DEVELOPMENT OF TOBACCO (NICOTIANA TABACCUM) YIELD ESTIMATION MODELS USING AGRONOMIC AND REMOTE SENSING TECHNIQUES

BY

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DECLARATON

I, EZEKIA SVOTWA do hereby declare to the Senate of the University of Zimbabwe that this product is of my own investigation except where acknowledged.

To the best of my knowledge, this work has not been presented previously for any degree or similar award to this University or any other University.

Signed………………………………………………

Date………………………………………………
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DEDICATION

This work is dedicated to my parents Mr Tobias Svitwa Ngorima and Mrs Francisca Takapfukirwa Ngorima. May God richly bless you with a long life and many grand children.
ABSTRACT

Farmers need to monitor crop growth and development and obtain early estimates of final yield. The unavailability of a comprehensive method for estimating crop yield leads to contradicting estimates, subjective national statistics and general planning inefficiency by stakeholders. In this study, experiments were conducted to select a suitable index for assessing varietal, planting date and fertilizer management influence on tobacco canopy reflectance. A hand-held multispectral radiometer was used to take canopy reflectance measurements. This was followed by an investigation into the relationship among canopy reflectance, in-season dry mass and final crop yield. The experiments were conducted at Kutsaga Research Station, near Harare in Zimbabwe. The MODIS satellite derived NDVI was used to assess tobacco growth, estimate crop area and final yield. The relationship between reflectance measurements from the multispectral radiometer and those from the MODIS satellite were used in up-scaling the multispectral radiometer derived yield estimation models for application on the sampled tobacco fields within a radius of 150 km from Harare.

In this study, it is demonstrated that although simple ratio index (SRI) had a stronger relationship with biophysical parameters such as above-ground dry mass, plant population and plant height than NDVI, the latter was selected for use because of its stronger relationship with total nitrogen. Varieties, planting dates, and fertilizer application levels could be separated using spectral data between 9-12 weeks after planting. The different planting times could be separated from 0 to 9, 10 to 12, 13 to 18 and 18 to 22 weeks after planting, thus demonstrating these as the optimum period for collecting spectral data for tobacco yield estimation. The mass at untying-NDVI regression coefficient of determination decreased with later planting from September ($R^2 = 0.79$), October ($R^2 = 0.64$), November ($R^2 = 0.695$) and finally December ($R^2 = 0.515$). The yield-NDVI regression models for the September and the October-planted crops were statistically similar ($p = 0.424$), and so were those for the November and December planted crops ($p = 0.541$). There were no significant differences ($p = 0.220$) among the mass at untying - NDVI regression curves for K RK 26, T 66 and K E1 and for the fertilizer application levels ($p = 0.167$). Since the relationships among tobacco in-season dry mass and yields with NDVI were not affected by tobacco variety and fertilizer application levels, a combined model for estimating tobacco yield using NDVI was developed.
Using remote sensing based on the MODIS satellite derived NDVI data, the third to fourth week of November and the third to fourth week of February were the optimal times for discriminating the September-October from the November-December planted tobacco. The tobacco crop areas for the 2010/2011, 2011/2012 and 2012/2013 cropping seasons were estimated, and yield estimates were calculated from the long-term cropped yield-area regression model. An up-scaling factor from the multispectral radiometer derived model to the MODIS derived model was developed, and a model for estimating tobacco yield using NDVI was derived. A regression analysis of the observed versus predicted yield was significant (p<0.05). The results show that tobacco yield can be estimated from the MODIS satellite derived NDVI using the model: 

$$Y_{tot} = A(48.28 \times \text{av NDVI}_{\text{MOD}} - 37.51 \times \text{av NDV}_{\text{IMOD}} + 8.003)$$ 

It is recommended that the model be used by tobacco industry to complement existing methods.
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CHAPTER 1: GENERAL INTRODUCTION

1.1 Crop monitoring and yield forecasts
Crop monitoring is essential for determining the health and physiological status of a growing crop and for yield estimation (Bronson et al., 2003). Indicators such as total leaf number, leaf length, leaf diameter and stem height (Baez Gonzalez et al., 2005) are useful for assessing the physiological status of the crop and can provide a general guide for the expected crop yield. However, these parameters are often difficult to monitor within a season and on a large scale due to resource and time limitations (Vogel, 1985; Craig and Atkinson, 2013).

The current conventional crop yield forecasts rely on a combination of seed purchase records. However growers may buy seed for speculative purposes and may fail to establish a crop. In some cases, the established crop fails due to poor management. Growers also estimate yield through records of cropped land area and visual crop assessment of such biophysical properties as plant height, leaf size, stem thickness and the general vigour of growth. Since farmers’ records of crop production records may not be complete, these forecasts may not be accurate (USDA, 1999).

Some existing statistical models relate meteorological parameters to crop yield and production (FAO, 1986). Although use of statistical models has allowed fairly accurate yield forecasting, the nature and relationship between crop yield and some growth parameters may not be easily determined. Statistical models, for example, are location specific, and the use of a representative statistic in developing a yield model may not reflect conditions in extreme situations. In addition, the process of collecting statistical data can be tedious and time consuming, and thus preclude large-scale investigations (Garvin, 1985).

1.2 The Agronomic determinants of crop yield
Successful crop production depends on, among other factors, variety, fertilizer management, planting date and environmental parameters such as temperature, rainfall and soil type. These factors also affect plant physical properties and chemical composition. Visual crop quality assessment is done by subjective evaluation, and determines the prices of most leaf crops. In
tobacco the visual appearance of crop products is one of the first quality determinants made by buyers resulting in the decision for the initial purchase, while subsequent purchases may be more related to texture and flavor (Mitcham et al., 2003).

Tobacco leaf characteristics, chemical composition, burning quality and aroma are the most important factors in determining quality. Leaf characteristics are primarily hereditary in nature, but may be modified by factors such as rainfall and temperature distribution across the season and nutrient management, topping and de-suckering (TRB, 2010). Topping refers to the removal of the flower bud along with some upper leaves in order to stimulate growth and development of tobacco plants. When left untopped, tobacco plants will channel nutrients and energy towards flower and seed production at the expense of the harvestable part, the leaf, resulting in yield and quality losses. The optimum leaf number after topping depends on variety, but generally ranges between 16 and 22 (TRB, 2010). The removal of suckers, which grow vigorously after topping, is called desuckering. Suckers are removed either by hand, chemical but often by employing both methods.

Plant responses to fertilizer generally vary among varieties. A high yielding variety uses fertilizer more efficiently than low yielding ones at any level of fertilization, even in years of subnormal rainfall (Su et al., 2006). The soil is the major source of nutrients required for crop growth and soil mineral composition as influenced by fertilizer management, affects the crop canopy mineral composition, and the way the canopy interacts with solar radiation. Quantification of biochemical concentrations in plants is a goal in the study of plant response to nutrient supply in its environment (Dungan et al., 1996). These biochemicals, including amino acids and proteins, sugars and carbohydrates, cellulose, tannins and lignin are critical and are related to growth, allocation as well as plant defence and have primary absorptions in the near infrared region (Johnson and Billow, 1996. This phenomenon has allowed the development of practical, operational methods of near infrared spectroscopy in which biochemicals are quantified in dried, ground organic material.

There are various methods used to assess nutrient content in plants. Blackmer and Schepers (1995) reported procedures developed to determine leaf nutrient status, using a tool that monitors
leaf chlorophyll content but these measurements are time-consuming and require a number of observations to characterize the whole field. The Kjeldahl digestion and Dumas combustion have been used as reference methods for nitrogen determination in plants (Muñoz-Huerta et al., 2013). The tool Minolta Spad 502 chlorophyll meter, works by measuring light transmittance through a leaf at 650 nm, which lies between the two primary wavelengths 645 and 663 nm, and is associated with chlorophyll activity (Blackmer et al., 1994). The chlorophyll molecule contains a large proportion of total leaf nitrogen and, therefore, measurements of chlorophyll concentration can provide an accurate indirect assessment of plant nitrogen status (Moran et al., 2000). These measurements are, however, time-consuming and require a number of observations to characterize the whole field.

1.3 Canopy properties and remote sensing

Remotely sensed satellite data provide powerful means for monitoring changes in the crop canopy during a growing season (Thomason et al., 2007). Plant biochemical compositions such as chlorophyll concentration, water content and starch concentration can be estimated from spectral reflectance characteristics of plants (Hatfield et al., 2008) and are directly linked to the vigour and health of crops. Selective absorption and reflection of electromagnetic energy influenced by plant pigments and available water are detected by sensors in specific regions of the electromagnetic spectrum (Wang et al., 2010).

Remote sensing has been used widely in wheat assessment to characterize properties of vegetation, estimate yield, estimate total biomass (Bao, 2009), and monitor plant health and plant stress (Jackson et al., 1983). Remote sensing data obtained from agricultural fields can be used in the identification and mapping of crops as well as monitoring crop vigour and environmental stress (Broge and Leblanc, 2001).

Remote sensing methods have been developed and implemented to estimate crop nutrient status, particularly nitrogen, in a specific area or in the entire field (Muñoz-Huerta et al., 2013). It provides rapid and near-real-time detection of nutrient status in the field and could be very helpful for site-specific nutrient, and in particular, nitrogen management. In recent years, spectral measurements have been used for rapid and non-destructive estimation of crop nitrogen status.
Several studies have examined technologies involving remote sensing to quantify nitrogen stress. Blackmer et al. (1994) found that reflectance near 550nm measured on detached maize leaves from a field nitrogen fertilizer experiment was able to separate nitrogen treatments. Spectral indices derived from the reflectance spectral bands were indirectly related to the nitrogen content of the crop, (Reusch, 2003). Researchers have found nutrient stressed canopies to have a lower spectral reflectance in the NIR and higher red wavebands when compared with unstressed canopies (Genc et al., 2013). Other studies estimated leaf nitrogen status by measuring reflectance spectra. Osborne et al. (2002) and Graeff et al. (2001, 2003) showed that nutrient deficiencies could be identified and quantified by means of reflectance measurements based on selected stress specific wavelength ranges.

By using spectroradiometers, reflectometers, imagery from satellite sensors and digital cameras, optical properties such as crop canopy reflectance, leaf transmittance, chlorophyll and polyphenol fluorescence, have been measured to estimate nitrogen in crop plants (Zhou, et al., 2010). There are some commercial ground-based active-mounted sensors such as Yara N-Sensor, GreenSeeker, Cropscan and satellite-mounted sensors, all of which measure crop canopy reflectance in the visible and/or IR wavebands (Muñoz-Huerta et al., 2013). A positive relationship has been found between optical parameters and plant nitrogen status using remote sensing based non-destructive techniques. The results from such measurements have been used in crop status monitoring for yield estimation.

1.4 Remote sensing support to crop area estimates and yield forecast

Knowledge of canopy light interception and absorption is fundamental for understanding many aspects of crop growth and productivity, and for crop modeling (Rosati, 2001). The interaction between light and intercepting molecules in the canopy results in scattering and absorption by the atomic bonds, electrons or atoms in the molecule. The wavelength at which absorption and reflection takes place is specific for the atomic bonds of the intercepting target (Mutanga and Skidmore, 2007) and the molecular architecture of the target, making the identification of individual chemical components within the intercepting canopy possible (Ferweda, 2005). The spectral absorbance properties of chemical components in plant leaves are manifested in the
reflectance spectra of leaves and this offers the opportunity of using measurements of reflected radiation as a non-destructive method for quantifying pigments (Blackburn, 2006).

Vegetation has a unique spectral signature which enables it to be distinguished readily from other types of land cover in an optical/near-infrared image and the spectral characteristics of vegetation vary with wavelength. Leaf chlorophyll strongly absorbs radiation in the red (630-690 nm) and blue (450-520 nm) wavelengths but reflects green (520-600 nm) wavelengths and the internal structure of healthy leaves act as a diffuse reflector of near-infrared (760-900 nm) wavelengths (Samuoliene et al., 2010). The reflectance is, hence, low in both the blue and red regions of the spectrum, due to absorption by chlorophyll for photosynthesis and, has a peak at the green region which gives rise to the green colour of vegetation (Ali, 2010). In the near infrared (NIR) region, the reflectance is much higher than that in the visible band due to the cellular structure in the leaves and, hence, vegetation can be identified by the high NIR but generally low visible reflectance (Ali, 2010).

Measuring and monitoring the infrared reflectance could then be used to determine crop health. Well managed crop canopies appear greenest at 550 nm (Blackmer et al., 1994), becomes red or yellow with decrease in chlorophyll content due to poor fertilization, and this greenness is generally recognized as an indication of nitrogen status for many agronomic crops (Thomas and Oerther, 1972). Work by Su et al. (2006) showed that different nutrients and fertilizer application levels had a considerable effect on the leaf chemical composition. Mackown et al. (2000) reported that the level of tissue nitrated in crops, as determined by the level of N fertilization, may be a suitable diagnostic test of crop nitrogen sufficiency that could be used for nitrogen management decisions as well as yield and quality predictions. By measuring the energy that is reflected by a crop canopy surface over a variety of different wavelengths, a spectral signature for different varieties and fertilizer management can be distinguished, and the information can be very useful in crop yield and quality predictions.

By measuring the quantity of radiation in each of the wavelengths, the plant canopy characteristics can be defined (Mutanga and Skidmore, 2007). The differences in leaf greenness, textures, shapes or even how the leaves are attached to plants, determine the amount of reflected,
absorbed or transmitted energy. Such relationships are used to determine spectral signatures of individual plants, which are unique to plant species (Nowatzki et al., 2004). Spectral signatures make it possible to use remote sensing in studying changes in specific crop growth and development in the field and relate these to final yield and quality. The comparison of the reflectance values at different wavelengths is used to determine plant vigour. The most common index that is used for this purpose is the Normalized Difference Vegetation Index (NDVI). NDVI compares the reflectance values of the red and NIR regions of the electromagnetic spectrum, and NDVI value of each area on an image helps identify areas of varying levels of plant vigour within fields (Kidwell, 1990). Research has shown that NDVI is directly related to the photosynthetic activity (Myneni et al., 1995). NDVI was found to be a sensitive indicator of canopy structure and chemical content aspects such as green biomass, green leaf area index, chlorophyll content and leaf nitrogen (Gamon et al., 1995). These could also be considered when developing models for estimating seasonal biomass production for either individual species or communities.

Remote sensing surveys have successfully been conducted elsewhere in forecasting yield in paddy rice (Mohd et al., 1994), maize (Baez-Gonzalez, 2005) and potatoes (Wu et al., 2007). It is generally asserted that some improvements in the timeliness and accuracy of crop yield forecasting can be made by employing remote sensing techniques (Craig and Atkinson, 2013). Fairly accurate crop yield forecasting models can be developed by improving our understanding of the influence of such factors as crop varieties, fertilizer application levels and even the time of planting. Yield is a result of complex interactions among these agronomic factors together with genetic and climatic factors (Beljo et al., 1999).
1.5 Justification

As summarised by the TIMB (2013) tobacco is one of the major agricultural exports in Zimbabwe. The crop accounts for 10.7 per cent of the country's gross domestic product (GDP). Between 2004 and 2013 Zimbabwe’s average annual production of flue cured tobacco was 94, 1 million kg which was sold at an average 2.7 USD per kg. When the marketing season closed in 2013, some 166.5 million kg of tobacco had been sold at an average price of 3.70 USD per kg, realising US$616.1 million in sales.

Tobacco growers need to monitor crop growth and development and obtain early estimates of final yield (Senay, et al., 1998), as this is a regulatory requirement by the Tobacco Industry and Marketing Board (TIMB). In the present circumstances, unavailability of a comprehensive and accurate method for estimating national tobacco volume has often led to contradicting estimates, subjective national statistics and general planning inefficiency by stakeholders. The current tobacco yield estimation is based on the Garvin model (1986), seed tracking approach and the statistical and crop condition assessment approaches. Such conventional methods of scouting are often labour intensive and are based on data collected from a specific sampled area and, hence, their accuracy is questionable (Garvin, 1985). Variable crop conditions are only distinguishable to the trained and experienced eye. The development of a more objective and practical remote sensing based model for yield estimation could assist tobacco stakeholders with more precise data on tobacco growth characteristics, area and final yield that would be available for export.

With the use of remote sensing, plant physiological and morphological differences can be distinguished in the field and even identify tobacco lands under different varieties and fertilizer management levels. Tobacco production managers may be aware of the productivity differences within and among fields, and may benefit from the potential value of using variable rate technology instead of using uniform applications to estimate crop output. Site-specific information on varieties, fertilizer management and cultural practices may improve the accuracy of yield forecasting and, remote sensing offers the potential to provide quantitative and timely information on agricultural crops over large areas (Clevers et al., 1996). Multispectral imaging sensors are able to view more than one particular band of energy. These bands are selected in
various regions of the electromagnetic spectrum, based on the optimum range of energy being reflected by the objects observed. In-season canopy images have also been found useful in predicting yields in maize, soybean, and cotton (Ma et al., 2001; Senay et al., 1998; Vellidis et al., 1999).

Developing a model to forecast or estimate tobacco yield could be very useful for decision making in the tobacco industry. A yield estimation model for tobacco could also assist stakeholders to accurately determine total energy requirements for curing. For government, an accurate prediction of the crop size is a useful planning tool in view of the revenue generated by tobacco, for determining import–export policies, government aid for farmers, and allocation of subsidies for agricultural programmes.

By using satellite imagery instead of traditional sampling techniques, tobacco yield forecasts can be generated earlier than traditional estimates; and because they are based on satellite images, these forecasts can be updated frequently throughout the growing season, thus tracking growth and development to different conditions as the season progresses. The signatures from satellite imagery will then be used as inputs for the yield estimation models in order to come up with the volume estimate of the crop. Remote sensing enables observations over large areas at regular intervals, making it useful even in large-scale crop modelling (Gallo and Flesch, 1989; Moulin et al., 1998). Use of satellite imagery also enables the verification farmers’ claims of seedbed area established, size of irrigated and dry land tobacco crops, varietal proportions in the field and even monitoring disease development as well as adherence to legislation on tobacco destruction dates. Varietal distribution and nutrient fertilizer management effects can also be easily monitored and factored in the final yield forecast.
1.6 Study hypothesis and objectives
The main aim of this study was to develop models for predicting flue-cured tobacco yield using remote sensing and agronomic techniques. This study sought to (i) test the possibility of using spectral techniques to separate tobacco varieties under different planting times and fertilizer regimes using both the hand-held radiometer and satellite data; (ii) establish quantitative relationships between remotely sensed measurements and chemical composition and yield; and (iii) develop a tobacco yield forecasting model using agronomic information and spectral techniques.

1.6.1 Hypotheses
- Tobacco canopy biophysical and chemical characteristics can be estimated by reflectance indices
- Tobacco planting dates, varieties and fertilizer application levels can be separated using spectral data
- Tobacco crop area and yield can be quantified from remotely sensed measurements
- A tobacco yield forecasting model can be developed using agronomic and spectral data.

1.6.2 Specific objectives
The specific objectives were to:
(1) Identify a suitable reflectance index for assessing the responses of tobacco varieties to varying fertilizer management levels;
(2) assess the spectral reflectance of tobacco varieties planted at different planting dates, under variable fertilizer management levels;
(3) derive the relationship between tobacco canopy reflectance, leaf total nitrogen, leaf dry mass and cured leaf yield;
(4) determine the relationships between hand-held multispectral radiometer measurements and moderate resolution satellite spectral reflectance;
(5) estimate tobacco crop area and yield using crop canopy spectral reflectance and
(6) develop a model for estimating tobacco yield using optical satellite data.
1.7 Research approach

In this study, two sensors were used in the process of developing models for crop yield estimation models. Measurements were made at field level using a multispectral radiometer, with five bands from 450 to 1750 nm, and later from the Moderate-resolution Imaging Spectroradiometer (MODIS) satellite data. The MODIS is a key instrument aboard the Terra and Aqua, Earth Observation Satellites that are timed so that it passes from north to south and south to north across the equator in the morning and in the afternoon respectively. Tobacco was used as a reference crop.

