused by the structural or physiognomic characteristic and differences between the crops (Galvao, 2011). Developments in sensor technology i.e., from multi-spectral to hyperspectral offers improved accuracies of over 85% (Lobell and Asner, 2003; Pieterse, 2016; Lu, He and Dao, 2019) at spectral discrimination due to improved sensitivity to subtle changes in biophysical and biochemical properties (Lobell and Asner, 2003; Thenkabail, Enclona, Ashton and Meer, 2004; Mariotto *et al.*, 2013; Koppe *et al.*, 2016; Lu, He and Dao, 2019).



Fig; showing reflectance regions to discriminate crops using different crop characteristics Fig; showing reflectance regions to discriminate crops using different crop characteristics

For all crops, bands in the visible region are most optimal for crop species discrimination with red as the most commonly occurring region for crop discrimination (e.g.,Galvao et.al., 2009;

Mariotto et.al., 2013; Thenkabail et.al., 2004;)followed by green and then blue (Mariotto et.al., 2013; Verrelst *et al.*, 2015). Other regions include the NIR and early SWIR regions (Manjunath and Ray, 2011). For each of these regions, chlorophyll strongly absorbs in blue and red regions while Structural variability is represented by the NIR region and water content in the Short infrared which are discriminating factor controlling leaf reflectance (Dhumal, Kale and Mehrotra, 2013; Dhumal *et al.*, 2015).

A quantitative comparison of reflectance spectra should be able to preserve more of this subtle but important spectral information thus carried out using matching or similarity techniques (Sobhan, 2007).

2.3.1 Characteristics that influence spectral discrimination

At species level, spectral variation between targets is subtle hence discrimination is made difficult (Abbasi, 2019; Mirzaei *et al.*, 2019). Phenology, physiochemical characteristics, plant functional type (common response to certain environmental influences) are some of the factors that influence reflectance and absorption in crops ((Technology *et al.*, 2003; Peña-barragán *et al.*, 2011; Nogueira *et al.*, 2016; Hariharan *et al.*, 2018). The selection of images is influenced by the mapping objective, climatic condition and technical issues for image interpretation (Xie, Sha and Yu, 2008). The performance of sensor at spectral variation in reflectance spectra is enhanced by its resolution and signal to noise ratio.

It should be noted that high spectral resolution provides better accuracy compared to high spatial resolution (Galvao *et.al*, 2018). Alchanatis and Cohen highlighted importance of hyperspectral images with respect to their unique spectral bands, spatial attributes and image processing algorithms that show the added value mapping plant biophysical and biochemical properties of agricultural crops (Alchanatis and Cohen, 2011).also, hyperspectral sensors such as Hyperion can cover only limited areas and lack repeating cycles (Lobell and Asner, 2003; Lu, He and Dao, 2019).

In general, limitations to crop discrimination using remote sensing include i)effects of large soil background, ii) adaptions to environment (which makes reflectance of some plants different), iii)phenological changes due to climate iv) the possibility of non-linear mixing v) variations in chlorophyll, plant structure, succulence and pigments and vi) changes in land use and the relative impact of vascular tissue (Thenkabail, Enclona, Ashton and Meer, 2004; Pieterse, 2016).

2.6 Techniques for crop discrimination using spectra and optimal band selection

With no single best approach available, the optimal bands that best minimize correlation , high information and discriminate crops are determined using comprehensive analysis to provide complimentary and supplementary information i.e., i) principal component analysis (PCA), (ii) lambda–lambda R2 models (LL R2M), (iii) stepwise discriminant analysis (SDA) (Thenkabail, Enclona, Ashton, Legg, *et al.*, 2004; Jain *et al.*, 2007).

2.6.1 Principal Component Analysis (PCA)

This involves the establishing of prominent bands most prominent bands to capturing highest variance in targets and eliminate data redundancy by identifying and eliminating the least important bands (Mariotto *et al.*, 2013). It involves a factor analysis in which a proportion of the total variability in the dataset explained by each principal component established by its corresponding eigen value that indexes the bands' factor loading/ weighting/eigen vector (Thenkabail, Enclona, Ashton, Legg, *et al.*, 2004). It is a statistical technique to transform data into principal components such as to discriminate and identify redundant bands in relation to target data and is explored for each crop.