The study focused on three tobacco varieties, four planting times and three fertilizer levels. The three varieties used in the research were Kutsaga root-knot resistant 26 (K RK26), Kutsaga root-knot resistant 66 (T 66) and Kutsaga white mould (Erisiphe cichoracerum var nicotiana) resistant 1 (K E 1). K RK 26 and T 66 are currently the most popular varieties among growers, with an adoption rate of 63, 5 % and 5,2 % respectively (TRB, 2012). T 66is still at the testing stage and was envisaged to dominate because of its higher yielding potential of 4 - 4.5 t-ha$^{-1}$ compared to 3.5 – 4 t-ha$^{-1}$ for K RK 26 (TRB, 2012). K E1 is an old variety, rarely grown commercially, which at Kutsaga, is used as a standard in all tobacco variety trials. The potential yield for K E1 ranges from 2.5 to 3 t-ha$^{-1}$. The time to maturity for K RK 26, T 66 and K E1 in the seedbed is 72 – 80 days after sowing, while in the field, the three varieties take 18 – 20 weeks, 18 – 22 and 16 – 18 weeks after planting respectively (TRB, 2010)

Fertilizer is the main determinant of crop yield and, up to 1999, the large-scale commercial farming subsector accounted for most of the fertilizer consumption and fertilizer application levels in the large-scale commercial farming subsector were comparable with those in developed countries (Mashingaidze, 2004). Generally, the resource poor small scale commercial and communal tobacco growers use low fertilizer application levels, which in this experiment were assumed to be 0 – 50 % of the levels recommended by the results of soil analysis (Mashavave, 2003). The resettled and commercial tobacco growers generally strive to adhere to the recommended rates and they collect soil samples from their fields for testing in soil testing laboratories and some among this group may even apply higher rates than recommended,
according to their yield expectations and the general history of the tobacco lands (Mashingaidze, 2004).

Four planting times from September to December represent the normal and conventional planting times for tobacco (TRB, 2010). September and October are for the irrigated and the supplementary irrigated tobacco crop respectively, while November and December planting times are for the rainfed crop. Planting time generally affects yield in that the earlier the crop is planted the higher the yield and quality and the reverse is generally true (Fankow-Lindber, 2006; Kgasago, 2006). The earlier planted summer crop is subjected to periods of stress, which stimulate the development of a dense and deep root system. The crop becomes vigorous when the first rains are received during mid October and the dense root system will promote nicotine manufacture as well as fertilizer and water uptake (Werner et al., 2010). The November and the December dry land crops, on the other hand, are generally subjected to high incidences of pests and diseases, and the heavier rains during this period increase and promote high weed growth which compete with tobacco (TRB, 2010). Consequently the quality and yield of tobacco is lower than that for September and October crops.

The study site for the experimental work was Kutsaga Research Station because of the availability of facilities such as the experimental fields, appropriately demarcated for tobacco research, new and old tobacco varieties, the analytical chemistry laboratories for soil and plant tissue analysis and availability of a purpose-purchased hand-held multispectral radiometer.

The survey project area lies between 29.6812° S and 32.2783°S latitude and between -18.734° E and -7.6°5 E longitudes, at an altitude of 1300 m to 1500 m (TRB, 2010).

The five band CROPSCAN, Inc. Multispectral radiometer (MRS 5) system (Cropscan, 2013) was used in collecting radiometric data from the experimental tobacco canopy. The radiometric data was used for calculating reflectance ratios for assessing flue-cured tobacco response to fertilizer and planting date differences and all these would be related to the final crop yield. The MSR 5 has been used for similar work (Belford et al., 1993; Bronson et al., 2003) and is
compatible with the LANDSAT 7 TM spectral bands (Cropscan, 2013), a feature which would enable later up-scaling and modelling.

As summarised by NASSA (2013), the Moderate-resolution Imaging Spectro-radiometer (MODIS) is a key instrument aboard the Terra and Aqua, Earth Observation Satellites that are timed so that it passes from north to south and south to north across the equator in the morning and in the afternoon, respectively. Terra MODIS and Aqua MODIS are viewing the entire Earth's surface every 1 to 2 days, acquiring data in 36 spectral bands. The MODIS satellite was chosen for this research because of its spatial resolution of 250 m by 250 m which was considered detailed enough for the quantification of variability within flue-cured tobacco fields. For modelling purposes, the extent of the study area was suitable enough to cover all the four farming sectors, commercial, small scale commercial, resettled farmers and the communal farmers that participate in tobacco production.

Regression analysis was used for this study because of easy applicability. Similar approaches were applied in relating canopy reflectance of wheat (Huang et al., 2012, Huang et al., 2013), maize (Prasad et al., 2005; Baez-Gonzalez et al., 2005; Sibley et al., 2014), grapes (Liu, 2013) and sugarcane (Lumsden et al., 1998; Lofton et al., 2012) to yield. In this study a similar approach was employed. Historical statistical information on the relationship between land area and yield were later incorporated, and the weekly crop assessment and inventory reports that are currently issued by the Ministry of Agriculture, Mechanisation and Irrigation Development (Crop Production Branch) and the Tobacco Industry and Marketing Board were used as standards.
1.8 Organization of the study
The study is written as stand-alone chapters, each capturing an essential aspect of the specific objectives of the study.

Chapter 1 provides an overview on the agronomic determinants of crop yield and general remote sensing application and support to crop area and yield estimation. The objectives and the general research organisation and outline are also highlighted.

Chapter 2 is on literature review. It covers the application of remote sensing in crop yield estimation, and relates the approaches successfully used in other crops to flue-cured tobacco. The chapter provides relevant physical processes in the transfer of radiation from space to the earth’s surface and its interaction with different target surfaces. An overview of existing canopy reflectance biophysical characteristic models is given, while giving emphasis on the factors that contribute to flue-cured tobacco yield differences.

Chapter 3 presents the results of the screening of the four channels of the MSR 5 for usability and the derived indices of NDVI and SRI for assessing flue-cured tobacco varieties response to fertilizer management in relation to biophysical parameters and leaf chemical composition (Objective 1).

Chapter 4 presents the results on assessing the spectral separability of flue-cured tobacco varieties that were established at four planting times and under varying fertilizer application levels (Objective 2).

In Chapter 5 the results relating flue-cured tobacco canopy reflectance with in-season plant dry mass and cured leaf yield are presented (Objective 3).

Chapter 6 presents the results on how operational remote sensing techniques were used in an NDVI based algorithm for tobacco area estimation. The tobacco yield estimate was then made using a long-term yield area regression model (Objective 5).
Chapter 7 demonstrates the up-scaling of the multispectral radiometer based Yield-NDVI model using the MODIS satellite data and the development of a MODIS based Yield-NDVI model using the upscaled data (Objectives 4 and 6).

Chapter 8 synthesizes the findings of the study. It further presents the implications of these findings to the estimation of tobacco crop volume at field, district, provincial and national levels, and finally, several conclusions and recommendations for future research are made.
CHAPTER 2: REMOTE SENSING APPLICATIONS IN TOBACCO YIELD ESTIMATION IN ZIMBABWE

Abstract
This manuscript reviews the scientific basis of remote sensing and examines the role of remote sensing in crop yield forecasting. It concludes with a discussion of challenges of applying remote sensing in tobacco yield estimation in Zimbabwe. Tobacco crop area and yield forecasts are important in stabilizing tobacco prices at the auction floors. Currently, tobacco yield estimation in Zimbabwe is based on statistical surveys and ground-based field reports. These methods are costly, time consuming, and are prone to large errors. Remote sensing can provide timely information on crop spectral characteristics which can be used to estimate crop yields. The interaction between the incident electromagnetic energy with the atomic structures of the intercepting soil, rocks, plants, water and man-made objects, determines the proportion of energy that is absorbed and the proportion reflected. The relationship between reflected, absorbed and transmitted energy is used to determine spectral signatures of individual plants. The development of vegetation indices for crop canopies enabled quantification of agronomic parameters like leaf area, crop cover, biomass, crop type, nutrient status, and yield. Remote sensing application in agriculture in Zimbabwe is still very limited. Research should focus on identifying suitable reflectance indices that are related to tobacco growth and yield. Varietal yield response to fertilizer application levels, planting dates should be established and suitable temporal windows for spectral data collection for yield forecasting purposes should be identified. The challenges of the different tobacco land sizes have to be overcome by identifying suitable methods to separate the tobacco crop from the adjacent competing crops and non-crop vegetation surfaces. Suitable vegetation indices can be employed in determining the spatial distribution of the crop and in establishing the cropped area. Area-yield relationships can be used to estimate the final yield of the crop.

This chapter is based on
2.1 Background

Zimbabwe is the largest producer of tobacco in Africa and the world’s fourth-largest producer of flue-cured tobacco (*Nicotiana tabacum*) after China, Brazil, and the United States of America. Tobacco production has been the leading driver behind the 34% growth in Zimbabwe’s agriculture between 2008 and 2009 (Tobacco Facts, 2009). Between 2004 and 2013, the number of tobacco growers in Zimbabwe increased by 260% to 78,576, with a corresponding crop area increase of 101.3% to 88,627 ha, while total production also increased from 69 million kg to 166.6 million kg within the same period (TIMB, 2013).

Crop area and yield forecasts play an important role in stabilizing tobacco prices at the auction floors. Crop forecasting is the practice of predicting crop yields and productivity before the harvest actually takes place, typically a couple of months in advance (TIMB, 2013). Zimbabwe mostly relies on crop reports/field visits from extension officers and statistical models for crop yield forecasts (FAO, 2008). However, data from crop estimates, which are obtained through surveys conducted after harvest, are in most countries available quite late for early warning purposes.

Crop yield estimation in many countries is based on conventional techniques of data collection and ground-based field reports (Reynolds et al., 2000). A variety of mathematical models relating to crop yield have also been proposed in recent years for many crops (Wheeler et al., 2000). In Zimbabwe, crop surveys are mostly used in estimating crop yield (FAO, 2008). The method is costly, time consuming and is prone to large errors due to incomplete ground observations, leading to poor crop yield assessment and inaccurate crop area estimations (Reynolds et al., 2000). Remote sensing data has the potential and the capacity to provide spatial information ranging from field, district, provincial, national and even at a global scale for features and phenomena on earth on an almost real-time basis. Use of remote sensing techniques has the potential to provide quantitative and timely information on agricultural crops over large areas, and many different methods have been developed to estimate crop yields (Moran et al., 2000). In general, the use of remote sensing was aimed at reducing the number of samples of ground surveys, making it less expensive (Doraiswamy, 2005). With the application of remote
sensing in agriculture, there is potential not only for identifying crop types, but also of estimating crop yield (Reynolds et al., 2000).

2.2 The remote sensing science
Remote sensing practice gathers information about an object without physically coming into contact with the object (Nowatzki et al., 2004). Remote sensing has been used to characterize properties of vegetation, estimate yield, estimate total biomass, and monitor plant health and plant stress (Wu et al., 2007). The sun is the source of all the electromagnetic energy that is used in a passive remote sensing system (Figure 2.1).

![Figure 2.1: Components of a remote sensing system (Source: Liew, 2001)](image)

The electromagnetic spectrum can be divided into several wavelength regions, among which only a narrow band from about 400 to 700 nm is visible to the human eye (Kyro, 2003). There are, however, no sharp boundaries among these regions. The boundaries shown in Figure 2.2 are approximate and, there are always overlaps between two adjacent regions.
Figure 2.2: The electromagnetic spectrum (Source: Liew, 2001)

The visible light, as summarised in the ENVI Userguide (2005) is a narrow band of electromagnetic radiation that extends from about 400 nm (violet) to about 700 nm (red). The various colour components of the visible spectrum fall within the following wavelength regions (Fig. 2.2):

- Red: 610 - 700 nm
- Orange: 590 - 610 nm
- Yellow: 570 - 590 nm
- Green: 500 - 570 nm
- Blue: 450 - 500 nm
- Indigo: 430 - 450 nm
- Violet: 400 - 430 nm

In remote sensing the visible and near infrared wavelength regions are predominantly used. The interaction between the incident energy with the atomic structures of the intercepting soil, rocks, plants (Figure 2.3), water and man-made objects, determines the proportion of energy that is absorbed and the reflected proportion (Keller et al., 2008).
From the principle of conservation of energy, the interrelationship among these interactions, as cited by Short (2008) can be expressed as

\[ E_1 = E_R + E_A + E_T \]

where \( E_1 \) is the incident energy, \( E_R \) is the reflected energy, \( E_A \) is the absorbed energy and \( E_T \) the transmitted energy. All energy components are a function of wavelength.

Remote sensing devices detect the reflected energy, which is then used to characterize the properties of the intercepting object. The proportion of energy that is reflected, absorbed and transmitted varies, for different targets, depending on composition and condition of the material, and this permits the distinction between objects in an image (Nowatzki, 2004).

The wavelength of the target also determines the proportion of reflected, absorbed and transmitted energy. As summarized by Nowatzki (2004), green vegetation has higher reflectance at green wavelengths and will appear “green” in colour, while water bodies have high absorption at ‘green’ and ‘red’ wavelengths and high reflectance at ‘blue’ wavelengths will be ‘blue’ colour.
When yellow is observed at a vegetated area, it is a product of electromagnetic energy at red and green wavelengths, and it’s a sign of senescing vegetation, where chlorophyll quantity is greatly diminished.

Remote sensing has contributed to, among other things, understanding of the earth’s dynamic processes like changes in the distribution of arable and non-arable land, monitoring the environment at various scales, from local, regional to global levels, improving scientific knowledge of the structure and dynamics of the earth’s land cover and land-use and detecting vegetation change with time (Quarmby and Reid, 1996).

The interactions among reflected, absorbed, and transmitted energy on plant canopies can also be detected by remote sensing. The differences in leaf colours, textures, shapes or even how the leaves are attached to plants, determine how much energy will be reflected, absorbed or transmitted. The relationship between reflected, absorbed and transmitted energy is used to determine spectral signatures of individual plants (Nowatzki et al., 2004).

### 2.3 Target spectral signature

All types of land cover absorb a portion of the electromagnetic spectrum within a range of possible values described as a “signature” of electromagnetic radiation (Liew, 2001). When this signature is recorded by a sensor, it becomes possible to classify a remotely sensed image on the basis of an understanding of the wavelengths that are associated with the main features on the target object. The reflectance spectrum of the target object is a plot of the fraction of radiation reflected, as a function of the incident wavelength, and serves as a unique signature for the material (Short, 2008).

In principle, a material can be identified from its spectral reflectance and this premise provides the basis for multispectral remote sensing, as these spectral signatures are unique to plant species (Nowatzki et al., 2004).

Silleos et al. (2003) summarized interaction of healthy canopies of green vegetation with certain portions of the electromagnetic spectrum. Chlorophyll causes strong absorption of energy in the
visible regions, mainly for use in photosynthesis. This absorption peaks in the red and blue areas of the visible spectrum. The near-infrared region of the spectrum, at the same time, is strongly reflected through the internal structure of the leaves. Remote sensing of soils shows a continuous increase in the reflectance signal, but there is interdependency on texture, organic matter and soil moisture content (Irons et al., 1989).

The reflectance of bare dry soil, bare wet soil as opposed to a cropped field, under wheat that is at full canopy cover, was demonstrated by Jackson and Huete (1991) (Figure 2.4). The two demonstrated the possibility of monitoring a wheat field from the early stages when bare ground only can be detected, up to full canopy cover. As the crop develops, the red band decreases from A (bare soil) or B (wet soil) reaching C at full cover. The Near infra red output also increases from E (dry soil) or F (wet soil) to D. However, the value of D can be lower for a stressed or diseased crop as argued by Short (2008).

Figure 2.4: Spectral reflectance of dry bare soil, wet bare soil and wheat (Source: Jackson and Huete, 1991)
Using this premise, one can also use remote sensing to identify stressed areas of a crop field by first establishing the spectral signatures of healthy growing plants and identifying stressed plants from an altered spectral signature.

The understanding of leaf reflectance has led to the development of various vegetation indices for crop canopies to quantify various agronomic parameters like leaf area, crop cover, biomass, crop type, nutrient status, and yield (Hatfield et al., 2008). It is feasible to detect water stressed, diseased and pest infested plants in the field, as stress is indicated by a progressive decrease in Near-IR reflectance accompanied by a reversal in Short-Wave IR reflectance (Figure 2.5) (Short, 2008).

Figure 2.5: The decrease in Near-IR reflectance, accompanied by a reversal in Short-Wave IR reflectance due to stress (Source: Short, 2008)

Short (2008) also illustrated the differences in the spectral signatures for soybean and crops that had different severities of leaf damage due to water stress (Figure 2.6), where a progressive decrease in infrared reflectance was observed with increase in severity of leaf damage.
A significantly greater proportion of the sunlight is reflected in the near-infrared band of the electromagnetic spectrum, wavelengths that are beyond the limit of human perception. By comparison, bare soil and dead vegetation exhibit a smooth increase in reflectance with increasing wavelength, and no appreciable hump in the green or the infrared wavelengths (Bauer, 1985).

![Figure 2.6: The differences in the spectral signatures for soybean crops that had different severities of leaf damage due to water stress (Source: Short, 2008)](image)

It has been demonstrated that the near-infrared reflectance of vegetation is more sensitive to changes in plant health than the visible wavelengths (Campbell, 2002). Near-infrared images of plants therefore offer more information about plant health and vigour than visible colour images.

Through field and laboratory studies, a variety of narrow spectral band features have been shown to be related to changes in vegetation condition, including the physiological characteristics such as chlorophyll amount and/or type (Gitelson and Merzlyak, 1998) and canopy chemical characteristics (Gao and Goetz, 1995)
By measuring the quantity of radiation in each of the wavelengths, the plant canopy characteristics can be defined (Mutanga and Skidmore, 2007; Ferweda, 2005; Moran et al., 2000). As explained by Broge and Leblanc, (2001), healthy vegetation has low reflection of visible light (from 0.4 to 0.7 μm), since visible light is strongly absorbed by chlorophyll for photosynthesis and, at the same time, a health plant has high reflection of near-infrared light (from 0.7 to 1.1 μm). The portion of reflected near-infrared light depends on the cell structure of the leaf (Toulios et al., 1998). In fading or unhealthy leaves, photosynthesis decreases and cell structure collapses resulting in an increase of reflected visible light and a decrease of reflected near infrared light (Broge and Leblanc, 2001).

**2.4 Vegetation Indices**

Vegetation Indices (VIs), calculated from combinations of reflectance values of two or more wavelengths, quantify properties of vegetation (Prasad et al., 2006). Vegetation indices, as summarized by Broge and Leblanc (2001), are based on the characteristic reflection of plant leaves in the visible and near-infrared portions of light. By applying a “Vegetation Index” to the satellite imagery, concentration of green leaf vegetation can be quantified (Viña et al., 2004). The distinctive absorption characteristics of incident visible and near infrared sunlight by photosynthetically active tissue in plants means vegetation indices tend to correlate highly with such plant physical parameters as leaf area index, chlorophyll content, wet and dry biomass and percent ground cover; all related to plant health and final yield. The comparison of the reflectance values at different wavelengths can thus be used to determine plant vigour (Tucker, 1979).

The simple ratio vegetation index (SR=NIR / Red), first described by Jordan (1969), contrasts the high reflectivity of plant materials in near infrared wavelengths to the intense chlorophyll pigment absorption, and correspondingly low reflectance, in red wavelengths (R) (Elvidge and Chen, 1995).

Another common index, the Normalized Difference Vegetation index (NDVI) (Rouse, 1974; Jackson et al., 1983) normalizes the difference in near infrared and red reflectance by the sum of the near infrared and red reflectance and, together with the former index, the two ratio indices
minimize the effects of changing solar illumination of ground targets due to sun-elevation angle and sun-earth distances (ENVI User's Guide, 2005). The NDVI has been considered to be a useful tool for crop yield assessment models, using various approaches such as simple integration, to reflect vegetation greenness (Prasad et al., 2006). The index responds to changes in the amount of green biomass, chlorophyll content, and canopy water stress and, hence, is the most commonly used in assessing crop vigour, vegetation cover and biomass production from multispectral satellite data (Balaselvakumar and Saravanan, 2006). The index is calculated from the Near Infrared (NIR) and Red (R) bands of either hand-held or satellite sensors using the formula: \[ \text{NDVI} = \frac{(\text{NIR} - \text{Red})}{(\text{NIR} + \text{Red})}. \] According to Kidwell (1990) the NDVI value of each area on an image helps identify areas of varying levels of plant vigour within fields.

The validity of crop yield models with the NDVI is determined by the strengths of association between the two variables included in the model (Jayroe et al., 2005). It is also essential to have an understanding of the relationship between yield and NDVI at different phenological stages of a crop for selecting appropriate date of satellite pass to include in the model (Jayroe et al., 2005).

Research has shown that NDVI is directly related to the photosynthetic activity and hence energy absorption of plant canopies, typical examples include the Leaf Area Index (LAI), biomass and chlorophyll concentration in leaves, plant productivity and fractional vegetation cover (Myneni et al., 1995). These could also be considered when developing models for estimating seasonal biomass production for either individual species or communities. Remote sensing surveys have been successfully conducted elsewhere in forecasting yield in paddy rice (Mohd et al., 1994), maize (Haboudane et al., 2008) and potatoes (Wu et al., 2007).
2.5 Remote sensing applications in crop area assessment

Remote sensing has been used for some time to characterize properties of vegetation, to estimate yield, to estimate total biomass, and to monitor plant health and plant stress (Wu et al., 2007). The interaction of the incident energy with the atomic structures of soil, rocks, plants, bodies of water and man-made objects, governs how much energy is absorbed and thus how much is reflected (Keller et al., 2008). It is this reflected energy that is detected by the remote sensing devices, and used to characterize the properties of a plant.

Visible (reflected light) and near-infrared (absorbed light) can be used to detect plant stress as a result of water shortages, nutrient deficiencies, and pest attack (Jackson et al., 1983). The contrast of light reflectance provides an assessment of the vegetation, thus provide a powerful tool for monitoring changes in the crop canopy over the growing season and can provide crop developmental information that is time-critical for site-specific crop management (Landau et al., 2000). Vegetation assessments become objective, faster, easier, and more reliable. Spatial information can be provided at a global scale of features and phenomena on earth on an almost real-time basis (Wheeler et al., 2000). Use of remote sensing techniques has the potential to provide quantitative and timely information on agricultural crops over large areas, and many different methods have been developed to estimate crop yields (Moran et al., 2000; Bausch, 2000). The numbers of samples for ground surveys are reduced, making it less expensive (Doraiswamy et al., 2005). With the application of remote sensing in agriculture, there is potential in both identifying crop classes and in estimating crop yield (Reynolds et al., 2000).

Spectral measurements from crops can be used in estimating crop parameters such as leaf area index (Baez-Gonzalez et al., 2005), plant population, and even canopy total nitrogen status during the growth cycle of the crop (Haboudane et al., 2008). Vegetation indices simplify data from multiple reflectance bands to a single value correlating to physical vegetation parameters, such as biomass, productivity, leaf area index, or percent vegetation ground cover (Tucker, 1979). Single reflectance bands are combined into a vegetation index in order to minimize the effect of such factors as optical properties of the soil background, illumination, and view
geometric as well as meteorological factors on the canopy radiometric properties (Monteith, 1990).

2.6 Need for a remote sensing based tobacco yield estimation model
Use of satellite imagery would also enable the verification farmers’ claims of seedbed area established, size of irrigated and dry land tobacco crops, varietal proportions in the field and even allow monitoring of disease development and adherence to aspects of Government legislation. Varietal distribution, nutrient and cultural management effects can also be easily monitored and factored in the final yield forecast.

Tobacco yield estimates are essential for marketing of the crop as well as infrastructure development and policy-making (TIMB, 2005). When yields and volume are over-estimated, tobacco merchants prepare and avail more money than required for the anticipated leaf volume and consequently prices fall when the expectation is not met (TIMB, 2005). When yields are understated, merchants avail less money and this consequently causes market prices to fall. Policy planning and infrastructure allocation becomes biased when based on inaccurate or variable tobacco estimates. Planted area estimates and field visits often present the challenge of not accurately representing the overall production picture because it is difficult to assess every farm every year due to accessibility challenges, financial constraints and the temporal function of assessments.

2.7 Recommended research
Remote sensing application in Zimbabwe is still very limited, largely due to the perception that satellite data is expensive to obtain and complicated to process (Thomas et al., 2008). This could partially be a result of research focus on high resolution spectral imagery from commercial satellites such as Quickbird that have been used extensively in developed countries leading to their wide adoption in yield estimation for various crops as outlined by Wu et al. (2007). Indirect relationships between cereal yield and satellite-derived vegetation indices have been developed and can accurately predict yields (Gallo and Flesch, 1989).
Satellite sensing presents the challenge of spectral confusion when imaging crops with planting dates spaced closely together or crops with near similar spectral signatures (Gallo and Flesch, 1989). When the spectral resolution of a remote sensing instrument is comparatively low, it can be difficult to distinguish target crop species from other crops that may be in vegetation growth at the same time (Knipling, 1970). The spectral distinction of closely related species can be achieved by several methods such as using high spectral resolution sensors to identify specific wavelength regions that are unique to specific plant species (Tucker, 1979). Assuming the spectral resolution of the instrument in use is of adequate capacity such as high resolution Hyperion EO-1 platforms, discrimination can be based on the differences picked in specific wavelength regions affected by the growth and development of a species as demonstrated in the United States on trials to distinguish field peas, wheat, barley and slashed wheat from the baseline soil reflectance (Ferri et al., 2004).

Tobacco cultivation in Zimbabwe is guided by law (TIMB, 2005) which states that tobacco can only be planted on or after the 1st of September up until the 31st of December of each growing season (TRB, 2010). This limits the prospective window when land use change associated with tobacco area estimation can be done to practical time frames since any crop canopy reflectance detected by satellite instruments before the 1st of September can easily be ruled out as those of flue-cured tobacco. Most commercially grown crop species in Zimbabwe will not be in production by this time since they are dependent on rainfall distribution which does not normally begin until November (TRB, 2010). The dominant reflection, therefore, detectable during September is that of the winter wheat that should be in the senescence stage and ploughed lands in preparation of tobacco planting (TRB, 2011). Senescing wheat can be easily identified and separated from tobacco planted by the relatively higher reflection in the visible spectrum electromagnetic range than tobacco which would be in active growth and early development stages. Bare soil displays a characteristic spectral signature characteristic of an increasing linear profile, making it very easy to separate the September planted tobacco crop from adjacent bare fields (TRB, 2011).

The October-planted crop has a distinct difference of temporal spacing from the September (TRB, 2011). Therefore, the two crops appear to develop parallel to each other and this again
makes separation and estimation relatively easy. The position of the red edge and corresponding reflective responses in specific wavelength sections can be used accurately to distinguish crop species that occur in the same temporal time (TRB, 2011).

In tobacco there is a direct relationship between vegetation response and crop vigour, yield and biomass. In crops like wheat, maize, and sorghum biomass becomes a function of accumulated density but does not directly and wholly contribute to crop yield (Ferri et al., 2004). The nature of yield-canopy reflectance relationships may be reversed in such crop species as cotton whose economic yield function is inversely related to biomass (Yang et al., 2004), even though the agronomic plant parameters such as stem height, leaf number, and vegetation plant biomass may be positively correlated to vegetation indices (Carlson and Ripley, 1997). Interestingly, spatial resolution can significantly affect the ability of a satellite sensor to identify subtle differences in crops (Toulios et al., 1998).

Research on the application of remote sensing in flue-cured tobacco estimation should seek to address the challenges that may arise from tobacco with different fertilizer management regimes. Small-scale farmers generally apply lower rates of fertilizer as compared to the large scale commercial farmers. It may be possible to overestimate crop yields in the small scale set up, or underestimate large scale crops if fertilizer management differences cannot be accurately detected using remote sensing techniques.

Research work should focus on whether the model should separate crops established under low fertilizer from those receiving recommended and higher than recommended rates (Ferri et al., 2004). Research should also focus on establishing whether the yield of different flue cured tobacco varieties can be predicted by the same remote sensing based model (Marumbwa et al., 2006). The most applicable means of using remote sensing instruments for yield estimation may lie in the ability of instruments to separated tobacco established on different planting dates (Manatsa et al., 2011).

According to Garvin (1985) tobacco yield estimation in Zimbabwe is possible from parameters such as plant height, leaf number, and dry mass. It is, therefore, feasible to use NDVI to estimate biomass and eventually, yield of flue-cured tobacco. Garvin (1985) also argued that varietal
There are several vegetation indices that were developed for purposes of monitoring and quantifying crop growth and development. Among these are the NDVI (Tucker, 1979) and the SRI, and the relationship between these and the biophysical parameters of the tobacco crop must be studied. The tobacco cropping season spans from September to April (TRB, 2010). The planting periods for these are continuous from September to December (TIMB, 2005). Research should focus on identifying a suitable index that can separate the crops in the different planting dates and then estimate yield accurately. For each planting time, there is need to establish the temporal window for collecting remote sensing data in order to achieve the best yield prediction ability (Jiang et al., 2008).

The tobacco sector in Zimbabwe is divided into the smallholder and commercial sector, with the former contributing about 80% of total tobacco produced in the country. The majority of these smallholder tobacco farmers grow the crop on 1 -3 hectare fields (TIMB, 2005; TIMB, 2013). The challenge has to be overcome by identifying a suitable satellite, with sufficient spectral resolution to separate the tobacco crop from the adjacent competing crops and non-crop vegetation surfaces.

The suitable index should be strongly correlated with tobacco in-season dry mass and yield for it to be suitable for use in crop yield forecasting (Jian et al., 2008). However, another approach could be to use the vegetation indices to establish tobacco cropped area (Manatsa et al., 2011) and then apply the long-term area yield relationship to estimate yield.
CHAPTER 3: AN EVALUATION OF THE NDVI AND SIMPLE RATIO INDEX FOR THE ASSESSMENT OF TOBACCO FLOAT SEEDLINGS RESPONSE TO FERTILIZER MANAGEMENT

Abstract
Remotely sensed vegetation indices that are calculated from using the red and infrared bands of radiometers have been used to estimate plant biomass. These indices are of limited value as they saturate at high vegetation densities. This experiment sought to evaluate potential use of the vegetation indices in assessing tobacco float seedling varieties’ response to different fertilizer application levels. A randomised complete block design, with 3 varieties × 4 fertilizer application levels was used. The N: P: K treatments were applied at 7, 21 and 35 days after sowing, while nitrogen fertilizer application levels were applied at 42 days. Reflectance measurements were taken using a multispectral radiometer (Cropscan MRS 5) at 49, 56, 64 and 79 days after sowing on 8 tray plots, using a multispectral radiometer. Mature seedling samples were harvested at day 79 and, stem lengths were determined before processing for total nitrogen analysis. All the five wavelength bands of the radiometer, NDVI and the SRI had a strong relationship with fertilizer application level. Both NDVI and SRI for the variety T 66 were greater (p < 0.05) than those for K RK26 and KE1. The SRI had a higher coefficient of determination (R²) with seedling dry mass, seedling count/tray and stem length than NDVI. NDVI had a higher coefficient of determination (R² = 0.914) with total N than the SRI (R² = 0.80). The minimum threshold SRI and NDVI values for optimum growth (100% fertilizer) were 0.72 and 6.1, respectively. The results suggest that both the NDVI and SRI can be used to assess tobacco growth response to fertilizer application level. The NDVI was chosen as a suitable index for assessing tobacco growth response to fertilizer application level because of its stronger relationship with leaf total nitrogen.

This chapter is based on:
Introduction

Nutrient stress adversely affects seedling growth vigour, productivity and overall quality (Jackson, 1983). Early detection of nutrient stress in crops facilitates the timely application of corrective cultural practices before stress adversely affects seedling yield and quality (Ikisan, 2000, Moran et al., 2000). Generally, growers visually monitor seedlings for nutrient stress symptoms and, according to Moran et al., (2000) visual assessment is qualitative at best with terms ‘good’ or ‘poor’ frequently used to describe crop condition. A possible alternative to visual seedling health monitoring is the use of optical sensors that rely on light to assess the physiological status either at the leaf or canopy levels (Bauer, 1975).

Leaf nitrogen concentration is an important indicator of plant fertilizer requirements. Nitrogen (N) is a constituent of chlorophyll (Broge et al., 1997). Nitrogen deficiency in tobacco plants decreases chlorophyll and soluble protein content, causing a progressive loss in green colour starting in the older leaves and reduced texture, nitrogen and nicotine contents. Nitrogen deficiency in tobacco plants also causes reduction in the rate of leaf expansion and canopy development (Thomas and Gausman, 1977). Excessive nitrogen fertilizer application in tobacco results in large and dark-green leaves which are difficult to colour during curing (Broge et al., 1997).

Research on the use of remote sensing in quantifying plant nitrogen status has targeted pigment-based reflectance indices or the position of the chlorophyll red-edge (Liew, 2001; Mutanga and Skidmore, 2007). However, canopy reflectance has the potential to rapidly estimate tobacco seedling N status, and hence, seedling vigour and quality (Bauer, 1975). According to Katalin (2011) visible and near-infrared wavelength bands can be used to detect plant stress as a result of water shortages and nutrient deficiencies. It is important that the detection of plant nitrogen status is conducted at an early stage of crop development. This requires identification of spectral wavebands or indices in which vegetation reflectance is most responsive to unfavourable growth conditions.

The leaves of a given plant species tend to have a characteristic surface, thickness, internal structure and pigment content. Similarly, the canopy’s horizontal and vertical extents tend to
have a characteristic structure, which is determined by the size, shape, and orientation of the plants and their leaves and by the cultural practices or environment and growing conditions. All these factors influence the leaf and canopy optical properties and, the reflection patterns received by sensors represent the integration of their effects (Tucker, 1979).

The reflectance at plant canopy level is similar, but is slightly modified by the non-uniformity of incident solar radiation, plant structures, leaf areas, shadows and background reflectivity (Eitel et al., 2010). Airborne sensors receive an integrated view of all these effects, and each crop or vegetation type tends to have a characteristic signature which enables its identification, and possibly, species response to environmental factors like moisture, nutrient and disease to be determined (Jackson et al., 1983).

Vegetation indices (VIs) are combinations of surface reflectance at two or more wavelengths. These indices are designed to highlight a particular property of vegetation (Tucker, 1979). By comparing the results of different VIs and correlating these to field conditions, it is possible to determine the indices that best correlate with crop agronomic parameters of interest (Walburg et al., 1982). Vegetation indices compare reflectance in the near-infrared range to another measurement taken in the visible.

Most VI’s compare the differences between the red and near-infrared reflectance. Red reflectance is sensitive to chlorophyll content and the near-infrared reflectance is sensitive to the mesophyll structure and leaf compositions (Blackmer et al., 1994). The greater the difference between the red and near-infrared reflectance, the greater the amount of green vegetation present (Lorenzen and Jensen, 1988). Small differences between the red and near-infrared reflectance indicate the influence of different plant stress, or background material such as soil or other non-green materials (Bauer, 1985). Spectral vegetation indices are related to a number of biophysical parameters including Leaf Area Index (LAI), percent vegetation cover, green leaf biomass, fraction of absorbed photosynthetically active radiation (fAPAR (Blackburn, 2002; Sellers, 1985), which in turn depend on the stage of crop development and the level of nutrient management of the crop. They, therefore, can be used as an alternative tool for estimating N status (Clay et al., 2006).
The most commonly used VI is the Normalized Difference Vegetation Index (NDVI). NDVI has been in use for many years to measure and monitor plant growth (vigour), vegetation cover and biomass production from multispectral satellite data (Tucker, 1979; Boegh et al., 2002). The index is calculated using the formula:

\[
NDVI = \frac{(NIR - Red)}{(NIR + Red)} \tag{1}
\]

As described by Jackson et al. (1983), the index is considered a good indicator of amount of vegetation and, hence, useful in distinguishing vegetation from soil.

The Simple Ratio (SR) index, another well known VI, is defined by the equation:

\[
SR = \frac{NIR}{R} \tag{2}
\]

The index becomes high with increasing vegetation density and plant health, thus indicating the amount of biomass. The value of this index for green vegetation ranges from 2 to 8 (Eitel et al., 2010). Other indices are the Blue Normalized Difference Vegetation Index, Green Vegetation Index, Chlorophyll Index and the Nitrogen Reflectance Index (Gallo and Flesch, 1989).

This research sought to identify suitable reflectance ratios for assessing the nitrogen status, vigour, quality and quantity of tobacco seedlings in the seedbed. The information would be useful in the estimation of tobacco seedbed area as well as seedling vigour using remote sensing and therefore, it is important in forecasting tobacco crop yield.

### 3.2 Materials and methods

#### 3.2.1 Study site

The experiment was carried out in the 2010 and 2011 seedbed seasons, between the months of June and September, at the Tobacco Research Board/ Kutsaga Research Station, near Harare in Zimbabwe. The Tobacco Research Board (TRB) was reconstituted as a statutory body under the Tobacco Research Act in 1950. The change to a statutory research was preceded by the
formation of the Tobacco Research Advisory Board in 1936 and 1938 and the opening of Kutsaga Research station in 1954.

Kutsaga is located 16 km to the South East of the capital, Harare, between Longitude 31°08’ E, Latitude 17° 55’ S, and at an altitude of 1000 m to 1500 m (TRB, 1986). The long-term annual average rainfall for the site is 850 mm. The annual average temperature is 18.6°C and the range average monthly temperature is 8°C. The site is dominated by light, well drained sandy soils and they are position two on the soil catena. These are typically moderately deep to deep well drained soils (TRB, 2010).

### 3.2.2 Fertilizer application levels.

The fertilizer application levels were applied by hands in quantities shown in Table 3.1.

<table>
<thead>
<tr>
<th>Variety</th>
<th>Fertilizer Level</th>
<th>Nitrogen (g N ha⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>K RK 26</td>
<td>0 %</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>50 %</td>
<td>138</td>
</tr>
<tr>
<td></td>
<td>100 %</td>
<td>276</td>
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<tr>
<td></td>
<td>150 %</td>
<td>414</td>
</tr>
<tr>
<td>T 66</td>
<td>0 %</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>50 %</td>
<td>138</td>
</tr>
<tr>
<td></td>
<td>100 %</td>
<td>276</td>
</tr>
<tr>
<td></td>
<td>150 %</td>
<td>414</td>
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<tr>
<td>KE 1</td>
<td>0 %</td>
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<td></td>
<td>50 %</td>
<td>138</td>
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<td></td>
<td>100 %</td>
<td>276</td>
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<tr>
<td></td>
<td>150 %</td>
<td>414</td>
</tr>
</tbody>
</table>

### 3.2.3 Trial management

Tobacco seedlings were raised according to the recommendations by Mazarura, (2004). The N: P: K treatments were hand-applied in float water at 7, 21 and 35 days after planting in the form of floatfert (4.5% N; 2.7% P₂O₅; 4.2% K₂O) (density = 1.069 g L⁻¹), while N treatments were applied at 42 days after planting. The recommended floatfert application rate of 6 L ha⁻¹ equivalent) was split-applied at 7 (1 L ha⁻¹ equivalent), 21 (2 L ha⁻¹ equivalent) and 35 days (3 L ha⁻¹ equivalent) after sowing. Ammonium nitrate (34.5 % N) was applied at 800 g ha⁻¹ equivalent
(TRB, 2010). Total recommended N (100 %) is 276 gN ha\(^{-1}\). One hectare equivalent of float seedling comprises of 72 trays of seedling, each holding 72 seedlings.

3.2.4 Experimental design
A randomised complete block design, with 3 variety \(\times\) 4 fertilizer application levels and three Kutsaga tobacco varieties (K RK26, T 66 and KE1) were used (Section 1.6). Each plot had sixteen 242-cell float trays each measuring 67 cm x 34.5 cm and, of these, 8 central trays were assessed. The experiment was replicated 4 times.

3.2.5 Field measurements

3.2.5.1 Spectral data
Canopy reflectance measurements were taken from the 8 central trays in each plot, using a hand-held multispectral radiometer (Cropscan MSR-5, 450–1750 nm). The radiometer simultaneously measures irradiance and radiance to provide canopy surface reflectance. The data acquired represented the average reflection from the area sampled. The measurements were taken after every 7 days on clear cloudless days.

The Multispectral Radiometer (MRS 5) was positioned vertically, facing downward at 1 m above seedling canopies, and measurements were taken around solar noon to minimize the effect of diurnal changes in solar zenith angle. Ten measurements were taken from the 8 tray sampling area and reflectance measurements were averaged for each sampling plot to estimate a single reflectance value.

Both Normalized Difference Vegetation Index (NDVI) and Simple Ration Index (SRI) values were calculated using the reflectance measured from Channel 3 (Ch3 - visible: 630-690 nm) and Channel 4 (Ch4 - near infrared: 760-900 nm) of the multispectral radiometer.

1. \[ \text{NDVI} = \frac{(\text{Ch4}-\text{Ch3})}{(\text{Ch4}+\text{Ch3})} \]
2. \[ \text{SRI} = \frac{\text{Ch4}}{\text{Ch3}} \]

Where

\[ \text{NDVI} = \text{Normalized Difference Vegetation Index} \]
SRI = Simple Ratio Index

3.2.5.2 Seedling data

In order to establish the relationship among spectral measurement and biophysical and chemical properties of the tobacco plant, seedlings in each tray were counted and, mature seedling samples were harvested at 79 days after sowing. Tobacco seedling quality is determined in terms of seedling stem length, stem thickness and leaf total nitrogen. In this experiment only the stem lengths were measures using a ruler. For every treatment, seedlings were sampled for stem lengths measurement at pulling, before samples were dried and seedling dry matter was measured and a sample of 50 seedlings was ground for laboratory total nitrogen measurements using the Kjeldahl method. The Kjeldahl method is the standard method of nitrogen determination (Sreenivasan and Sadasivan, 1939; Cole, 1969; Muñoz-Huerta et al., 2013) commonly used in determining the total nitrogen/crude protein content of organic substances.