Principle components are established using eigen values and eigen vectors

It is easy to implement, interprete, good with numerical values and successful at identifying most important variables i.e. strong correlations and reduces overfitting. However, data standardization is a must before PCA such as to obtain optimal PC's .

2.6.2 Stepwise Discriminant Analysis (SDA)

This involves stepwise selection of bands that best discriminate a combination of crops i.e., test strength of separability while discriminating a combination of species. At each step, the variable that contributed most to the separability model is added and if one or more variables in the model fails to meet the retention criterion, the variable contributing the least is removed such that no other variables meet the criterion and the process stops.

This is based on Wilks Lambda; a test statistic indicative if the discriminatory power of bands for a combination of crops. Wilks Lambda provides overall accuracies and errors of omissions and commissions and involved a stepwise selection (Klecka, 1980) of wavebands from the image data sets with a values ranging from 0 -100 to determine the separability among multiple classes [35].

2.6.3 Lambda-lambda R2 model

This determines the correlation between all possible combinations of bands such as to identify redundant bands/ collinearity and is plotted on contour plots where λ1 by λ2 band matrices are generated. This helps determine areas rich/ unique information and areas of data redundancy.

2.4 Comparison of the sensors for crop discrimination

Previous studies have employed Hyperion to crop discrimination and achieved accuracies >85% (e.g., (Thenkabail, Enclona, Ashton and Meer, 2004; Thenkabail, Enclona, Ashton, Legg, *et al.*, 2004; Mariotto *et al.*, 2013; Thenkabail *et al.*, 2013a; Aneece, 2018). Studies prior to this have employed its use obtaining accuracies >60% (Lobell and Asner, 2003; Thenkabail, Enclona, Ashton, Legg, *et al.*, 2004; Govender *et al.*, 2008; Koppe *et al.*, 2016).

On the other hand, a few other studies found that hyperspectral data did not generate a considerably higher accuracy than multispectral data. Yang and Everitt [21] evaluated airborne hyperspectral images and multispectral images for detecting rangeland weed species and found that the hyperspectral images achieved only a slightly higher classification accuracy than multispectral images. Koppe *et al.* [22] compared performance of hyperspectral EO-1 Hyperion imagery and multispectral EO-1 ALI data for estimating winter wheat properties (e.g., biomass, nitrogen concentration, and plant height) and concluded that the hyperspectral products yielded only slightly better results than the multispectral. These studies suggest that hyperspectral imagery does not always perform better than multispectral imagery for vegetation properties mapping.

3 Methodology

3.1 Data acquistion

Remote sensing data were acquired over the study area, with concurrent ground reference data-of the pixels intersecting the ground data points were extracted from each satellite image/ Google Earth satellite image for each band using GIS. Data were collected to coincide with the Hyperion, OLI and EO-1 ALI image acquisitions and the peak of the dry season for study area. This data was collected for the crops every 1-3 days coincident – or maximum 1 day lapse with the dates of the satellite overpass. Hyperion, ETM+ and EO-1 ALI were checked for cloud cover below 10%.

3.2 Image pre-processing

1. Band selection

Band selection hyperion- Hyperion imagery consists of 242 spectral bands from which calibrated and free of noise and atmospheric window effects bands are selected. For EO-1 ALI, ETM+ and OLI, only multi-spectral bands were selected.

2. Atmospheric, geometric correction and conversion to surface reflectance.

As products subject to the same geometric correction procedures, L1T images acquired at different dates over the same path/row satisfy the spatial match required for time series analysis. In spite of this, image geometric co-registration was visually assessed by checking the spatial match of some randomly selected field boundaries within the study area across the time series. Atmospheric correction and conversion to absolute surface reflectance from radiance was performed using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) tool in ENVI 4.8 (Exelis Visual Information Solutions), which incorporates the MODTRAN4 radiation transfer code (Berk et al., 1999; Thenkabail, Enclona, Ashton, Legg, et al., 2004; Thenkabail, Enclona, Ashton,& VanDerMeer, 2004; Thenkabail et al., 2002, 2011) using FLAASH tool.

3. Collection of ground spectra

Reflectance spectra is collected from all images for different regions of interest. This is presented in tabular format to allow statistical analysis. Spectra is collected for each crop type and from each image with reference spectra collected from Google Earth Engine Image

3.3 Data analysis

All statistical analyses were performed using Statistical Analysis System (SAS Institute, 2009). The methods used to discriminate crop types and identify are discussed below.