3.2.6 Data Analysis

The NDVI and SRI calculated from Channel 3 and 4 reflectance data were subjected to an analysis of variance and statistically significant treatment effects were separated using Fisher’s least significant differences (LSD) test at 5%. The data was analysed using Genstat 9.2. Regressions for the spectral data were run using GraphPad Prism Version 6.05 and graphs were constructed using Excel 2007.
3.3 Results

Average reflectance values were used to plot the spectral response curve (Figure 3.1). All varieties displayed a similar S shaped spectral reflectance signature with peaks at channel 2 (520 - 600 nm) and channel 4 (760 – 900 nm), and dips at channels 1, 3 and 5 (1550 – 1750 nm) (Figure 3.1). The spectral signature for bare soil was more or less straight with less pronounced peaks and dips.

Figure 3.1: Spectral reflectance signatures for the variety x fertilizer application levels

Key:
- Channel 1 = 450-520 nm
- Channel 3 = 630-690 nm
- Channel 5 = 1550-1750 nm
- Channel 2 = 520-600 nm
- Channel 4 = 760-900 nm
Channel 1 (450 – 520 nm) reflectance values for all the three varieties had a negative relationship with the fertilizer application level (Appendix 3.1; Figure 3.2). KE1 at 0 % recommended fertilizer treatment (0 g N ha⁻¹) had the highest reflectance on channel 1 (9.869). Reflectance values for the other varieties at 0 g N -ha⁻¹ were 9.32 (KRK 26) and 8.92 (T 66). KE1 at 150 % of the recommended fertilizer (414 g N-ha⁻¹) had the lowest reflectance (3.139). Reflectance values for the other two varieties at 414 g N -ha⁻¹ fertilizer application level were 3.44 (KRK 26) and 3.18 (T 66).

The slopes for the relationships between channel 1 and fertilizer application level for the three varieties were statistically similar (p=0.9441) (Appendix 3.1) making it possible to calculate one slope for all the data (R² = 0.810) (Figure 3.2).

Figure 3.2: The relationship between channel 1 (450 – 520 nm) reflectance values and fertilizer application level (gN ha⁻¹)

Channel 2 (520 – 600 nm) (Figure 3.3), channel 3 (630 – 690 nm) (Figure 3.4) and channel 5 (1550 – 1750 nm) (Figure 3. 6) followed the same pattern as channel 1 (450 – 520 nm), showing
a negative relationship with the fertilizer application level (Appendix 3.2; Appendix 3.3; Appendix 3.5) ($R^2 = 0.9097, 0.8174$ and $0.6918$ respectively).

Figure 3.3: The relationship between channel 2 ($520 – 600$ nm) reflectance values reflectance values and fertilizer application level ($gN ha^{-1}$)
The slopes for the relationships between channel 2, channel 3 and channel 5 with fertilizer application levels for all the three varieties were statistically similar ($p=0.6396$; $p=0.8876$; $p=0.899$ respectively) making it is possible to calculate one slope for all the data ($R^2 = 0.9097$; $R^2 = 0.8174$; $R^2 = 0.6918$ respectively) (Figure 3.3; Figure 3.4; Figure 3.6).

![Figure 3.4: The relationship between fertilizer channel 3 (630 – 690 nm) reflectance values and fertilizer application level (gN ha$^{-1}$)](image)

$y = 3E-0.5x^2 - 0.034x + 13.62$

$R^2 = 0.834$

$p < 0.0001$

Reflectance ($\%$) K RK 26
Reflectance ($\%$) T 66
Reflectance ($\%$) KE1
Pooled

Poly. (Reflectance ($\%$) K RK 26)
Poly. (Reflectance ($\%$) T 66)
Poly. (Reflectance ($\%$) KE1)
Poly. (Pooled)
Channel 4 (760 – 900 nm) reflectance values (Figure 3.5) had a positive relationship with fertilizer application level ($R^2 = 0.8328$) (Appendix 3.4). Percentage reflectance increased as the rate of fertilizer increased from 0 g N-ha$^{-1}$, reaching the highest at 414 g N-ha$^{-1}$. T 66 at 414 g N-ha$^{-1}$ recommended fertilizer had the highest reflectance value (42.414).

The slopes for the relationships of channel 4 and fertilizer for the three varieties were statistically similar ($p=0.982$) making it is possible to calculate one slope for all the data (Appendix 4).

Figure 3.5: The relationship between fertilizer channel 4 (760 – 900 nm) reflectance values and fertilizer application level (gN ha$^{-1}$)

Other channel 4 reflectance values at 414 g N-ha$^{-1}$ were 40.5 (K RK26) and 40.2 (KE1). The 0 g N-ha$^{-1}$ rates had the lowest reflectance values for all the 3 varieties (K RK26 = 22.5; T 66 = 23.97 and KE1 = 22.3).
Figure 3.6: The relationship between channel 5 (1550 – 1750 nm) reflectance (%) values and fertilizer application level (gN ha-1)

Because of the similarity of the varieties’ reflectance response to fertilizer application level at all the five channels of the multispectral radiometer, all the reflectance values were pooled in assessing the response of vegetation indices response to fertilizer application level.
Both NDVI and the SRI were positively correlated with the fertilizer application level (Figure 3.7). The coefficient of determination for SR and fertilizer application level ($R^2 = 0.92$) was greater than that for NDVI and fertilizer application level ($R^2 = 0.89$).

Figure 3.7: The relationship between NDVI/SRI and fertilizer application level (gN ha$^{-1}$) at 72 days after sowing

Both NDVI and SRI for T 66 were greater ($P < 0.05$) than those for K RK26 and KE1. K RK26 and KE1 varieties had statistically similar ($P < 0.05$) reflectance values. There was also significant ($F < 0.001$) variety x fertilizer application level interaction effects on seedling canopy reflectance (Appendix 3.8 a, b)
Figure 3.8: Changes in NDVI (a) and SRI (b) between 49–79 days after sowing.

The coefficient of determination between both NDVI and SRI with seedling dry mass were high ($R^2 = 0.974$ and $R^2 = 0.892$ respectively) (Figure 3.9).
Figure 3.9: The relationship between seedling count $m^{-2}$ and NDVI/ SRI

The seedling count-$m^{-2}$ versus NDVI coefficient of determination ($R^2 = 0.749$) was comparable to that for seedling count versus the SRI ($R^2 = 0.684$) (Figure 3.10). The same trend was also noted on the regression of NDVI ($R^2 = 0.917$) and SRI ($R^2 = 0.941$) with seedling length (Figures 3.11). NDVI ($R^2 = 0.662$) showed a stronger coefficient of determination with total nitrogen than the SRI ($R^2 = 0.373$) (Figure 3.12).

Figure 3.10: The relationship between seedling count $m^{-2}$ and NDVI/ SRI
Figure 3.11: The relationship between seedling length and NDVI/SRI

Figure 3.12: The relationship between total leaf N (mg g\(^{-1}\)) and NDVI/SRI at pulling (72 days after sowing)
3.4 Discussion

The S-shaped spectral response curve generated from the seasonal average reflectance values for the variety fertilizer application levels was typical for green plants as vegetation has a unique spectral signature which enables it to be distinguished readily from other types of land cover in an optical/ near-infrared image (Tucker, 1979). This characteristic is due to strong absorption by chlorophylls in the red region, internal leaf scattering in the near-infrared and strong absorption by water in the infrared beyond 1.3\(\mu m\) (Nowatzki et al., 2004; Demetriades-Shah et al., 1990). The reflectance of a plant canopy is similar, but is modified by the non-uniformity of incident solar radiation, plant structures, leaf areas, shadows, and background reflectivities (Hatfield et al., 2008). Species discrimination is made possible when airborne sensors are used because these receive an integrated view of all these effects, and each crop or vegetation type tends to have a characteristic signature (Liew, 2001).

The lower the fertilizer application level, the higher the reflectance values channel 1, 2, 3 and 5, while channel 4 increases as the fertilizer application level increased. This implies that all the channels of the multispectral radiometer can be used in assessing tobacco response to fertilizer application. The reflectance values in the blue (Channel 1) and red (Channel 3) regions of the spectrum were, as suggested by Ustin et al. (2004), due to high absorption by chlorophyll for photosynthesis, while the peaks observed at the green (Channel 2) region were also typical of the green colour of vegetation (Daughtry et al., 2000). In the visible spectral region, the high absorption of radiation energy is due to leaf pigments, primarily the chlorophylls, although the carotenoids, xanthophylls, and anthocyanins also have an effect (Gitelson et al., 2001; Casanova et al., 1998). Use of reflectance values for all the channels, or VIs calculated from these could enable researchers to identify the health status of seedlings and estimate the quantities that could be transplantable. Channels 3 and 4 are used in the calculation of both NDVI and SRI.

The coefficients of determination for Channels 1, 2, 3 and 5 and fertilizer application levels were, however, negative and treatment differences were so small that an experienced person would be needed to accurately apply these in plant vigour assessment. Channel 4, with a positive relationship could be easier to apply, but like the other 3 channels, the treatment differences were also minimal for easy application in plant vigour assessment. The reflectance values at the
channels would depend on the amount of energy that falls on top of the canopy and this varies according to the time of the day, season and weather conditions (Monteith, 1977). A tool for crop growth assessment could be the one that minimizes these effects.

The higher reflectance in the near infrared (NIR) region than the visible band could be due to the cellular structure in the leaves that cause scattering of electromagnetic energy (Knipling, 1970). Broge et al. (1997) attributed the increase in the near infrared reflectance to increases of biomass and the number and size of leaf cell layers. The differences in the NIR reflectance values among varieties and fertilizer application levels (Figure 5) could be an indication of varietal differences in the ability to exploit environmental resources for biomass production.

There were also significant (Appendix 3.6) fertilizer application level effects on seedling canopy reflectance. The SRI showed a stronger relationship ($R^2 = 0.948$) than NDVI ($R^2 = 0.924$). Generally, the lower the reflectance in the green and the red regions of the electromagnetic radiation, the healthier is the target vegetation (Jackson, 1986). Well-managed crop canopies naturally appear greenest, and become red or yellow with decrease in chlorophyll content due to poor fertilization (Su et al., 2006). Both the SRI and NDVI could thus be used in assessing the nutrient status for tobacco seedlings. Corrective measures in cases of nutrient deficiency could be taken if the seedlings are assessed early, while at a later phenological stage seedling responses could be used to estimate the quantity of seedlings that could be available (Thomas and Gausman, 1977).

There were significant ($p < 0.05$) NDVI differences among the tobacco varieties while SRI values for the varieties were statistically similar ($P > 0.05$) (Appendix 3.6). Plant variety has significant influence on the reflective property of the plant through the physical, biochemical, and morphological characteristics of the canopy (Hatfield et al., 2008; Endo et al., 2000). The higher NDVI values for T 66 that those for K RK 26 and K E1 could imply that the former is genetically more superior in biomass production. In addition it could also be easy differentiating the variety T66 from the other two, and possibly calculating their proportions in the seedbed and even in the field using NDVI and SRI profiles.
The seedling dry mass and seedling length relationships with both NDVI and SRI (Figure 3.11, Figure 3.13 respectively) were indicative of possible application of the two in tobacco seedling quality assessment. The seedling dry mass and seedling length are both measures of biomass and quality which, according to Mutanga and Skidmore (2007), are affected by plant N status. The coefficients of determination between seedling count/tray with both NDVI ($R^2 = 0.749$) and SRI ($R^2 = 0.684$) were also significant ($p < 0.05$) enough to be applicable in estimating seedling populations in a tobacco floatbed using remote sensing.

Both NDVI and SRI were maintained at around their peak levels between days 49 and 79. Generally, in the tobacco floatbed no additional fertilizer is added on seedlings after day 42, except for corrective applications where nutrients would have been lost through loss of water. Quality and quantity estimations made after all fertilizers are applied could, therefore, be relied upon, and any repeated measurements taken thereafter could be used for verification of earlier findings.

The high coefficient of determination ($R^2$) between NDVI and SRI with total N (0.662 and 0.373) translated to an increase in canopy reflectance as nitrogen concentration in the leaves decreases at low nutrient levels (Fridgen and Varco, 2004). Past research has associated nitrogen deficiencies with decreasing amounts of chlorophyll in cotton (Yang et al., 2004), and maize (Walburg et al., 1982). The NDVI and SRI ranges for the 100–150% fertilizer application levels were comparable with those that were associated with high plant health and vigour in past research (Walburg et al., 1982; Clay et al., 2006).

### 3.5 Conclusions

The spectral response curve can be used to assess seedling vigour in response to fertilizer management levels. Channels 1, 2, 3 and Channel 5 can also be used in tobacco seedling vigour assessment because of their significant ($p < 0.0001$) relationship with fertilizer application level. Both NDVI and the SRI were highly correlated with fertilizer application levels, and could be used in assessing crop response to fertilizer application levels. The two indices clearly showed the differences in the fertilizer and variety × fertilizer interactions. The strength of the relationship was also maintained up to the time of seedling pulling. The variety T 66 can be
distinguished from K RK26 and K E1 using canopy reflectance. Since these have different yield potentials (Section 1.6), the potential cropping areas for these could be separately determined, if such differences could be sustained after planting.

Both NDVI and the SRI were highly correlated with seedling DM, seedling height and seedling count/ m². The NDVI x leaf total N relationship had a higher coefficient of determination that that of the SRI x leaf total N. In this study the NDVI was a better reflectance index for assessing crop response to fertilizer management levels compared to the SRI. Although simple ratio index (SRI) had a stronger relationship with biophysical parameters such as above-ground dry mass, plant population and plant height than NDVI, the latter was selected for use because of its stronger relationship with total nitrogen. Thus, the selection of these specific wavelengths and utilization of the leaf reflectance ratios appear to provide means to estimate fertilizer application level, seedling DM, seedling height and seedling count/ m² and leaf total nitrogen throughout the growing season. The results indicate that leaf reflectance measured non-destructively can be used for real-time monitoring of tobacco plant nitrogen status.
CHAPTER 4: ASSESSING THE SPECTRAL REFLECTANCE OF FLUE-CURED TOBACCO VARIETIES UNDER FARM MANAGEMENT

Abstract

Techniques for estimating and mapping crop varieties and growth response to fertilizer and planting date are important for crop monitoring for yield forecasting purposes. This experiment evaluated the potential to discriminate tobacco varieties, fertilizer application levels and planting date using NDVI. A split plot design with four planting dates, September, October, November, and December, as main plots, three varieties K RK 26, T 66 and K E1 as subplot, and fertilizer application levels as sub-subplots was used. Reflectance measurements were taken from 5 m × 5 m sampling plots, using a multispectral radiometer from the age of six weeks after planting. The September, October, and November-planted crops had significant variety x fertilizer interaction differences (\(p<0.05\)) from the age of 10 weeks up to the end of season. T 66 and K RK26 varieties had similar (\(p>0.05\)) NDVI values and these were greater (\(p<0.5\)) than those for K E1. The 100% and the 150% fertilizer application level treatments had similar (\(p>0.05\)) NDVI and both were greater (\(p<0.05\)) than the 50% fertilizer application level treatments. All of the fertilizer and variety treatments at the December planting dates had similar reflectance characteristics (\(p>0.05\)), which were lower (\(p<0.05\)) than the September and October planting dates. The results showed that for the September, October and the November planting dates, varieties, and fertilizer levels could be distinguished using NDVI starting from 10 weeks after planting. The December planted tobacco varieties and fertilizer levels could not be distinguished using the NDVI. The results of the experiment provide the possibility to map variety, fertilizer and planting date variations in tobacco crop NDVI using remote sensing.

This chapter is based on:
4.1 Introduction

Flue-cured tobacco variety, planting time, and fertilizer management can influence yield and quality differences. These factors affect plant canopy biophysical properties and chemical composition. Su et al. (2006) reported the considerable effect that different nutrients and fertilizer application levels have on plant leaf chemical composition. According to Mackown et al. (2000) an understanding of the level of fertilizer application may help in yield and quality predictions.

It is widely accepted that nitrogen (N) plays a key role in the production of tobacco. Nitrogen is a constituent of chlorophyll and the molecular structure of the chlorophyll molecule incorporates a large proportion of total leaf nitrogen in the form of protein. Several studies have found that foliar chlorophyll concentration provides an accurate, indirect estimate of plant nitrogen status (Blackburn, 2002).

Fertilizer management affects the crop canopy mineral composition and the way the canopy interacts with solar radiation (Moran et al., 2000). Interaction between light and intercepting molecules in the canopy results in scattering and absorption by the atomic bonds, electrons, or atoms in the molecule (Mutanga and Skidmore, 2007). The wavelength at which the processes of absorption or reflection take place is highly specific for the atomic bonds and the molecular architecture of the intercepting target, making the identification of individual chemical components within the intercepting canopy possible (Ferweda, 2005).

Canopy reflectance of irradiance can be used as a rapid means of assessing the N status both at individual plant and at crop canopy level, and can be a predictor of final yield (Boegh, et al., 2002). The spectral absorbance properties of chemical components in plant leaves are manifested in the reflectance spectra of leaves (Gitelson and Merzlyak, 1998). This offers the opportunity of using measurements of reflected radiation as a nondestructive method for quantifying pigments as affected by level of crop management (Blackburn, 2002). Similar cases of use of radiometric data for crop assessment and N estimation have been reported on a wide range of crops (Blackmer and Schepers, 1995; Hansen and Schjoerring, 2003).
The spectral characteristics of vegetation vary with wavelength. Analysing vegetation using remotely sensed data requires knowledge of the structure and function of vegetation and its reflectance properties (Asner, 1998). Leaf chlorophyll strongly absorbs radiation in the red and blue wavelengths but reflects in the green wavelength (Daughtry et al., 2000). The internal structure of healthy leaves acts as a diffuse reflector of near-infrared wavelengths. Measuring and monitoring the infrared reflectance can be useful in determining crop health (Liew et al., 2008).

Well-managed crop canopies appear greenest and become red or yellow with decrease in chlorophyll content, for example, due to poor fertilization, senescence or diseases (Haboudane et al., 2004). Blackmer and Schepers (1995) were able to separate N treatments using the near 550 nm reflectance measured on maize leaves detached from a field N fertilizer experiment and also found that nutrient-stressed canopies had a lower spectral reflectance in the NIR and higher red wavebands when compared with unstressed canopies. Osborne et al. (2002), Graeff et al. (2001) and Graeff and Claupein (2003) identified and quantified nutrient deficiencies by means of reflectance measurements based on selected stress specific wavelength ranges. Aase et al. (1987) reported a relationship between wheat in-season dry matter and NIR/red ratios, suggesting that reflectance measurements could be used to estimate plant leaf dry matter.

The health and yield of tobacco crop depends on good agronomic practices which include, among other parameters, applying the recommended fertilizer application levels and selection of appropriate planting dates and varieties (Stocks, 1994). Planting commences on 1 September and endon31December in Zimbabwe as required by legislation (DR&SS, 2014). These dates, however, are likely to shift due to climate change. The date of the start of effective rainfall has also been reported to have shifted and the wet season length is also becoming shorter, as evidenced by the observed increases in mean dry spell length and reductions in rain day frequency over Zambia, Malawi and Zimbabwe during the rainfall season (Trocaire, 2013). Resource poor farmers in Zimbabwe generally apply less than the required fertilizer application levels, as recommended by soil analysis results, mainly due to lack of financial resources (Magadlela, 1987). These practices have an impact on the final yield of the crop.
The Normalized Difference Vegetation Index (NDVI) is the most commonly used spectral index in assessing crop vigor, vegetation cover, and biomass production from multispectral satellite data (Jackson et al., 1983; Eitel et al., 2010). As described by Jackson et al. (1983), the index is considered a good indicator of plant biomass and is useful in distinguishing vegetation from soil. Benedetti and Rossini (1993) used NDVI in assessing wheat growth rate and successfully applied the information in estimating yield.

The monitoring of crop phenology by remote sensing is very important for many practical agronomic applications, including yield forecasting (Curnel and Oger, 2006). Accurate analysis of crop temporal and spatial variations throughout the season can be used to interpret crop spectral responses to agronomic management (Tucker et al. (1979). It is essential to quantify the relationship between spectral properties of tobacco and agronomic parameters for assessing crop condition and for forecasting yield. The use of effective remote sensing techniques in crop growth studies would reduce the need for extensive field sampling, as only few samples would only be required for ground truthing (Osborne et al., 2002).

Therefore, the objective of this work was to evaluate the use of NDVI to separate tobacco crop planted on different dates, tobacco varieties and fertilizer management levels. The experiment also sought to establish the most optimal time for taking spectral measurements for purposes of identifying achieving the above objective. It was hypothesized that spectral signatures for the selected three tobacco varieties, the four fertilizer levels, and the four planting dates could be distinguished and that that suitable times for separating planting dates, varieties and fertilizer application levels could be established.
4.2 Materials and Methods

4.2.1 Study Area

This experiment was conducted at Kutsaga Research Station over two seasons, during summer for the 2010-2011 and 2011-2012 seasons. The experiment was carried out under irrigation on a sandy loam soil. Before 2011 the experimental site had been planted to tobacco followed by three years of *Chloris gayana* cv. Katambora Rhodes grass (Mazarura and Chisango, 2012).

The experimental plots were located on well-drained granitic sands (72.8% sand, 8.8% silt, and 18.4% clay) which were low in available nitrogen, medium in available phosphorus, and high in available potassium content throughout the profile (Table 4.1). During February of 2010 and 2011 the plots were disked after a three-year Katambora grass fallow period to incorporate grass. Dolomitic lime was applied at a rate of 600-760 kg ha\(^{-1}\) as recommended by soil test results to raise the soil pH from 5.3 to 6.3, levels optimum for tobacco production (Table 4.1).

4.2.2 Trial design

A split plot design with four planting dates, September, October, November, and December, as main plots, 3 varieties as subplot, and four fertilizer levels as sub-subplots was used (Table 4.1). Each treatment was replicated four times. Three tobacco varieties, K RK26, T 66, and K E1 were used (refer to section 1.6), while three fertilizer application levels (50%, 100%, and 150% recommended) were applied by hand (Table 4.2).
Table 4.1: Soil analysis and fertilizer recommendations for experimental plots

<table>
<thead>
<tr>
<th>Experimental Block</th>
<th>N (kg ha⁻¹)</th>
<th>P₂O₅ (kg ha⁻¹)</th>
<th>K₂O (kg ha⁻¹)</th>
<th>Required nutrient rate (kg ha⁻¹)</th>
<th>Lime (kg ha⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-</td>
<td>140-160</td>
<td>70-100</td>
<td>-:20:17</td>
<td>760</td>
</tr>
<tr>
<td>2</td>
<td>-</td>
<td>100-120</td>
<td>70-100</td>
<td>-:20:17</td>
<td>-</td>
</tr>
<tr>
<td>3</td>
<td>-</td>
<td>100-120</td>
<td>70-100</td>
<td>-:20:17</td>
<td>600</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
<td>80-100</td>
<td>70-100</td>
<td>-:20:17</td>
<td>600</td>
</tr>
</tbody>
</table>

Each sampling plot consisted of 5 rows, each with 32 plants spaced at 56 cm. The inter-row distance was 1.2 m. The recommended compound C (6 % N:17 % P₂O₅:15 % K₂O) fertilizer application level from soil test results was 700 kg ha⁻¹, while that for ammonium nitrate (34.5 % N) was 96 kg ha⁻¹ at 4 weeks after planting and 75 kg ha⁻¹ after topping.

Table 4.2 Variety and fertilizer application levels

<table>
<thead>
<tr>
<th>Variety</th>
<th>Fertilizer application level (%)</th>
<th>Compound C (6:17:15)(kg ha⁻¹)</th>
<th>Ammonium Nitrate (kg ha⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>4 weeks after planting</td>
</tr>
<tr>
<td>K RK 26</td>
<td>50</td>
<td>350</td>
<td>48</td>
</tr>
<tr>
<td>K RK 26</td>
<td>100</td>
<td>700</td>
<td>96</td>
</tr>
<tr>
<td>K RK 26</td>
<td>150</td>
<td>1050</td>
<td>144</td>
</tr>
<tr>
<td>T 66</td>
<td>50</td>
<td>350</td>
<td>48</td>
</tr>
<tr>
<td>T 66</td>
<td>100</td>
<td>700</td>
<td>96</td>
</tr>
<tr>
<td>T 66</td>
<td>150</td>
<td>1050</td>
<td>144</td>
</tr>
<tr>
<td>K E1</td>
<td>50</td>
<td>350</td>
<td>48</td>
</tr>
<tr>
<td>K E1</td>
<td>100</td>
<td>700</td>
<td>96</td>
</tr>
<tr>
<td>K E1</td>
<td>150</td>
<td>1050</td>
<td>144</td>
</tr>
</tbody>
</table>

NB: Fifty percent (50 %) fertilizer = 50 % of the amount of fertilizer recommended from soil testing results.
4.2.3 Trial Management

The normal planting practice at Kutsaga (TRB, 2010) involves the application of an initial sprinkler overhead pre-irrigation of 50–60 mm at about 60 days before transplanting the tobacco. At transplanting, 4-5 liters of water is applied in the planting hole. A 15 mm settling in irrigation was applied just after planting, followed by a 28-day stress period to promote root development, after which, 25–30 mm was applied to facilitate a nitrogenous fertilizer application. Subsequent irrigation was based on open pan evaporation readings.

Recommended management practices like weed control, pest control and sucker control were followed (TRB, 2010) except for N: P: K levels and planting times, which were treatments in the experiment (Table 4.1).

The N : P : K treatments were hand-applied in bands, about 10 cm deep and 30 cm to each side of a row at planting. Nitrogen treatments were applied at about 4 weeks after transplanting and after topping at 8 weeks after planting. Rainfall data was collected from a meteorological station that is located in the research station Table 4.3.

Table 4.3: Monthly rainfall data for Kutsaga research station during the 2010-2011 and 2011-2012 cropping seasons

<table>
<thead>
<tr>
<th>Month</th>
<th>2010/11 rainfall (mm)</th>
<th>2011/12 rainfall (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>October</td>
<td>1.0</td>
<td>38.2</td>
</tr>
<tr>
<td>November</td>
<td>103.7</td>
<td>129.2</td>
</tr>
<tr>
<td>December</td>
<td>219.1</td>
<td>127.9</td>
</tr>
<tr>
<td>January</td>
<td>178.5</td>
<td>332.2</td>
</tr>
<tr>
<td>February</td>
<td>126.7</td>
<td>152.1</td>
</tr>
<tr>
<td>March</td>
<td>84.6</td>
<td>58.4</td>
</tr>
<tr>
<td>April</td>
<td>48.8</td>
<td>31.2</td>
</tr>
<tr>
<td>May</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>TOTAL</td>
<td>762.4</td>
<td>869.2</td>
</tr>
</tbody>
</table>
4.2.4 Reflectance data collection

Reflectance measurements were taken from the age of six weeks after planting at 7 day intervals on 5 m × 5 m square sampling plots, using a hand-held multispectral radiometer (Cropscan MSR-5, 450–1750 nm), after all fertilizer application level treatments had been applied. The multispectral radiometer (MRS 5) was positioned facing vertically downward at 1 m above crop canopies, and measurements were taken around solar noon to minimize the effect of diurnal changes in solar zenith angle. In total, 10 measurements were taken per treatment and reflectance measurements were averaged for each sampling plot to estimate a single reflectance value. The field of view for the multispectral radiometer was 30°, while the ground field of view of the instrument, at a radius of half the height of the instrument above the target, was 50 cm radius. The Latitude and Longitude for the whole experimental area and for each treatment plot were taken using a Garmin Personal Navigator (GPS V) to enable repeated sampling at the same location. The Normalized Difference Vegetation Index (NDVI) was calculated from the spectral bands obtained in Channels 3 and 4 which correspond to the red (630–690 nm) and near-infrared (NIR) (60–900 nm) regions of the MSR 5, respectively, using the following formula:

\[
\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}
\]  

The average NDVI data for the two seasons were used for the analysis.

4.2.5 Data Analysis

The NDVI data was subjected to an analysis of variance and statistically significant treatment effects were separated using Fisher’s least significant differences (LSD) of 5 %. The data was analysed using Genstat 9.2. Student’s t-test for comparison of means was used to compare the planting date effect on NDVI and graphs were plotted using GraphPad Prism Version 6.05.
4.3 Results

The September-planted crop’s NDVI reached a peak of 0.7–0.85 at 10–13 weeks after planting (Table 4.4). During the earlier stages (1 to 9 weeks after planting), all the variety and fertilizer application levels were statistically similar (p > 0.05). There were significant (p < 0.05) effects of fertilizer level on NDVI starting from 10 to 19 weeks after planting. At ‘peak’ NDVIs for 100% and 150% fertilizer application levels were statistically similar (p < 0.05).

Table 4.4: NDVI temporal profiles for the September 15 planted crop

<table>
<thead>
<tr>
<th>VARIETY</th>
<th>FERTILIZER</th>
<th>Weeks after planting</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>7</td>
<td>8</td>
</tr>
<tr>
<td>KRK26</td>
<td></td>
<td></td>
</tr>
<tr>
<td>50 % Fertilizer</td>
<td>0.65</td>
<td>0.79</td>
</tr>
<tr>
<td>100 % Fertilizer</td>
<td>0.69</td>
<td>0.82</td>
</tr>
<tr>
<td>150 % Fertilizer</td>
<td>0.69</td>
<td>0.82</td>
</tr>
<tr>
<td>T 66</td>
<td></td>
<td></td>
</tr>
<tr>
<td>50 % Fertilizer</td>
<td>0.64</td>
<td>0.80</td>
</tr>
<tr>
<td>100 % Fertilizer</td>
<td>0.65</td>
<td>0.82</td>
</tr>
<tr>
<td>150 % Fertilizer</td>
<td>0.65</td>
<td>0.82</td>
</tr>
<tr>
<td>K E1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>50 % Fertilizer</td>
<td>0.61</td>
<td>0.75</td>
</tr>
<tr>
<td>100 % Fertilizer</td>
<td>0.61</td>
<td>0.73</td>
</tr>
<tr>
<td>150 % Fertilizer</td>
<td>0.63</td>
<td>0.76</td>
</tr>
<tr>
<td>VARIETY*FERTILIZER</td>
<td>F-</td>
<td></td>
</tr>
<tr>
<td></td>
<td>L.S.D</td>
<td></td>
</tr>
<tr>
<td>FERTILIZER</td>
<td>50 % Fertilizer</td>
<td>0.63</td>
</tr>
<tr>
<td>100 % Fertilizer</td>
<td>0.65</td>
<td>0.79</td>
</tr>
<tr>
<td>150 % Fertilizer</td>
<td>0.65</td>
<td>0.80</td>
</tr>
<tr>
<td></td>
<td>F-</td>
<td></td>
</tr>
<tr>
<td></td>
<td>L.S.D</td>
<td></td>
</tr>
<tr>
<td>VARIETY</td>
<td>K RK 26</td>
<td>0.68</td>
</tr>
<tr>
<td>T 66</td>
<td>0.64</td>
<td>0.81</td>
</tr>
<tr>
<td>K E1</td>
<td>0.62</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td>F-</td>
<td></td>
</tr>
<tr>
<td></td>
<td>L.S.D</td>
<td></td>
</tr>
</tbody>
</table>

NDVI for the 50% fertilizer level was the smallest (p < 0.05). In the September-planted crop, varieties started showing significant (p<0.05) NDVI values from 7 weeks after planting when canopy reflectance measurements started. The varieties T 66 and K RK26 NDVIs were statistically similar (p > 0.05) and were significantly greater than that for K E1 treatments.
between 10 and 12 weeks after planting. There was no variety x fertilizer level interaction effect (p > 0.05).

NDVI for all the treatments in the October-planted crop rose sharply from week 6 after planting to peak at 10 weeks after planting (Table 4.5). Beyond the ‘peak’, NDVI also fell to reach the minimum at 14 - 15 weeks after planting. Like the September planting, all the treatments had similar (p > 0.05) NDVI from 6 weeks after planting until the age of 10 weeks, when a peak NDVI was attained. The 100% and the 150% fertilizer levels of T 66 and K RK26 were also statistically similar (p> 0.05) and were significantly greater than both their 50% fertilizer and all the K E1 treatments. Like the September-planted crop there was no interaction effect observed between variety and fertilizer application level (p> 0.05).

Table 4.5: NDVI temporal profiles for the October 15 planted crop

<table>
<thead>
<tr>
<th>VARIETY</th>
<th>FERTILIZER</th>
<th>Weeks after planting</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>5</td>
</tr>
<tr>
<td>KRK26</td>
<td>50 % Fertilizer</td>
<td>0.36</td>
</tr>
<tr>
<td>KRK26</td>
<td>100 % Fertilizer</td>
<td>0.37</td>
</tr>
<tr>
<td>KRK26</td>
<td>150 % Fertilizer</td>
<td>0.31</td>
</tr>
<tr>
<td>T 66</td>
<td>50 % Fertilizer</td>
<td>0.40</td>
</tr>
<tr>
<td>T 66</td>
<td>100 % Fertilizer</td>
<td>0.36</td>
</tr>
<tr>
<td>T 66</td>
<td>150 % Fertilizer</td>
<td>0.37</td>
</tr>
<tr>
<td>K E1</td>
<td>50 % Fertilizer</td>
<td>0.40</td>
</tr>
<tr>
<td>K E1</td>
<td>100 % Fertilizer</td>
<td>0.40</td>
</tr>
<tr>
<td>K E1</td>
<td>150 % Fertilizer</td>
<td>0.41</td>
</tr>
<tr>
<td>VARIETY*FERTILIZER</td>
<td>F-PROBABILITY L.S.D</td>
<td>0.22</td>
</tr>
<tr>
<td>FERTILIZER</td>
<td>F-PROBABILITY L.S.D</td>
<td>0.06</td>
</tr>
<tr>
<td>FERTILIZER</td>
<td>F-PROBABILITY L.S.D</td>
<td>0.39</td>
</tr>
<tr>
<td>FERTILIZER</td>
<td>F-PROBABILITY L.S.D</td>
<td>0.38</td>
</tr>
<tr>
<td>FERTILIZER</td>
<td>F-PROBABILITY L.S.D</td>
<td>0.36</td>
</tr>
<tr>
<td>VARIETY</td>
<td>K RK 26</td>
<td>0.35</td>
</tr>
<tr>
<td>VARIETY</td>
<td>T 66</td>
<td>0.38</td>
</tr>
<tr>
<td>VARIETY</td>
<td>K E1</td>
<td>0.40</td>
</tr>
<tr>
<td>VARIETY</td>
<td>F-PROBABILITY L.S.D</td>
<td>0.008</td>
</tr>
<tr>
<td>VARIETY</td>
<td>L.S.D</td>
<td>0.03</td>
</tr>
</tbody>
</table>

For the November planting, the fertilizer application level effect also followed a comparable trend to the September and October plantings (Table 4.6). Minimum NDVI was attained at 15
weeks after planting. From 12 weeks after planting, the varieties showed significant \( p<0.05 \) NDVI differences. There was no variety \( \times \) fertilizer level interaction and there were no significant \( p>0.05 \) varietal differences.

Table 4.6: NDVI temporal profiles for the November 15 planted crop

<table>
<thead>
<tr>
<th>VARIETY</th>
<th>FERTILIZER</th>
<th>Weeks after planting</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>5</td>
</tr>
<tr>
<td>KRK26</td>
<td>50 % Fertilizer</td>
<td>0.25</td>
</tr>
<tr>
<td>KRK26</td>
<td>100 % Fertilizer</td>
<td>0.27</td>
</tr>
<tr>
<td>KRK26</td>
<td>150 % Fertilizer</td>
<td>0.24</td>
</tr>
<tr>
<td>T66</td>
<td>50 % Fertilizer</td>
<td>0.31</td>
</tr>
<tr>
<td>T66</td>
<td>100 % Fertilizer</td>
<td>0.30</td>
</tr>
<tr>
<td>T66</td>
<td>150 % Fertilizer</td>
<td>0.27</td>
</tr>
<tr>
<td>K E1</td>
<td>50 % Fertilizer</td>
<td>0.25</td>
</tr>
<tr>
<td>K E1</td>
<td>100 % Fertilizer</td>
<td>0.28</td>
</tr>
<tr>
<td>K E1</td>
<td>150 % Fertilizer</td>
<td>0.27</td>
</tr>
</tbody>
</table>

The December-planted crop attained maximum NDVI at 8 to 9 weeks after planting and this was maintained to 10 weeks after planting (Table 4.7). There were no significant \( p<0.05 \) fertilizer application level differences from the first sampling to the end of reaping, 13 weeks after planting.
Table 4.7: NDVI temporal profiles for the December 15 planted crop

<table>
<thead>
<tr>
<th>VARIETY</th>
<th>FERTILIZER</th>
<th>Weeks after planting</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>5</td>
</tr>
<tr>
<td>KRK26</td>
<td>50 % Fertilizer</td>
<td>0.34</td>
</tr>
<tr>
<td>KRK26</td>
<td>100 % Fertilizer</td>
<td>0.44</td>
</tr>
<tr>
<td>KRK26</td>
<td>150 % Fertilizer</td>
<td>0.37</td>
</tr>
<tr>
<td>T 66</td>
<td>50 % Fertilizer</td>
<td>0.39</td>
</tr>
<tr>
<td>T 66</td>
<td>100 % Fertilizer</td>
<td>0.39</td>
</tr>
<tr>
<td>T 66</td>
<td>150 % Fertilizer</td>
<td>0.35</td>
</tr>
<tr>
<td>K E1</td>
<td>50 % Fertilizer</td>
<td>0.28</td>
</tr>
<tr>
<td>K E1</td>
<td>100 % Fertilizer</td>
<td>0.39</td>
</tr>
<tr>
<td>K E1</td>
<td>150 % Fertilizer</td>
<td>0.31</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>VARIETY*FERTILIZER</th>
<th>F-PROBABILITY</th>
<th>L.S.D</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.53</td>
<td>0.47</td>
</tr>
<tr>
<td></td>
<td>0.04</td>
<td>0.51</td>
</tr>
<tr>
<td></td>
<td>0.30</td>
<td>0.17</td>
</tr>
<tr>
<td></td>
<td>0.74</td>
<td></td>
</tr>
</tbody>
</table>

The seasonal average NDVI values for the September and October-planted crops were similar (p> 0.05) and both were significantly greater than those for the November and the December-planted crops. There was a general fall of NDVI with later plantings. At all fertilizer levels, K E1 had the highest NDVI in the October-planted crop.
The different planting times could easily be separated between 0 and 9, 10 to 12, 13 to 18 and 18 to 22 weeks after planting the start of the season (Appendix 4.1), making it possible to use varieties and fertilizer level NDVI averages in assessing the seasonal NDVI profiles for the different planting times (figure 4.1).

**Figure 4.1: Averaged NDVI profiles for the September, October, November, and December-planted crops**

The September-planted crop had the longest growing period of 22 weeks, as compared to the 17, 15, and 12 weeks for the October, November, and December-planted crops, respectively (Figure 4.1). The September-planted crop could be separated from later plantings in the first 6 weeks of establishment. Between 6 and 16 weeks of the tobacco growing season, the September and the October crops were spectrally mixed. The November-planted crops could be separated from the
September and October crops of their significantly (t< 0.05) greater NDVI. This was well before the December-planted crop was planted. The September-planted crop NDVI declined at 15 weeks after planting, when the October-planted crop was at peak. Only the December-planted crop was actively growing in the field beyond 24 weeks after the start of the experiment. A summary of the approximate times for collecting reflectance data for separating the crops is presented in Appendix 4.1

4.4 Discussion
The general NDVI profiles for the four planting times (Figure 4.1) first increased, reaching a peak in 8 – 12 weeks after planting, and decline, thus, according to Tucker (1979), following the same pattern as the leaf area index. The spectral characteristics of tobacco varieties in the major growth stages generally up to 10 weeks after planting were very similar, making it difficult to separate variety and fertilizer effect using a single layer. These findings ware in tandem with those of Peng et al. (2009).

The September and October-planted tobacco had higher seasonal average NDVI than the November and December-planted crops. This could have resulted from the dry conditions under which these September and October-planted crops are established. The crops are generally subjected to 4–6 weeks of dry conditions before irrigation is applied or rains received (TRB, 2010). The moderate stress is considered beneficial to the tobacco plants, as deeper root development is encouraged in preparation for the rapid growth phase between 6 and 10 weeks. The additional root development results in increases in yield and quality of the cured leaf (Stocks, 1994). In addition, the stimulation of root development subsequently promotes the attainment of a desirable chemical composition.

Generally, periods of severe water stress causes a negative spectral response (Negeswara-Rao et al., 1988) and consequently low NDVI profiles. The general decline of seasonal average NDVI with later plantings is similar to the documented response of tobacco yield to planting time, (TRB, 2010), showing the potential for NDVI to be used in developing yield forecasting models (Moore, 2010).
The separation of flue-cured varieties and fertilizer levels using NDVI could be conducted from 10 weeks after planting when NDVI differences became significant. The 10-weeks after planting stage generally coincides with full canopy and maximum leaf expansion. Reaping of the bottom 2-4 leaves will have just commenced at 9 weeks after planting. At this maximum growth stage, the potential of the different crops in the field, as determined by variety and fertilizer management, could easily be detected and considered in overall yield estimation.