- Stepwise discriminant analysis approach for crop type discrimination (separability analysis);

Stepwise discriminant analysis was performed using PROC STEPDISC procedure in SAS using Wilks Lambda statistic at $p < 0.0001$; level of significance 0.999 to generate wavebands and their wilk's lambda, a criterion/statistic to show variability. The higher the Wilk's lambda, the lesser the separability between crop types (0 means 100% separability of crops). At each step, the variable is tested against the f test. The values of Wilk's lambda are indicative of separability i.e., the less the value of Wilk's lambda, the greater spectral differentiation between the species types. Finally, the Wilk's lambda values are plotted against the number of bands to determine the number of bands sufficient to best separate the crops (when the curve becomes asymptotic or near-asymptotic) and their wavelength centers. This approach is used for Wilk's lambda tests for all sensor images.

- Principal component analysis approach for crop type discrimination

Principal component analysis (PCA) (Pearson, 1901) establishes prominent bands most important for capturing highest variance in data, and helps eliminate data redundancy. The PCA is explored for each crop separately to determine how best the characteristics of that crop are captured. The PCA was performed using the PRINCOMP procedure in SAS at 95% confidence . The relative contribution of each waveband to a PC is indexed by the band's factor loading in the corresponding eigenvector which explains the variability in data explained by various PCAs, and the resulting eigenvectors associated with each band help determine the importance of the band (the higher the eigenvector, the greater the importance of the band). PCAs are applied to both HNBs and MBBs.

- Correlation between narrow bands for determining optimal hyperion narrow bands (Contour plots of Hyperion bands)

In this, the lambda ($\lambda 1$) by Lambda ($\lambda 2$) R2 models (LL R2M) is performed to provide a rigorous search criterion or data-mining technique to highlight redundant wavebands from wavebands with unique information content (where i, j = n wavebands). Lambda-by-lambda R2 contour plots of Hyperion bands (LLR2 PHBs) are obtained from the matrix of bivariate R2 values developed using PROC CORR algorithm of SAS. For each data set, the R2 matrixes are calculated for each class (e.g., corn). We calculated R2 values only below or above the diagonal of the matrix, as values on either side of the diagonal were the transpose of one another. The lower the R2 value, the less redundancy between two wavebands i.e., two highly correlated wavebands indicate a redundancy in that they are providing similar information. Thus, lambda (k1)-vs.-lambda (k2) plotted areas with the least R2 values for two wavebands were the areas with the highest information content. The squared coefficients, R2, values were plotted in Lambda ($\lambda 1$) by Lambda ($\lambda 2$) plots to determine the HNB-centers and widths that provide the best and the redundant information. The correlation (r) values were converted to R2 and reported.

The correlation analysis between the n narrowbands of Hyperion generates an n*n matrix values plotted against $\lambda 1$–$\lambda 2$ contour plots. The areas of high correlation (high R2 values, blank regions) between two wavebands signify band redundancy; thus, areas of lowest R2 are the most informative. The most informative bands are selected

- Discriminant model and error matrices for determining optimal hyperspectral narrow bands and validation

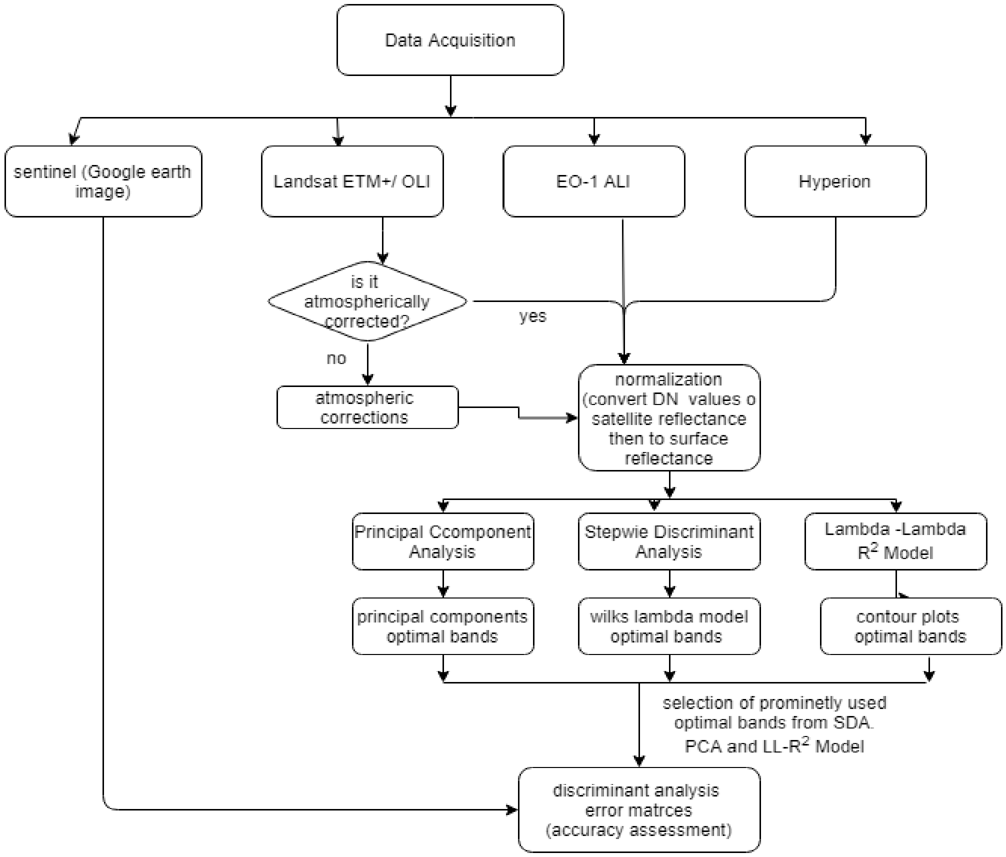
To assess the sensors' accuracy in discriminating crop types, a linear discriminant function based on the pooled covariance matrix is performed using the discriminant analysis. The classification criterion is based on either the individual within-group covariance matrices or the pooled covariance matrix; it also accounts for the prior probabilities of the groups. The hyperspectral band reflectivity data of the crop types are fed into the discriminant model. The input wavebands were the most frequently occurring wavebands resulting from the Wilk's lambda, PCA, and (λ1) by (λ2) plots of hyperspectral and data as discussed in previous sections. Each observation, from an independent dataset, was placed in the class from which it has the smallest generalized squared distance. DISCRM was also used to compute the posterior probability of an observation belonging to each class. This result in error matrices (Congalton & Green, 2009).
Omission errors were calculated using data from Google Earth sentinel images as the ratio of false negatives to the total number of pixels belonging to a particular crop type. Commission errors were calculated as the ratio of the false positives to the total number of pixels belonging to a particular crop type. The overall classification accuracy was computed based on correctly classified pixels along the diagonal of an error matrix. and is calculated as:

$$\text{Overall accuracy} = \frac{\Sigma_{i=1}^{k} n_{ii}}{n} \times 100(\%) \qquad (3)$$

where n is the total number of validation pixels, nii is the number of pixels classified into crop type i (or diagonal agreement of the confusion matrix), and k is the number of crop types.
The Khat was then computed so as to normalize the accuracy assessments between datasets and data types as follows:

$$K_{\text{hat}} = \left(N \sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} X_{+i} X_{i+} \right) \Bigg/ \left(N^2 - \sum_{i=1}^{r} X_{i+} X_{+i} \right) \qquad (4)$$

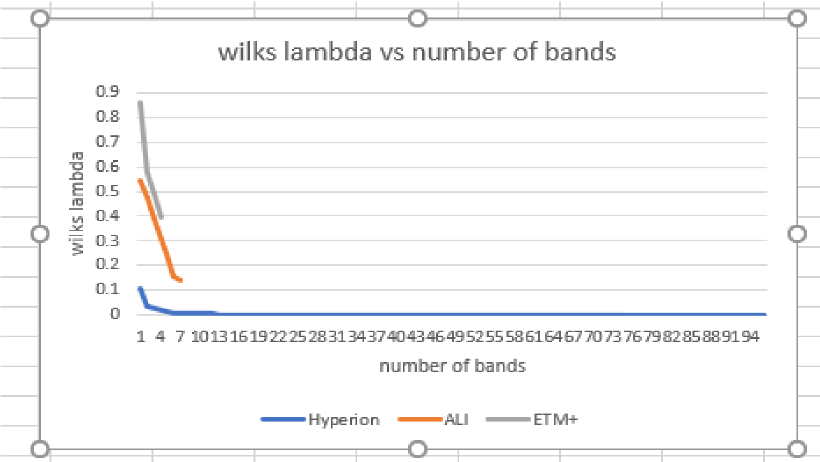
where r is the number of rows in the matrix; Xii is the number of observations in row i and column i; Xi + and X+I are the marginal totals of i and column i, respectively; and N is the total number of observations (Bishop et al., 1975).
The methodology above is summarized in the figure below.