The higher NDVI for both 100 and 150% recommended fertilizer application levels for T 66 and K RK26 could be an indication of higher yield potential for the two varieties, compared to K E1. According to Jiang et al. (2003), NDVI reflects the growing status of green vegetation, thus making the task of crop monitoring and crop yield estimation by remote sensing realizable. The different rates of decline of NDVI after the peak could be due to fertilizer x variety treatment and related variety specific ripening rates (Gondola, 1994).

A long growing period is important in increasing the crop leaf area duration (LAD), which is very essential for accumulation of biomass (Devndra et al., 1983; Saleem et al., 2009). In the experiment, crop growth period generally decreased with late planting in the experiment.

The similarity of NDVI for the three varieties in September could be an indication of equal yield potential under such growing conditions, making it possible to estimate combined area and yield forecast for the three varieties. The yield potentials of K RK 26, T 66 and K E1 are 3.5 – 4 t ha⁻¹, 4 – 4.5 t ha⁻¹ and 2.5 – 3 t ha⁻¹ respectively (TRB, 2010).

Although the December-planted crop remained in the field beyond 24 weeks after the September planting date, spectral confusion due to weeds, other crops, and even sucker regrowth from earlier planted crop could make its separation difficult.

Using the seasonal NDVI profile, the three varieties K RK 26, T 66 and K E1 and the effect of different fertilizer levels could be distinguished, making it possible to use to use NDVI averages in assessing the seasonal NDVI profiles for the different planting times. NDVI profiles for the four planting dates could be used to select periods at which the single layer phase NDVIs
were significantly different (p < 0.05). This would enable separate monitoring of crops for specific planting dates. As observed by Jiang et al. (2003), crop area estimation for the different planting dates could be realized using remote sensing techniques on the basis of time serial NDVI data together with agriculture calendars.

4.5 Conclusions

Tobacco varieties and fertilizer level effects could be distinguished using spectral data from a single layer image after the attainment of peak canopy reflectance. Crops planted on different planting dates had different seasonal NDVI profiles. Periods where the profiles were significantly different could be used in calculating crop area forecasts. The varieties T 66 and K RK26 could not be distinguished by both NDVI calculated from single remote sensing image layer and temporal NDVI profiles in the field, while KE 1 could be separated from at least 10 weeks after planting from a single layer image. Under-fertilized tobacco could be distinguished in the field by its lower NDVI than the optimally and over-fertilized crop from at least 10 weeks after planting using single layer images. Using seasonal NDVI profile, the three varieties K RK 26, T 66 and K E1 and the effect of different fertilizer levels could not be distinguished. The second to last week of November and the period from late February to end of March were the optimal times for discriminating the September-October planted tobacco from the non-irrigated November-December tobacco. The results showed that for the September, October and the November planting dates, varieties, and fertilizer levels could be distinguished using NDVI starting from 10 weeks after planting. The December planted tobacco varieties and fertilizer levels could not be distinguished using the NDVI. The results of the experiment provide the possibility to map variety, fertilizer and planting date variations in tobacco crop NDVI using remote sensing. Using time series NDVI data with agricultural calendars, tobacco planted on different planting dates could be separated and each crop area can thus be separately determined using remote sensing.
CHAPTER 5: SPECTRAL INDICES, IN-SEASON DRY MASS AND YIELD RELATIONSHIP OF FLUE-CURED TOBACCO

Abstract

Plant biomass accumulation is related to canopy spectral characteristics and the relationship between the two can be used to estimate total biomass and crop yield. A field experiment was carried out at Kutsaga research station in Zimbabwe, to investigate the relationship between tobacco canopy spectral characteristics and tobacco biomass. A randomized complete block design, with four planting dates, September, October, November, and December, each with 3 varieties, KRK 26, T 66 and K E1 and 3 fertilizer levels, 50 %, 100 % and 150 % of recommended amount were used. Starting from 6 weeks after planting, reflectance measurements were taken from one row, using a multispectral radiometer. Plants from the other 2 rows were also measured, and the above-ground whole plants were harvested and dried for NDVI x dry mass regression analysis. The central row was harvested, cured, and weighed. Both the NDVI and mass at untying declined with late planting. Regressions for the spectral data were run using GraphPad Version 6.05 and graphs constructed using Excel 2007. In-season dry mass-NDVI regressions had the highest coefficient of determination at 8–12 weeks. The mass at untying-NDVI coefficient of determination also decreased with later planting from September ($R^2 = 0.79$), October ($R^2 = 0.64$), November ($R^2 = 0.695$) and finally December ($R^2 = 0.515$). The yield versus NDVI regression models for the September and the October-planted crops were statistically similar ($p = 0.424$) and so were the November and December planted crops ($p = 0.541$). There were no significant differences among the mass at at untying-NDVI regression curves for KRK 26, T 66 and K E1 ($p = 0.220$) and so were the fertilizer levels ($p = 0.167$). Separate models for tobacco yield estimation using NDVI were developed for the September-October and November-December crops. Since relationship between in-season dry mass and yields with NDVI was not affected by tobacco variety and fertilizer application level, a combined model for estimating tobacco yield using NDVI was also developed. The results of the experiment are promising for estimating tobacco yield in the field using canopy NDVI at 10 – 12 weeks after planting.

This chapter is based on
5.1 Background

Monitoring agricultural crop conditions during the growing season and estimating the potential crop yields are both important for the assessment of seasonal production. Remote sensing data has both the potential and capacity to provide information on crop condition and health status on a regional scale and on an almost real-time basis (Reynolds et al., 2000; Doraiswamy et al., 2011; Doraiswamy et al., 2004). With the application of remote sensing in agriculture, there is potential not only for identifying crop classes, but also estimating crop yield (Reynolds et al., 2000).

Spectral measurements from crops can be used in estimating parameters such as leaf area index (Baez-Gonzalez et al., 2005), plant population, and even canopy total nitrogen status during the growth cycle of the crop (TRB, 2012). Vegetation indices simplify data from multiple reflectance bands to a single value correlating with physical vegetation parameters, such as biomass, productivity, leaf area index, or percent vegetation ground cover (Tucker, 1979). Single band reflectance is combined into a vegetation index in order to minimize the effect of such factors as optical properties of the soil background and illumination on the canopy Spectral properties (Verrelst et al., 2006).

Vegetation indices, as summarized by Gross (2005), are based on the characteristic reflection of plant leaves in the visible and near-infrared portions of light. By applying a “vegetation index” to the satellite imagery, intensity of greenness in vegetation can be quantified (Viña et al., 2011). The normalized difference vegetation index (NDVI) has been considered a useful tool for crop yield assessment (Prasad et al., 2006). The index responds to changes in the amount of biomass, chlorophyll content, and canopy water stress and, hence, is most commonly used in assessing crop vigour, vegetation cover, and biomass production from multispectral satellite data (Eitel et al., 2010; Jackson et al., 1983). NDVI is calculated using the formula \[ \text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \] (Jackson et al., 1983; Tucker, 1979).

The tobacco crop plays an important role in the economy of Zimbabwe, and in the 2012/2013 marketing season, 144 million kg of tobacco were sold, earning the country $525 million (TIMB, 2012). Crop area and yield forecasts play an important role in stabilizing tobacco prices at the
auction floors. Crop forecasting is the art of predicting crop yields and production before the harvest actually takes place, typically a couple of months in advance. Zimbabwe mostly relies on crop statistical forecasting/estimation, crop reports/field visits from extension officers, and statistical crop forecasts for crop yield forecasts (SADC, 2009). However, data from crop estimates, which are obtained through surveys conducted after harvests, are in most countries available late for early warning purposes.

An over estimation of the crop would jeopardize the grower’s profit in that it causes a fall in prices when supply exceeds the estimated volume. Under estimation, on the other hand, causes unnecessary panic and competition among buyers of the crop, causing a rise in the price of the crop. The timely evaluation of potential crop yields in general becomes important because of the huge economic impact crops have on the world markets (Doraiswamy et al., 2011) and in particular the importance of tobacco in the economy of Zimbabwe.

Remotely sensed measurements can be used in monitoring the effects of agronomic practices, which are considered in developing yield prediction models (Atzberger, 2012). This experiment investigated the relationship between canopy spectral characteristics of three tobacco varieties established on three planting dates and, under three fertilizer regimes, in-season dry matter and final yield. The objectives of the study were; (1) to develop models NDVI to in-season biomass and final yield and; (2) determine the optimal crop stage for collecting canopy reflectance measurements for NDVI-yield assessment. It was hypothesised that crop canopy spectral reflectance characteristics are directly related to biomass and final yield. It was also hypothesized that the strength of the relationship between in-season dry mass and yields expressed as mass at untying with NDVI was not affected by tobacco variety, planting date, and fertilizer application level. Derived models relating tobacco canopy reflectance with in-season dry mass and crop yield area useful in making early estimates of tobacco yield using canopy NDVI.
5.2 Materials and methods

5.2.1 Study area
The experiment was conducted at Kutsaga Research Station during the 2010 – 2012 cropping seasons. The experimental plots were located on well-drained granitic sands. During February of 2009 and 2010 the plots were disked after a three year Katambora grass fallow period to incorporate grass. Agricultural lime was applied at 600 to 760 kg, as recommended from soil test results, to raise the soil pH to 5.3 to 6.3, levels optimum from tobacco production. Recommended cultural and management practices like weeding, insect and disease control and topping were followed (TRB, 2010), except as regards N: P: K levels and planting times, which were treatments in the experiment.

5.2.2 Trial design
The experiment was laid out in a randomized complete block design with four blocks, with plantings on September 15, October 15, November 15 and December 15 each with 9 variety × fertilizer application levels (Table 5.1). The middle of each of each of the four month, September, October, November and December was selected for planting the crop because it was assumed that the average growing conditions of the month could be captured.

Three tobacco varieties, K RK26, T 66 and K E1 developed by Kutsaga Research Station were used (refer to section 1.6), while three fertilizer application levels (50 %, 100 % and 150 % of the recommended application rate) were applied by hand (Table 5.1). The N: P: K treatments were hand-applied in bands about 10 cm deep and 30 cm to each side of a row at planting. The N: P: K was applied as Compound C (6 % N; 17 % P₂O₅; 15 % K₂O) at a recommended rate of 700 kg ha⁻¹. The 50 % and 150 % rates were, therefore 350 kg ha⁻¹ and 1050 kg ha⁻¹ respectively (Table 5.1). Nitrogen fertilizer application levels as ammonium nitrate (34,5% N), and the recommended rate (100%) was 96 kg ha⁻¹ at 4 weeks after planting and 75 kg ha⁻¹ after topping at 6-8 weeks after planting.

Each sampling plot measured consisted of 5 rows; each with 32 plants spaced 56 cm apart. The interrow spacing was 1.2 m.
5.2.3 Trial management

The trial was managed as described in section 4.2.3

Table 5.1: Variety – fertilizer application levels

<table>
<thead>
<tr>
<th>Variety</th>
<th>Fertilizer application level (%)</th>
<th>Compound C (6:17:15) (kg ha⁻¹)</th>
<th>Ammonium Nitrate (kg ha⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>K RK 26</td>
<td>50</td>
<td>350</td>
<td>48</td>
</tr>
<tr>
<td>K RK 26</td>
<td>100</td>
<td>700</td>
<td>96</td>
</tr>
<tr>
<td>K RK 26</td>
<td>150</td>
<td>1050</td>
<td>144</td>
</tr>
<tr>
<td>T 66</td>
<td>50</td>
<td>350</td>
<td>48</td>
</tr>
<tr>
<td>T 66</td>
<td>100</td>
<td>700</td>
<td>96</td>
</tr>
<tr>
<td>T 66</td>
<td>150</td>
<td>1050</td>
<td>144</td>
</tr>
<tr>
<td>K E1</td>
<td>50</td>
<td>350</td>
<td>48</td>
</tr>
<tr>
<td>K E1</td>
<td>100</td>
<td>700</td>
<td>96</td>
</tr>
<tr>
<td>K E1</td>
<td>150</td>
<td>1050</td>
<td>144</td>
</tr>
</tbody>
</table>

5.2.4 Data collection

5.2.4.1 Spectral data

Spectral measurements were made weekly from 6 weeks after planting on 5 m x 5 m square sampling plots, using a hand-held multispectral radiometer (Cropscan MSR-5, 450–1750 nm), with the field of view (FOV) centering over rows. All treatment applications had been applied at this stage.

Spectral data from the four planting dates was used to construct temporal NDVI profiles and one, with typical stress free growth conditions was selected for the in-season dry mass-NDVI regression analysis. Above-ground samples were collected after a corresponding canopy reflectance measurement had been obtained. Some 10 plants were sampled from each variety x fertilizer x planting time treatment after spectral data collection at 8, 10, 12 and 14 weeks after planting. The Normalized Difference Vegetation Indices were calculated from the spectral bands obtained in the channel 3 and 4 of the MSR 5 which correspond to the red and near infra red (NIR), respectively, using the following formula:

\[ NDVI = \frac{(NIR - RED)}{(NIR + RED)} \]
The Multispectral Radiometer (MRS 5) was positioned facing vertically downward at 1 m above crop canopies, and measurements were taken around solar noon to minimize the effect of diurnal changes in solar zenith angle. In total, 10 measurements were taken per sampling area and reflectance measurements were then averaged for each sampling plot to estimate a single reflectance value.

Reflectance measurements were also taken on 10 individual plants per row from the other 3 rows. The latitude and longitude for the whole experimental area and for each treatment plot were taken using a Garmin Personal Navigator (GPS V) to enable repeated sampling at the same location.

5.2.4.2 In-season dry mass data
After taking reflectance readings, the above-ground whole plants were harvested and packed in khaki bags and dried in micro-barns at 60°C for 14 days. Dry matter measurements were later taken for reflectance/dry mass (DM) regression analysis. Three rows were also harvested, cured and mass determined just after curing, before handling losses were incurred. NDVI for the growth stage where there is the highest in-season dry mass – NDVI. The relationship was then selected for determining the mass at untying NDVI relationships. Mass at untying is the mass of cured flue cured tobacco just after the curing process, before the crop is graded. Mass at untying is recorded as the crop is removed (untied) from the clip after unloading from the curing barn.

5.2.4.3 Crop yield data
Each experimental plot was harvested and tied on clips and taken into the barns for curing. The curing process follows as recommended temperature schedule (TRB, 2010). At the end of the curing period, mass was determined using a digital scale, at the point of untying from the clips, before handling losses are incurred as applied by Zhang et al., (2012), and recorded as mass at untying.

5.2.5 Data Analysis
The data for the two seasons, 2010-2011 and 2011 to 2012 was averaged to get a single value. Regressions for the spectral data were run using GraphPad Version 6.05 and graphs constructed
using Excel 2007. All the fertilizer application levels in this experiment were pooled in regression calculation. In the previous experiment (Chapter 4) it had been established that fertilizer effects were significant on single layer images and could not be identified in NDVI profiles. It was also established that the NDVI x fertilizer levels regression slopes were statistically similar among the three varieties K RK 26, T 66 and K E1 (Chapter 3). The October-planted crop was sampled for NDVI and in-season dry mass analysis (Chapter Figure 4.1). This crop was selected because it was not subjected to long dry conditions after planting and, had a good establishment. In addition temporal NDVI profiles for the crop had the highest NDVI value, which would enable a wide variation of the DM-NDVI relationships. Rainfall data was collected from a meteorological station that is located in the research station.

**Table 5.2: Rainfall data for Kutsaga research station during the 2010-2011 and 2011-2012 cropping seasons**

<table>
<thead>
<tr>
<th>Rainfall (mm)</th>
<th>Season</th>
<th>2010/11</th>
<th>2011/12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Month</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>October</td>
<td></td>
<td>1.0</td>
<td>38.2</td>
</tr>
<tr>
<td>November</td>
<td></td>
<td>103.7</td>
<td>129.2</td>
</tr>
<tr>
<td>December</td>
<td></td>
<td>219.1</td>
<td>127.9</td>
</tr>
<tr>
<td>January</td>
<td></td>
<td>178.5</td>
<td>332.2</td>
</tr>
<tr>
<td>February</td>
<td></td>
<td>126.7</td>
<td>152.1</td>
</tr>
<tr>
<td>March</td>
<td></td>
<td>84.6</td>
<td>58.4</td>
</tr>
<tr>
<td>April</td>
<td></td>
<td>48.8</td>
<td>31.2</td>
</tr>
<tr>
<td>May</td>
<td></td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>TOTAL</td>
<td></td>
<td>762.4</td>
<td>869.2</td>
</tr>
</tbody>
</table>
5.3 Results
The relationship between NDVI and in-season dry mass became stronger from the first sampling date (8 weeks after planting), reaching the highest at 10 weeks before declining. Plants were not sampled for DM-NDVI analysis after week 14 because some plants had already been stripped of all leaves. On average two leaves are harvested per plant weekly from about 9 weeks after planting depending on ripening rate. Generally for plants topped at 18 leaves harvesting is complete 14-16 weeks after planting.

Figure 5.1: Dry mass (g/ plant) –reflectance relationship for the samples collected from (a) 8 weeks (b) weeks10 (c) 12 weeks and (d) 14 weeks after planting.
There was a general decline in both maximum NDVI and mass at untying with later planting, with least values attained in December planting. The mass at untying-NDVI coefficient of determination also decreased with later planting. The September coefficient of determination ($R^2 = 0.79$) was the highest compared to the October ($R^2 = 0.64$), November ($R^2 = 0.695$) and December ($R^2 = 0.515$) coefficients.

Figure 5.2: The relationship between the pooled September (A), October (B), November (C) and December (D) planted crop mass at untying (kg ha$^{-1}$) and maximum NDVI
The yield and NDVI regression models for the September and the October-planted crops were statistically similar slopes (p = 0.4238), making it possible to come up with one regression model relating tobacco yield and NDVI for the two crops (Figure 5.4a; Appendix 5.2).

![Figure 5.3: The relationship between the mass at untying for the (A) September-October (B) November-December-planted crops and maximum NDVI](image)

The yield and NDVI regression models for the November and the December planted crops were also statistically similar slopes (p = 0.5409), making it possible to come up with one regression model relating tobacco yield and NDVI for the two crops (Figure 5.4b; Appendix 5.3). The mass at untying-NDVI coefficients of determination ($R^2$) for the September-October and for the November December (Figure 5.4) were 0.741 and 0.681 respectively. In both September-October and the November-December, the best fitting curves for mass-at-untying versus NDVI were quadratic.

All the three varieties, K RK 26, T 66 and K E1 showed a quadratic relationship between mass-at-untying and NDVI (Figure 5.5). K E1 had the highest (mass-at-untying-NDVI coefficient of determination ($R^2 = 0.86$). In all the three varieties, the best fitting curves for mass-at-untying versus NDVI were quadratic (Figure 5.5). The differences among the mass at at Untying versus
NDVI slopes for K RK 26, T 66 and K E1 were not significant. The overall slopes were identical ($p = 0.2198$) (Appendix, making it possible to pool all the varieties for the mass at untying versus NDVI regression analysis (Figure 5.8).

![Graphs showing the relationship between mass at untying and NDVI for K RK26, T 66, and K E1.](image)

Figure 5.4: The relationship between (A) K RK26, (B) T 66 and (C) K E1 mass at untying (kg ha$^{-1}$) and maximum NDVI
All the three fertilizer levels; 50 % ($R^2 = 0.925$) 100 % ($R^2 = 0.966$), (R$^2 = 0.92$) showed significant ($p < 0.0001$) mass-at-untying NDVI yield relationships (Figure 5.6; Appendix 5.5).

Figure 5.5: The relationship between the mass at untying (kg ha$^{-1}$) for the (A) 50 % (B) 100 % and (C) 150 % fertilizer application level and maximum NDVI

The differences among the mass at at untying versus NDVI slopes for the 50%, 100% and 150% fertilizer levels were not significant ($p = 0.1666$) (Appendix 5.5) making it is possible to poole all the fertilizer levels for the mass at untying versus NDVI regression analysis (Figure 5.7).
Figure 5.6: The relationship between the pooled mass at untying and maximum NDVI

5.4 Discussion

The October-planted crop was selected for in-season dry mass-NDVI analysis because of the clear cloudless conditions during the times of data collection. Thin cloud coverage, according to Nuarsa et al., (2012), can lead to inconsistencies in the reflectance values, which will affect NDVI and, therefore, the selection of cloud-free images is one of the most important steps in the data collection.