Data Acquisition
sentinel (Google earth image)
Landsat ETM+/ OLI
EO-1 ALI
Hyperion
is it atmospherically corrected?
yes
no
atmospheric corrections
normalization (convert DN values o satellite reflectance then to surface reflectance
Principal Ccomponent Analysis
Stepwie Discriminant Analysis
Lambda -Lambda R^2 Model
principal components optimal bands
wilks lambda model optimal bands
contour plots optimal bands
selection of prominetly used optimal bands from SDA. PCA and LL-R^2 Model
discriminant analysis error matrces (accuracy assessment)

4.Results and Analysis

4.1 Stepwise discriminant analysis

The ability to discriminate the crop types was examined using stepwise discriminant analysis. The degree of separability at ($p<0.0001$; 99% confidence level) among cotton, maize and sugarcane using narrow bands from Hyperion and broadbands from ALI and ETM+ is shown in figure 2. Of these 54 bands, 48% are in NIR, 33% in SWIR and 19% in VIS portion of the spectrum. ETM reaches a Wilks of 0.84094 with 4 non-thermal bands; ALI a wilks of 0.5728 with 7 bands. This shows substantial intermix among crops. ETM+ centered around 565, 660, 825 and ALI around 565, 660, 790, 1250, 1650, 2215.



Variable	Frequency		
Name	Hyperion	ETM+	OLI
maize	29	17	19
sugarcane	34	19	23
cotton	29	15	14
mix	15	12	13

Figure 2; figure to show number of bands in from spectral discriminant analysis for the different images.

4.2 Principal Component Analysis

The purpose of PCA was to reduce redundancy by computing a set of wavebands that best explain the variability. Table 3 displays the PCAs of Hyperion, OLI and ETM+ across the different crops.

	PCA 1 (band center)	PCA2 (band center)	PCA3 (band center)	PCA 4 (band center)	PCA 1	PCA 2	PCA3
Hyperion							
cotton	1608	875	732	437	66	25	3
	1568	854	722	963			
	1588	824	712	1993			
	1578	794	742	953			
	1598	885	773	427			
Maize	1558	1992	1982	943	67	12	4
	1608	1064	2204	1488			
	1638	2083	933	915			
	1679	2153	2244	1144			

		2335	2163	933			
Sugarcane	722 712 1720 1709 1679	875 854 864 834 824	427 437 468 457 712	963 2325 2335 2355	48	16	11

Table1. showing principal components for Hyperion with variability.

The first PCA for Hyperion explains 66% of total variance in cotton fields, the second PCA explains 25%, up to the fifth explaining 1%. Two to five PCAs provide an accurate summary of the data, with two PCAs accounting for 90% of the total variance and five explaining 98%. The most important Hyperion HNBs involved with cotton PCA1 were 1608 nm, 1588 nm, 1568 nm, 1578 nm, and 1598 nm (table 1). Overall, for cotton, PCA1 was determined by HNBs in the EMIR (1300–1900 nm) and the PCA2 by the NIR (760–900 nm) wavebands. For maize crops, the first two and first five PCAs explained 75% and 91% of variance, respectively, with the first PCA determined mostly by EMIR, and PCA2 by FMIR wavebands. The most important bands lie in the region 1588-1679nm.

As in Hyperion, the wavebands dominating in PCA1s were located in the EMIR, and in PCA-2s in the NIR for the crops. Overall, across the crops, for Hyperion the first 2 PCAs explained about 90% variability and were dominated by HNBs in EMIR (1300–1900 nm) and NIR (760–900 nm) with sprinkling of bands from other wavelengths.

4.3 Correlation between bands

The correlation for 176 bands resulted in 15400 values each. The $\lambda1$–$\lambda2$ contour plots of cotton for Hyperion are shown in Figures below. The areas of high correlation (high R2 values, blank regions) between two wavebands signify band redundancy; thus, areas of lowest R2 are the most informative. For wheat, the most informative bands of both Hyperion and spectroradiometer are located in the NIR and the visual portion of the spectrum followed by FMIR and EMIR. For cotton, the most common Hyperion bands are located across the entire spectrum, mostly in the red-edge and FNIR, and the most common spectroradiometer bands are located in the blue, red-to- FNIR, and FMIR.

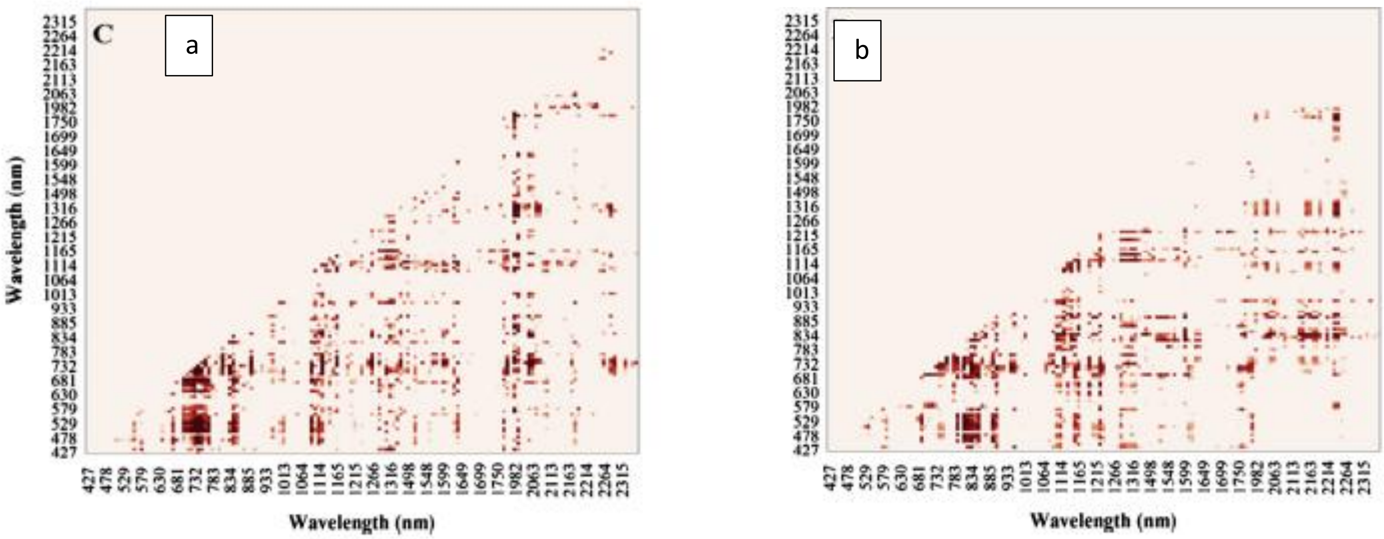


Figure 3;showing Lambda -Lambda plots for a) cotton b) maize using a select of bands.