NDVI-yield relationship increased with age up to 10–12-week after planting. As Negeswara-Rao et al., (1988) explained, the changes in spectral response of a crop are a function of phenological stages of the crop. The 10–12 weeks period, with the highest NDVI, could be an indication of the most suitable phenological stage to collect satellite data for yield forecasting.
Chlorophyll degradation related to leaf ripening occurring during the ripening stage causes an increase in the red spectral reflectance which is normally absorbed by chlorophyll (Gunnula et al., 2011). On the contrary, the NIR spectral reflectance decreases due to a change in leaf internal structure (Gunnula et al., 2011) resulting in the fall of NDVI (Gates et al., 1965). The fall in the in-season dry-mass-NDVI relationship from 14 weeks after planting is related to the decrease in canopy reflectance spectra at crop maturity stage that is brought about by reaping (Qiao et al., 2011), whiles the final yield remains unchanged.

The decrease in tobacco mass at untying with later planting at all variety × fertilizer application levels is well known (TRB, 2010). The maximum NDVI values for each variety decreased with later planting from September to December. The high coefficients of determination for all three varieties and fertilizer levels could also be an indication of the possibility to disregard the variety and fertilizer differences in the processes of developing yield forecasting models. This finding is of significance since fertilizer levels vary from farmer to farmer.

The coefficients of determination between mass at untying and NDVI for the September-October (0.741) and the November-December (0.681) planted crops were higher than the 0.65 that was established for wheat crop (Povkh et al., 2005) but lower than the $R^2 = 0.90 - 0.98$ that Jiang et al. (2003) found between wheat grain yield and NDVI. Tobacco, hence, has a unique NDVI which makes remote sensing a real possibility of accurately distinguishing tobacco from other crops. The established coefficients in this experiment were, however, high enough for tobacco yield to be estimated using Cropscan calculated NDVI. The yield models derived were quadratic, similar to the findings of Jiang et al. (2003) for wheat. The high value of the coefficient of determination indicated that the relationship between tobacco yield and NDVI was consistent (Nuarsa, 2012).

The similarity in the coefficients of determination between mass at untying and NDVI for the September and October-planted crops could be an indication of the need to combine the two, while the lower coefficients for the December planted crop could be an indication for the need for applying other separate techniques for estimating the December crop yield. As the channels of the sensor used in the experiment are LANDSAT Thematic Mapper compatible (I. C. T.,
2003), the models derived can be applicable in tobacco yield estimation using operational remote sensing data from the satellite.

The combined tobacco yield versus NDVI_{MSR5} coefficient of determination ($R^2 = 0.918$) was comparable with levels that were established by Nuarsa et al. (2012) for rice yields related to the MODIS derived NDVI. Similarly, high coefficients of determination were obtained between the average NDVI and rice age and the relationship was best described by a quadratic equation, with $R^2$ values ranging from 0.916 to 0.973. When the similar regression technique approaches were applied on canopy reflectance of wheat (Huang et al., 2012; Huang et al., 2013), maize (Prasad et al., 2006; Baez-Gonzalez et al., 2005; Sibley et al., 2013), grapes (Liu et al., 2013) and sugarcane (Lumsden et al., 1998; Lofton et al., 2012) comparable $R^2$ values were established.

5.5 Conclusions
The NDVI was highly correlated to in-season dry mass. The yield-NDVI regression for the combined September and the October-planted crops yielded and a high coefficient of determination and so were the combined November and the December-planted crops. There was a strong positive relationship between NDVI and flue-cured tobacco yield at all fertilizer levels and for all the tested varieties making it possible to combine varieties in a single model. Multispectral radiometer based model for tobacco yield forecasting; was derived. Thus tobacco yield for different planting dates, varieties and under varying fertilizer levels can be estimated from NDVI. There is, however, a need to establish the relationship between Cropscan multispectral radiometer 5 data and various satellite platforms before this information can be applied widely in satellite remote sensing.
CHAPTER 6: ESTIMATING TOBACCO CROP AREA AND YIELD IN ZIMBABWE USING OPERATIONAL REMOTE SENSING AND STATISTICAL TECHNIQUES

Abstract
In this study, remotely sensed data and field measurements were used to develop a method for estimating the tobacco crop area and yield. Between 2010 and 2013, starting from September to March, 203 tobacco fields were randomly selected and measured using global positioning system (GPS) unit. The sampled tobacco fields were classified into irrigated fields (September and October planted), and rainfed fields (November and December planted). Agricultural field boundaries from a pseudo natural colour composite LANDSAT Thematic Mapper (TM) satellite imagery were digitized and stacked, and a true colour image was used for visual interpretation of the images. The images were then georeferenced to ascertain position. The field boundaries were used to mask the tobacco fields using the MODIS imagery. Cloud free MODIS images covering the period September to March were downloaded. For each MODIS image, NDVI was estimated and NDVI profiles for tobacco for different planting times were calculated separately using data from sampled tobacco fields and compared. A Geographical Information System (GIS) programme, Environment for Visualizing Images (ENVI) 4.3, was used to calculate the area of the tobacco fields for each georeferenced MODIS image, using the NDVI for the tobacco fields. The area estimates of the September-October and November-December-planted crops were derived by extracting all pixels within the tobacco soils and cultivation field masks where the probability of belonging to either the September-October or November-December planting dates was equal to or greater than 95%. The results of this study indicated that, based on the MODIS derived NDVI data, the third to fourth week of November and the third to fourth week of February were the optimal times for discriminating the September-October from the November-December planted tobacco. The crop areas for the three seasons were estimated and yield estimates calculated from the long-term cropped yield-area regression model. The three seasons average yield estimates from remote sensing had an average error of -0.12%, compared to +12% for the conventional crop survey method. The study shows that tobacco area and yield can be estimated using remote sensing using remote sensing.

This chapter is based on
6.1 Background
Crop yield estimation is necessary, particularly in countries that depend on agriculture as their major contributor to the economy (Atzberger, 2012). Such predictions provide useful information for decision makers about potential reduction or increase in crop yields to allow for timely import and export decisions (Awosola-Olubode et al., 2008; Bouman, 1992). Knowledge of crop area at an early stage is very important in agricultural planning and policy-making at both national and regional levels (Casa and Ovando, 1996). Accurate estimates of crop yield are obtained if crop growth is monitored during the growing season (Clevers and Leeuwen, 1996).

Conventionally, quantitative estimates of crop condition in the field, cropped area, and yield are obtained from ground-based measurements (Awosola-Olubode et al., 2008). The current conventional tobacco yield forecasts in Zimbabwe rely on seed purchase records, land area and visual assessment of the crop (Craig and Atkinson, 2013). Therefore, it is necessary to investigate and use cheaper, faster reliable and reproducible methods for crop yield estimation.

Remote sensing, which provides time series data and a synoptic view of the landscape, is now widely used to assess crop condition in the field as well as estimate crop yield. The positive relationship between remotely derived vegetation indices such as the normalized difference vegetation index (NDVI) and biomass (Svotwa et al., 2012; Svotwa et al., 2013; Jackson et al., 1983; Eitel et al., 2010; Yin et al., 2010) has proved to be useful for predicting crop yield. Similarly, Gomes, (2006) proved that vegetation indices calculated from spectral data strongly relate to biomass and crop yield.

With the use of remote sensing technology, plant physiological and morphological differences can be distinguished within fields in real time, cost efficiently and timely (Huete et al., 2002). Remote sensing has facilitated a deeper understanding of the environment because it has many processes over a broad range of spatial and temporal scales, which can provide information on the actual status of agricultural crops (Kustas et al., 1994). Best results are obtained by using remote sensing data in estimating biophysical values regularly during the growing season and subsequently calibrating the growth models based on these estimates (Maas and Dunlap, 1989; Moulin et al., 1998).
Multispectral sensors such as LANDSAT TM and MODIS are able to view more than one particular band of energy selected in various regions of the electromagnetic spectrum (Prasad et al., 2006). Presently there are several systems that can provide regular coverage of the Earth's surface. These can regularly supply remotely sensed data of the whole area of the country or selected regions of economic interest to farmers such as farm land or field (Prasad et al., 2006). With the help of such data, the spatial distribution of the crops as well as their status and vigour in the growing period can be determined monitored (Reynolds et al., 2000).

In Zimbabwe, timely and reliable estimates of potential tobacco yield are important because tobacco is a substantial contributor and has an impact on the country’s economy. Thus, monitoring the growth and phenological development of the tobacco in the field is critical for obtaining early estimates of yield (Rizzi and Rudorff, 2005). However, in Zimbabwe the lack of an objective and robust method for estimating tobacco yield has often led to contradicting estimates being provided by different stakeholders. This compromises national planning and marketing of the crop. A more objective and simple method for yield estimation could assist tobacco stakeholders by providing precise data on tobacco growth characteristics, land area under tobacco and potential yield available for the export market.

In this study, remotely sensed (satellite) data and field measurements were used to develop a simple but robust model for estimating the hectarage under tobacco and the final yield. Remote sensing was used because it provides observations over large areas at regular intervals. This reduces the costs for obtaining crop estimates. It was hypothesized that from the Global Positioning System coordinates of the sampled tobacco fields planted on different planting dates, crop growth can be monitored throughout the season using NDVI calculated from remote sensing imagery. The derived NDVI can be used to estimate using GIS tools, tobacco cropped area in Zimbabwe. The computed area can be used as input data for the tobacco yield estimation model developed from long-term tobacco area-yield data.
6.2 Materials and methods

6.2.1 Study area

Figure 6.1: Spatial distribution of the tobacco growing districts of Zimbabwe (Source: TRB, 2010)

6.2.2 Climate

Tobacco is grown in three distinct areas in Zimbabwe and these are referred to as the fast medium and slow growing areas (Figure 6.1). Fast growing areas are generally below an altitude of 1280 m above sea level, where temperatures are generally warmer and, therefore, allow faster growth (TRB, 2010). Rainfall in this region ranges between 650 to 850 mm (Vincent and Thomas, 1960). Located on the central high veld are the medium growing areas that are found in a narrow band running from NE to SW through the capital city, Harare. The medium growing
areas receive an annual rainfall of 850 to 1000 mm per annum (Vincent and Thomas, 1960). Slow growing areas generally receive 1000 mm per annum and area above 1280 m above sea level (TRB, 2010)

6.2.3 Determining the agricultural field and tobacco soil masks

From September to October 2010 selected tobacco field boundaries were visually interpreted and digitized from a pseudo natural colour composite (bands 5, 4 and 3) of LANDSAT Thematic Mapper (TM) satellite imagery (Figure 6.2). The images covered the major tobacco growing regions in Mashonaland East, Mashonaland West, Mashonaland Central and Manicaland provinces of Zimbabwe. LANDSAT TM imagery was used to calculate the cultivation mask for two main reasons. LANDSAT images were downloaded from the internet free of charge at www.glovis.usgs.gov. The individual image bands were stacked in order to create a layer and then georeferenced in order to ascertain their true position. The LANDSAT TM spatial resolution of 30 m made it possible to accurately digitize fields of different sizes as illustrated in Figure 6.1. The purpose of this activity was to obtain an accurate map of fields within which tobacco field area estimation would be undertaken.

The crop field mask produced using steps described above, included all crops, yet tobacco is grown on sandy soils. To ensure that estimates provided covered the targeted crop, the FAO based soil map of Zimbabwe was digitized in a Geographic Information System (GIS), Integrated Land and Water Information System (ILWIS) 3.3, and sandy soils which are suitable for tobacco were extracted (Figure 6.2). This soil map was overlaid with the cultivated field mask to extract all fields that were on sandy soils, which are potential tobacco fields.
Figure 6.2: Some digitized fields based on the interpretation of the pseudo natural colour composite of the LANDSAT TM image of May 2010. The colour composite was: band 5 (red), band 4 (green) and band 3 (blue).

6.2.4 Reference data collection
Between September and January of three seasons, 2010-2011 to 2012-2013, fieldwork was conducted to identify tobacco fields and obtain data on the dates of tobacco planting. At least twelve (12) fields were randomly sampled from each of the 15 traditional tobacco growing districts of Zimbabwe (Figure 6.1).
A total of 203 tobacco fields located in Mashonaland East, Mashonaland West, and Manicaland provinces of Zimbabwe were randomly selected and measured using global positioning system (GPS) unit. To minimize edge effects, GPS measurements were made at the centre of tobacco fields. The average GPS error was 6 m.

Figure 6.3: Distribution of sandy soils suitable for tobacco in Zimbabwe.

The sampled tobacco fields were classified based on the dates of planting, into irrigated fields (planted in September and October), and rainfed fields (planted November and December). This
information was obtained from the field owners during the process of data collection. The spatial distribution of sample fields surveyed during fieldwork is shown in Figure 6.4

Figure 6.4: The spatial distribution of the tobacco fields sampled for yield forecasting
6.2.5 Temporal MODIS derived NDVI data for tobacco fields
To monitor tobacco growth in the field using remote sensing, cloud free MODIS images covering the period September to end of March were downloaded freely at http://MODIS-land.gsfc.nasa.gov/ and georeferenced. For each MODIS image, NDVI was estimated as follows:

\[
\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}
\]

where: NIR is reflectance in the Near Infrared band (846–885 \(\mu\text{m}\)) and RED is the reflectance in the Red (600–680 \(\mu\text{m}\)) band.

The mean temporal NDVI profiles for the September/ October-planted crops and those for the November/ December were calculated separately using data from sampled tobacco fields and assessed to determine the optimum date for discriminating the irrigated from the rainfed crops.

6.2.6 Mapping irrigated and non-irrigated tobacco
Logistic regression was applied on the 29th November 2010 image to estimate the probability that different fields in the tobacco field mask were under irrigated or a rainfed crops. The area estimates of the September-October and November-December-planted crops were derived using a Geographical Information System (GIS) programme; Environment for Visualizing Images (ENVI) 4.3, by extracting all pixels within the tobacco soils and cultivation field masks where the probability of belonging to either the September-October or November-December planting dates was equal to or greater than 95%.

6.2.7 Correcting for potential MODIS area under estimates
The spatial resolution of the MODIS imagery, which is 250 m, may lead to underestimation of the area under tobacco as fields which are smaller than 6.25 ha in area may be missed. To address this problem, a subsample of 19 fields was randomly selected and their area estimated using both MODIS and LANDSAT TM.
The fields were visually interpreted and digitized into a GIS regression function relating LANDSAT TM with MODIS area estimates (Figure 6.5).

Figure 6.5: Relationship between the MODIS-derived and LANDSAT TM-derived field area estimates.

The resultant regression function was then applied to the MODIS-derived tobacco area estimates for both irrigated and rainfed crops to correct for potential tobacco area underestimation.

Based on the NDVI profile for the November satellite data, the September-October tobacco crop area was estimated using the late November satellite data, taking advantage of the high contrast between irrigated tobacco and bare fields (Chapter 4). Due to the spectral confusion associated with the November-December-planted crop resulting from weeds and other crops (Chapter 4), the longer THE MODIS time series (September to April) and a Maximum Entropy Method (Maxent) algorithm (Phillip et al., 2006) were also applied to map the November-December-planted crop.
The Maxent approach seeks to extract as much information from a measurement as is justified by the data's signal-to-noise ratio. The approach was applied to calculate the probability that the field adjacent to the sampled November-December had a tobacco crop of the same planting time as this training sample. One major advantage of Maxent is that it only requires positive data for training and reduces the labour and time involved in manually collecting training data (Foody et al., 2006).

Finally, the MODIS-LANDSAT regression relationship was applied to correct for the potential area underestimation by the MODIS satellite. Furthermore, high resolution LANDSAT images of October 2011 and November 2011 were acquired to further validate the September-October area estimates.

6.2.8 Crop survey estimates
The Department of Agricultural, Technical Extension Services (AGRITEX) collects data on tobacco production activities at village level through the ward-based extension officers (AGRITEX, 2010; 2011; 2012; 2013). The information is mainly on area planted each week and general crop status. These statistics are sent to the national office through the district and the provinces for compilation into a national weekly report. At the end of the month, a monthly report is sent out to all tobacco industry stakeholders. In this study, the crop area estimates from the AGRITEX were used, as a standard against which the remote sensing estimates were compared.

6.2.9 Yield estimates
Long-term (40 year) tobacco cropped area and yield data (TIMB, 2012) was used to develop a cropped area-yield linear regression model.

\[ Y = 3.511X - 96929 \]
\[ R^2 = 0.9415 \]

Where
- \( Y \) is the crop yield in (tons)
- \( X \) is the estimated crop area (ha)
The overall model was multiplied by factor 0.8, which was experimentally established as the proportion that reached the market after handling losses are incurred as estimated by Garvin (1980).

The remote sensing based area estimates for the 2010-2011, 2011-2012 and the 2012-2013 cropping seasons were then used as input data for estimating the yield. The calculated estimates were compared with the actual volumes of tobacco delivered at the auction floors as reported by the Tobacco Industry and Marketing Board (TIMB, 2012; TRB, 2012).

The final area estimates for the irrigated and rainfed tobacco crops were derived after applying a correction factor based on the linear relationship between LANDSAT area estimates and MODIS area estimates. The September and October tobacco crops were combined into one class and the November and December tobacco crops into another, based on exploratory data analysis in Figure 6.6. The final area estimates for the 2010-2013 irrigated and rainfed tobacco crops (Table 6.1) were compared with the crop survey area estimates from the AGRITEX. From the crop survey area estimates, the Department of Agriculture and Extension also issues out yield estimates (Table 6.1). The accuracy of both remote sensing and survey based yield estimates was calculated as follows:

\[ Ac (\%) = \{ (Ye-Cd \text{ mkg})/ Cd \text{ mkg} \} \times 100 \]

Where

\[ Ac (\%) = \text{Accuracy expressed as a percentage} \]

\[ Ye = \text{estimated yield from either remote sensing based estimate or crop survey based estimate} \]

\[ Cd = \text{Crop delivered at the auction floors} \]

\[ \text{mkg = mass expressed as million kilograms} \]
6.3 Results

6.3.1 Spectral reflectance

The results for the 2012 – 2013 were not conclusive because of the prevailing weather conditions during the middle and latter parts of the two seasons, which prevented the complete collection of satellite data. There was so much spectral confusion between the November and the December-planted crops and, as a result, the 2011 – 2012 data (Figure 6.6) was used in the description of the season NDVI profile for the sampled tobacco fields.

Figure 6.6: Temporal MODIS derived NDVI profiles from September 2011 to April 2012, grouped by planting month.

The NDVI generally increased from 0.2 – 0.25 early in the season to reach a peak of 0.6 – 0.7 at 8 -12 weeks after planting (Fig 6.6). The September and October NDVI in the entire sampled crop field were statistically similar. During the third week of December, the September-planted crop NDVI was greater than that for October (Figure 6.5). Both NDVI for the September and the
October-planted crops were statistically greater than those extracted from the November and the December-planted fields. Around mid-January NDVI’s for all the September, October, November and December planted crops were similar (p < 0.005), but NDVI for the September and the October-planted crops were declining, while those for the November and the December-planted crops were still on the increase. Between mid and early March, the September and the October-planted crops were similar but lower than the November and the December-planted crops. The latter two were also similar. The results of this study indicate that, based on the MODIS derived NDVI data, the last week of November (A) and the first week of March (B) is the optimal time for discriminating the September and October planted tobacco from the November planted tobacco (Fig. 6.6).

NDVI profiles for September/ October irrigated crops were not separable and so were those for the November/ December-planted crops (Figure 6.6). As a result, the area estimates for the September/ October-planted crops were combined. Similarly, profiles for the November and December-planted crops were also combined.

6.3.2 Area and yield estimates
The three year average accuracy level for the remote sensing estimate (98.8 %) appeared more reliable, compared to the crop survey accuracy (113.6 %) (Appendix 6.1).

6.4 Discussion
The optimal times for discriminating the September and October planted tobacco from the non-November and December planted tobacco, which were the last week of November and late February to early March, were similar to those established in earlier experiments on yield forecasting using remote sensing (Svotwa et al., 2013; Svotwa et al., 2014). Also similar to this earlier work (Svotwa et al., 2014) is the difficulty associated with separating the December-planted crop from earlier planted crops using remote sensing.

The level of accuracy of 98.3 to 98.8 % in this study was comparable with the wheat estimation model developed by Zhang et al. (2003; 2012). The three year average remote sensing yield
estimate error (0.17 %) was smaller than the 12 % (Appendix 6.1) from the AGRITEX conventional crop survey method.

The application of regression techniques in calculating tobacco yield estimates from the 40 year yield and area historical data was not new. Garvin (1985; 1986) applied regression techniques in predicting tobacco yield from biophysical parameters, while Gomes (2006) applied the technique to establish the relationship between environmental factors of growth and yield of newly developed maize varieties.