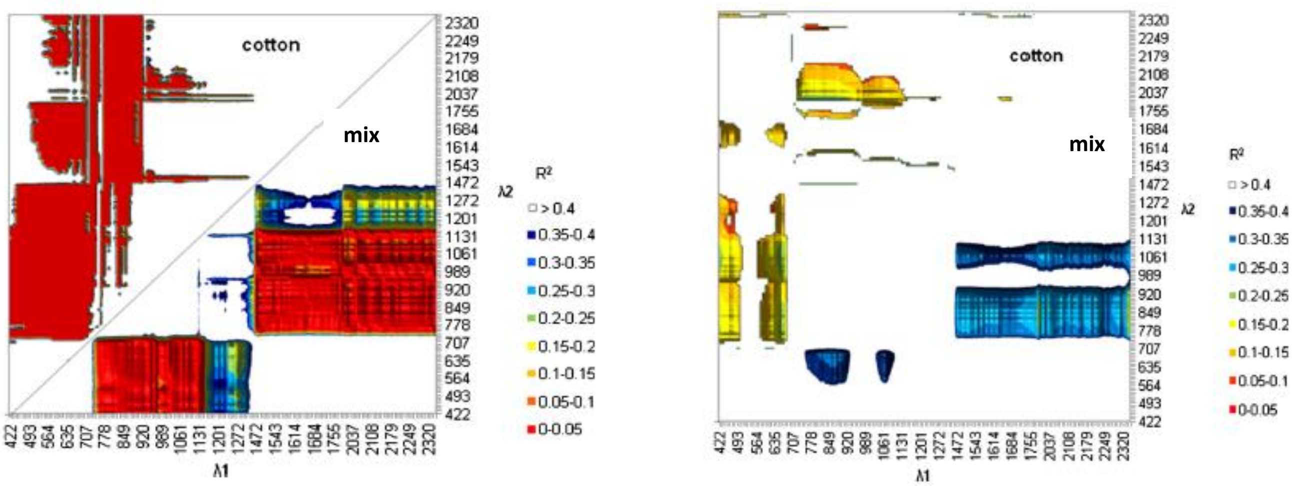
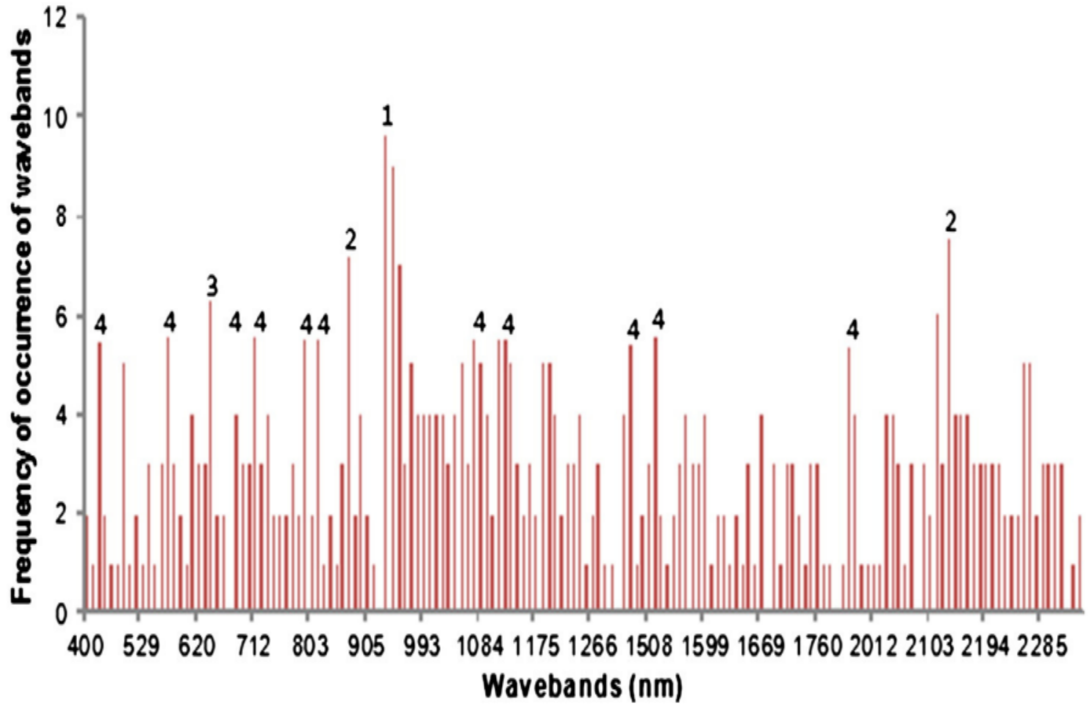


Figure 4; Lambda vs lambda plot of cotton against mixture of crops using a) all 176 bands from Hyperion. B) a selection of bands form the 176 bands.

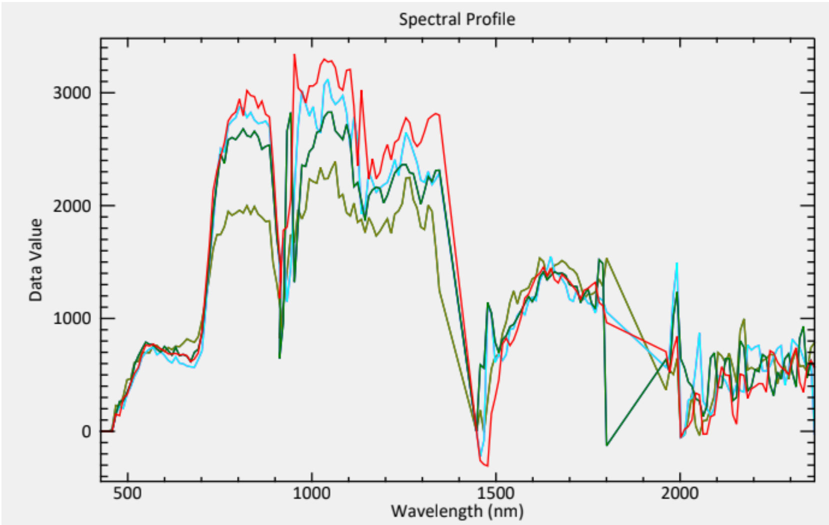
4.4. Frequency of occurrence, classification accuracies, and selection of best bands

Accuracy in discriminating crop types was examined by discriminant analysis using the most frequently occurring wavebands resulting from the LS-means, Wilk's lambda, PCA, and lambda–lambda correlation matrix for the hyperspectral sensors, and LS-means and Wilk's lambda for the multispectral sensors. The ranking of the best bands was used as input bands for classifying the crop types. When bands ranked within the same group (e.g. 680 nm and 690 nm) contained redundant information, only one band was selected as input. Such an approach helps in overcoming the Hughes' phenomenon (Thenkabail et al., 2011).

Based on this approach, the best 3, 5, 10, 15, and 25 Hyperion bands were selected (table 5). An overall accuracy of 90.2%was achieved using 25 narrow bands in classifying cotton, maize, and mix of crops.



When comparing the crop types, the best accuracy classification was found for alfalfa and maize (100%), followed by cotton (97.7%), sugarcane (95.6%), and least mix (30%). The largest error occurred for mix pixels misclassified as wheat with an omission error of 70%, probably due to water background reflection. In contrast, the overall accuracy of MBBs in crop type discrimination is lower than narrowbands even when using all the bands and for two crops only (cotton and wheat), as in the case of IRS (overall accuracy = 92.6%). Comparing the accuracy in discriminating the same three crops – cotton, maize, and wheat – between the multispectral ALI and IKONOS and hyperspectral Hyperion, the latter outperformed with only 12 bands (overall accuracy = 86%). ALI reached a maximum accuracy of 83.9% and 76.8% respectively using 9 and 4 bands respectively. The overall accuracy of the 6 non-thermal ETM+ bands was 54.3% in discriminating four crop types (cotton, maize, sugarcane, and mix), poor compared to the spectroradiometer which, with only one band centered at 432 nm.. However, it is important to note that it is possible to achieve over 90% classification accuracies using HNBs even when a greater number of crop types is involved, as illustrated for 5 crops using spectroradiometer data (Table 7). ForMBBs the classification accuracies decrease swiftly with greater number of crop types.



A list of hyperion optimal bands

NIR, FMIR - **885,943,2143 81.1**
blue, red, NIR, FMIR - **447,651,885,943,21443 82.3**
VIS, Red edge, NIR, MIR - **447,579,651,681,722,803,885,943,2143 83.5**
VIS, Red edge, NIR, FNIR, EMIR, FMIR **-447, 579, 651, 681, 722, 803, 885, 943, 1084, 1134, 1488, 2143 86**
VIS, Red edge, NIR, FNIR, EMIR, FMIR-
447,579,651,681,722,803,885,943,1084,1134,1488,1528,1982,2123,2143 87.2
VIS, Red edge, NIR, MSNIR, FNIR, EMIR, FMIR-
447,508,579,651,681,722,803,885,933,943,953,963,983,1064,1084,1094,
1124,1134,1144,1195,1205,1488,1528,1982,2123,2143,2264,2274

5.0 Conclusion and Recommendations

This study clearly identified the important as well as the redundant wavebands through: (1) principal component analysis and (2) very rigorous λ1 (400–2500 nm) by λ2 (400–2500 nm) contour plots involving 12,403 unique HVI model derived R-square values for each variable of each crop. These findings make significant contribution to data mining and in overcoming the Hughes' phenomenon. This is very valuable for future generations of satellites, such as the Hyperion mission, which could either gather data from hundreds of hyperspectral narrowbands like Hyperion, from which users will have to extract appropriate optimal wavebands relevant for their application (e.g., based on methods espoused in this paper), or, as an alternative, they could carry specialized optimal sensors with selective wavebands (e.g., as reported for Hyperion ., focusing to gather data for targeted applications such as agriculture or vegetation. This will reduce data volume and optimize time and resources in image pre-processing, analysis, and interpretation.

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