In general, losses depend on the level of fertilisation during the crop growth phase and later on correct condition of the crop before handling or grading (Garvin, 1986). On farms with poor handling facilities losses can be as high as 30 %, while losses for a correctly conditioned system can be as low as 15 % (Garvin, 1986). With the increase in the number of new tobacco growers who may generally not be fully prepared for the season, the proportion of tobacco that finally reaches the auction floors could be seriously overstated.

### 6.5 Conclusions

The results of this study indicated that, based on the MODIS derived NDVI data, the last week of November and the period between late January and early March are the optimal times for discriminating the irrigated from the non-irrigated tobacco. The estimation of the irrigated and non irrigated separately would help in improving the estimation of the December crops from the estimated total crop area using time series NDVI profiles. A remote sensing based method for estimating the tobacco hectarage using the MODIS satellite was developed. A linear model derived from the 40 year crop and area historical data, field based input data and freely available multi-temporal MODIS satellite data can be accurately applied to estimate tobacco yield. The model-derived yield closely resembled actual tobacco output delivered on the auction floors (Table 6.1). A spatial crop distribution from remote sensing accurately followed the overall pattern of the traditional tobacco growing regions of Zimbabwe. Future work could focus on providing yield distribution maps as the basis for efficient land use planning and to make direct estimation of crop yield from the spatial NDVI distribution.
CHAPTER 7: THE USE OF MULTISPECTRAL RADIOMETER AND MODIS SATELLITE DERIVED NDVI IN DEVELOPING MODELS FOR TOBACCO YIELD ESTIMATION.

Abstract
Up scaling involves the conversion of fine resolution data to course resolution data. The process of up scaling from ground point measurements to MODIS resolutions using high resolution imagery is necessary when converting ground sensor based models to satellite based applications. This experiment sought to develop models for up scaling multispectral radiometer based tobacco yield estimation models for application using the MODIS satellite data. A field survey and satellite earth observations were carried out. NDVI’s were calculated from ground based MSR5 and MODIS satellite based spectral measurements, collected from a 100 ha tobacco field. NDVI’s were also calculated from freely downloaded images from 38 randomly selected tobacco fields of at least five hectares in area in the tobacco growing regions of Zimbabwe. The up-scaling factor for NDVI_{MSR5} to NDVI_{MODIS} was derived. The overall NDVI_{MODIS} and NDVI_{MSR5} relationship was linear and positive (R^2 = 0.73). From the up scaling factor, a model for tobacco yield estimation using MODIS satellite based NDVI was developed. A linear regression of the observed versus predicted tobacco yield was highly significant (p < 0.05). The results show that tobacco yield can be estimated from the MODIS derived NDVI using the model: 

\[ Y_{tot} = A(48.28 \times \text{av NDVI}_{MOD}^2 - 37.51 \times \text{av NDVI}_{MOD} + 8.003) \]

This chapter is based on
7.1 Introduction

Spatial scaling takes information at one scale and uses it to derive processes at another scale (Jarvis, 1995). Up-scaling is when information at a lower spatial resolution is taken and transformed to the higher spatial resolution or downscaling, which works in opposite direction (Jarvis, 1995). Spatial resolution refers to the smallest unit or the minimum object that can be detected by remote sensing instruments.

The Cropscan multispectral radiometer (MRS5) is a hand-held field level remote sensing instrument with spectral bands that are similar to the first 5 bands of the LANDSAT Thematic Mapper (Cropscan, 2013). The MSR5 obtains passive reflective electromagnetic energy emitted from vegetation surfaces and expresses it as a proportion of the amount of electromagnetic energy that interacts with the vegetation surface. This therefore, enables it to characterize unique features of the vegetation with reasonable accuracy (Ma et al., 2001).

Reflectance of radiation wavelengths, as influenced by factors that affect the normal growth of plants, makes the radiometer useful in assessing the effects of such conditions as nutrient deficiency, diseases, waters stress, herbicide damage, varietal differences or general cultural practices on crop vigour, yield, or quality. The MSR5 derived spectral data is, therefore, applicable as input for models that describe normal plant growth for estimating crop yield and quality. Also important is its application in ground truthing for remote sensing based data collection exercises (ICT International, 2013).

The MRS5 was successfully applied in assessing plant diversity and productivity relationships in the United States of America (Masrillag et al., 2001). Dudka and Langton (1998) used the digital imagery from the MSR5 to evaluate disease incidence and yield loss caused by Sclerotinia stem rot of soybeans, while Ma et al., (2001) applied the MSR5 derived NDVI (NDVIMSR5) for early prediction of soybean yield. Other areas where MRS5 has been successfully applied include the detection and monitoring of defoliation, mortality and disturbances over forested landscapes (Nebeker and Evans, 2000), estimation of forage production (Olson and Cochran, 1995) and spatial analysis of white mold infection in soybean (Vigier, 2001).
The Moderate-resolution Imaging Spectro-radiometer (MODIS) consists of the Terra and Aqua earth observation satellites. The two are timed in such a way that they pass from north to south (Terra), and from south to north (Aqua), across the equator in the morning and in the afternoon respectively (NASA, 2013). The 250 m spatial resolution band is the one commonly used for agricultural applications, and because of its 2330 km swath, a large area of the earth’s surface can be monitored. This relatively high temporal resolution makes it a potential candidate for flue-cured tobacco assessments at a national scale.

Currently, MODIS satellite data are free, and have been successfully used in monitoring forest fires, post-fire burn area mapping, vegetation classification, biomass estimation, and soil degradation (Wang et al., 2010). Sibanda and Murwira (2012) applied multi-temporal MODIS satellite derived NDVI (NDVI\textsubscript{MODIS}) with ground data to distinguish cotton from maize and sorghum fields in smallholder agricultural landscapes of Southern Africa.

Svotwa et al., (2012; 2013) developed tobacco yield estimation models using a five band Cropscan multispectral radiometer (MSR5). From this work it was established that the tobacco canopy seasonal maximum NDVI\textsubscript{MSR5} is highly correlated with in-season dry mass and yield. From the work (Chapter 5) the multispectral radiometer based regression model for estimating tobacco yield was:

\[
Yield = 19.49 \times (NDVI\textsubscript{MSR5})^2 - 21.73 \times (NDVI\textsubscript{MSR5}) + 6.773
\]

Where (NDVI\textsubscript{MSR5}) is the maximum NDVI calculated from multispectral radiometer derived canopy reflectance data

Recommendations were also made that for the data to be applicable in tobacco yield estimation using satellite remote sensing there is need for up-scaling these NDVI\textsubscript{MSR5} based models using MODIS data. The MSR5 used for model development has low spatial resolution and a high revisit frequency according to the researchers’ design. The information derived using a MSR 5 has to be scaled up so that it can be applied for large area crop status monitoring and yield estimation.
In this research, models for estimating tobacco yield using MODIS satellite data were explored, using up-scaled ground based yield - NDVI$_{MSR5}$ relationships. It was hypothesized that the tobacco yield is positively correlated with NDVI$_{MSR5}$ and, that the relationship between NDVI$_{MSR5}$ and yield can be up-scaled to develop NDVI$_{THE\ MODIS}$ based models for large area crop assessment and yield estimation purposes.

7.2 Method

7.2.1 Study Area
The study was conducted through a field survey and satellite earth observations. The field survey was carried out at Kutsaga Research Station from 2010 to 2012.

During February of 2010 the experimental plots were disked to incorporate grass, after three years under Katambora grass rotation. Dolomitic lime was applied at a rate of 600 to 760 kg ha$^{-1}$ using recommendations as given by soil test results, to raise the soil pH from 5.3 to 6.3 levels. Recommended cultural and management practices which included pesticide application, fertilizer application, suckercide application as well as sucker control were done (TRB, 2010) except as regards N: P: K levels and planting times, which were treatments in the experiment.

7.2.2 Fertilizer application levels
In order to establish the relationship between spectral data and yield, there was need to create variable growth conditions (Mohammad, 2008) and, three varieties, four planting dates and three fertilizer levels were tested. Four planting dates (September 15, October 15, November 15 and December 15 each) were used.

7.2.3 Trial management
The N: P: K treatment were hand-applied in bands of about 10 cm deep and 30 cm to each side of a row at planting, while N treatments were applied at about 4 weeks after transplanting and after topping (at 7-9 weeks after planting). The recommended compound fertilizer application level from soil test results was 700 kg ha$^{-1}$ of Compound C (6% N; 17 % P$_2$O$_5$; 15 % K$_2$O),

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while that for ammonium nitrate (34.5% N) was 96 kg ha\(^{-1}\) at 4 weeks after planting and 75 kg ha\(^{-1}\) after topping (TRB, 2010).

7.2.4 Data collection

7.2.4.1 Spectral data collection

Previous research established that the maximum NDVI for flue-cured tobacco is attained between 10 and 12 weeks after planting (Svotwa et al., 2013; Svotwa et al., 2014). In order to correlate the NDVI calculated from MODIS satellite data with that calculated from the MSR5 data, a 100 ha of commercial tobacco, established on 4 planting time blocks of September (26 ha), October (22 ha), November (30 ha) and December (22 ha) at Kutsaga Research was set up. The land blocks were sufficiently large to allow for data collection from MODIS satellite which has a spatial resolution of 250 m. The field was managed as recommended (Section 6.6.1)

From each of the four blocks, 100 plants per block were systematically selected, and reflectance measurements were taken at 7 day intervals from the time of planting to 12 weeks after planting using the MSR5. Global Positioning Satellite Receiver (Garmin GPS V) was used map sampling points so as to allow repeatability. The average GPS error was 6 m. At almost the same period, MODIS satellite data for the four fields were downloaded and NDVIs calculated.

7.2.4.2 Field reflectance data

Thirty eight (38) fields of at least 5 ha were selected using stratified random sampling in the tobacco growing regions of Goromonzi, Seke, Marondera, Beatrice and Banket farming areas of Zimbabwe. This was above the n = 30 threshold, recommended by Gomez and Gomez (1983) as the minimum required sample size for the statistical data to approximate normal. Only tobacco fields of at least 5 ha were selected from the randomly selected areas of the tobacco growing regions, so as to avoid the problems associated with mixed pixels.

After the centres of the fields were marked using a Global Positioning Satellite Receiver (Garmin GPS V), growers’ contact details were taken for later communication on crop status and yields and for ground truthing purposes. The average GPS error was 6 m. Satellite images were freely downloaded from the USGS Glovis website: www.earthexplorer.usgs.gov for the 2012-2013 and
2013-2014 tobacco seasons. TMODIS 16-day NDVI data products were selected because of their high data return rates. Actual yield data from the 38 field was obtained from the tobacco growers and this was compared with the NDVI based yield estimates.

7.2.5 Data Analysis

The quadratic and linear regressions were done (Gomez and Gomez, 1983) to develop relationships between experimental tobacco yield and NDVI\textsubscript{MSR5}. A second order polynomial: \( Y = \beta_0 X^0 + \beta_1 X^1 + \beta_2 X^2 \) was applied.

1. \( Y = \beta_0 \text{NDVI}_{\text{MSR5}}^0 + \beta_1 \text{NDVI}_{\text{MSR5}}^1 + \beta_2 \text{NDVI}_{\text{MSR5}}^2 \)

Where \( Y = \) tobacco yield

\( \text{NDVI}_{\text{MSR5}} = \) Cropscan derived NDVI

\( \beta_0, \beta_1 \) and \( \beta_2 \) are constants

The yield estimation model (Chapter 5): \( Y = 19.49x^2 - 21.73x + 6.77; (R^2 = 0.918) \) was upscaled using factors derived from the relationship between NDVI\textsubscript{MSR5} and NDVI\textsubscript{MODIS} derived from the field experiment data regression analysis as follows:

2. \( \text{NDVI}_{\text{MSR5}} = k \text{NDVI}_{\text{MODIS}} + e \) (from the general linear model \( Y = mx + c \) where \( m = \) gradient, and \( c \) is the intercept)

\( \text{NDVI}_{\text{MSR5}} \) and \( \text{NDVI}_{\text{MODIS}} \) are as defined above

\( k \) and \( e \) are constant

3. Substituting 1 by 2:

\( Y = \beta_0 (k \text{NDVI}_{\text{MODIS}} + e)^0 + \beta_1 (k \text{NDVI}_{\text{MODIS}} + e)^1 + \beta_2 (k \text{NDVI}_{\text{MODIS}} + e)^2 \)

Where \( Y = \) Tobacco yield estimate

All other constants as defined above
7.3 Results

7.3.1 Canopy reflectance and yield relationship

The relationship between maximum NDVI and mass at untying (Chapter 5) can be expressed as:

Equation 1:

\[ Y = 19.49x^2 - 21.73x + 6.773 \]

\[ R^2 = 0.918 \]

Where

\( Y = \) Tobacco yield (t ha\(^{-1}\))

\( X = \) NDVI\(_{MSR5}\)

Therefore:

Yield = 19.49 (NDVI\(_{MSR5}\))^2 − 21.73 (NDVI\(_{MSR5}\)) + 6.773

7.3.2 The relationship between NDVI\(_{MSR5}\) and NDVI\(_{mod}\)

At any stage NDVI\(_{MSR5}\) was greater than NDVI\(_{MODIS}\) (Appendix 7.1). NDVI\(_{MODIS}\) reached a maximum of 0.6, compared to a maximum of 0.86 for NDVI\(_{MSR5}\). The overall mean NDVI\(_{MODIS}\) (0.42 ± 0.1), was less than NDVI\(_{MSR5}\) (0.58±0.25). The NDVI\(_{MSR5}\) : NDVI\(_{MODIS}\) ratio ranged from 1.00 to 2.13 and the mean ratio for the whole period was 1.37 ± 0.4 (Table 7.2).

At all the planting times there was a positive relationship between NDVI\(_{MOD}\) and NDVI\(_{MSR5}\). The coefficients of determination for NDVI\(_{MODIS}\) and NDVI\(_{MSR5}\) in the September and the October-planted crops were 0.81, 0.80 respectively, compared to 0.74 in the November-planted crop. For the December planted, the NDVI\(_{MODIS}\) and NDVI\(_{MSR5}\) relationship had a coefficient of determination (R\(^2\)) of 0.818 (Figure 7.3). The overall slopes were identical (P=0.1096) (Appendix 7.1) and, it is possible to calculate one slope for all the data (Figure 7.4). The overall NDVI\(_{MODIS}\) and NDVI\(_{MSR5}\) relationship was linear and positive (R\(^2\) = 0.73) (Equation 2).
7.3.3 Model development

Substituting (1) by (2)

Equation 3

\[ \text{Yield} = 19.49 \times (1.54 \text{ NDVI}_{\text{MODIS}} - 0.054)^2 - 21.73 \times (1.54 \text{ NDVI}_{\text{MODIS}} - 0.054) + 6.773 \]

Simplified to

\[ Y = 48.28 \times \text{NDVI}_{\text{MODIS}}^2 - 37.51 \times \text{NDVI}_{\text{MODIS}} + 8.003 \]

The average cropped area of the sampled fields was 20.5 ± 13.33 ha and from these, the average maximum calculated NDVI_{MODIS} was 0.584 ± 0.06. Tobacco yield from the sample area was calculated by multiplying the estimated yield per hectare by the area (equation 4)

Equation 4:

\[ Y_{\text{tot}} = A(48.28 \times \text{NDVI}_{\text{MODIS}}^2 - 37.51 \times \text{NDVI}_{\text{MODIS}} + 8.003) \]
Where

\( Y_{\text{tot}} \) is the total yield from a cropped area of \( A \) hectares, \( \text{NDVI}_{\text{MODIS}} \) is the average maximum MODIS satellite derived NDVI from the sampled fields.

\[
y = 48.28x^2 - 37.51x + 8.003 \\
R^2 = 1
\]

Figure 7.2: Model for tobacco yield estimation using MODIS satellite

A linear regression of the observed versus predicted tobacco yield was significant (\( p < 0.05 \)) (Figure 7.6; Appendix 7.2). Therefore, the model developed to estimate flue-cured tobacco yield by using upscaled MODIS satellite derived NDVI values is usable and accurate (95% significant level).
7.4 Discussion

The coefficients of determination among the September, October and the November tobacco yield and NDVI<sub>MSR5</sub> were comparable and had a range of 2.3%. Generally, the first two months of the tobacco season are fairly dry with low weed pressure and, the high coefficients of determination during this period could be due to absence of interference by weeds. The increase in wet conditions in November to December influenced weed growth, which may have resulted in the low in the Yield – NDVI<sub>MSR5</sub> coefficients of determination for the two crops.

The observed increase in NDVI with crop age is indicative of the increase in the canopy chlorophyll content as the crop grows (Harison and Jupp, 1989). Fasheun and Balogun (1992) suggested that the NDVI was related and sensitive to the biochemical properties of the leaf and phenological stage of crop respectively.
The higher NDVI_{MSR5} value compared to NDVI_{MODIS} could be the result of atmospheric interference. The strength of the coefficient of determination (R^2) between ground and satellite derived reflectance values in this research across all the planting time blocks (0.82 – 0.89) is comparable with the findings (R^2 = 0.84 - 0.89) of Wittamperuma (2011). When remote sensing data is collected from ground based sensors, the sensitivity of the instruments to agronomic variations is higher than that observed from satellite borne platforms due to reduced atmospheric interaction influencing ground based sensors (Ma et al., 2001). As a result, low spatial resolutions from ground sensors require an up-scaling exercise to a higher spatial resolution of satellite platforms that can enable large scale observations to be conducted simultaneously and in near real-time (William et al., 2008; Gieske, 2003) The technique then allows a more accurate comparisons of crop responses observed from two different platforms (Wang et al., 2010).

A single up-scaling model for the NDVI_{MSR5} –NDVI_{MODIS} data was finally used in the Yield – NDVI model because of the narrow range among the coefficients of determination obtained from the different land blocks that were used in the experiment. Both the number of data points used for the derivation of the pooled up-scaling factor from the field survey area and the number of fields used in the validation of the developed model (n = 38) were above the (n = 30) threshold, recommended by Gomez and Gomez (1983) as the minimum required sample size for the statistical data to approximate normal. The results can, therefore be relied upon.

Generally, the satellite derived NDVI limitations arise from spatial and temporal resolution differences as affected by sensor capabilities and environmental factors (Short, 2008). Common sources of error in satellite derived NDVI are mixed pixels that contain reflective data of two or more heterogeneous surfaces, and cannot be distinguished by the sensor (Huete, 2002) and the exhibited uncharacteristically low NDVI in the mixed pixel can be misleading (Hasen and Schjoerring, 2003)

Greater deviations of the actual yield from the expected were observed in the November and December than the September and the October-planted crops. Generally, the November and December plantings are mostly common in the smallholder sector and, in these areas, crop
records are less accurate than that of the commercial large scale tobacco growers (Wardlow et al., 2006) who mainly establish their tobacco crops in September and October with irrigation.

7.5 Conclusions

The up-scaling factor for the multispectral radiometer derived model to the MODIS derived was developed (Equation 2). The MODIS satellite derived NDVI was used to develop the tobacco yield estimation model (Equation 3). The predicted flue-cured tobacco yield (2.72 t/ha) was 88.32% of the observed yield (3.08 t/ha). A regression analysis of the observed versus predicted yield was significant. The model can be used to estimate yield of a particular tobacco field using NDVI value from satellite images. The results show that tobacco yield attributes can be estimated from the MODIS derived NDVI using the model: $Y_{tot} = A(48.28 \times NDV_{MODIS}^2 - 37.51 \times NDV_{MODIS} + 8.003)$. It is recommended that the model be used by tobacco industry to complement existing methods.
CHAPTER 8 SYNTHESIS: A NEW APPROACH TO TOBACCO YIELD ESTIMATION IN ZIMBABWE AND THE RECOMMENDED FURTHER WORK.

8.1 Introduction
Crop forecasting is the estimation of crop yields (t ha\(^{-1}\)) before the harvest. A crop forecast helps to stabilise prices on the market and provides useful information for both suppliers and buyers of the crop (Jayne et al., 2010). Crop pricing depends on the interplay between supply and demand of the crop. Buyers allocate money for buying the crop according to the crop volume expected on the market. The expected volume is essentially the quantity that is predicted by crop forecasters. If the predicted crop volume is less than the actual, a general shortage on the market will push crop prices up, while the reverse occurs for a higher crop volume than the estimated. Errors in crop estimation normally results in price distortions and general planning inefficiencies (Jayne et al., 2010).

A traditional approach to yield estimation involves two stages. The first stage involves the estimation of area under crop while the second stage involves the measuring of yield per unit area. The product of the two results gives a yield estimate. In the estimation of cropped area, forecasters use subjective methods. They use visual assessments of crop status to estimate the expected yield/unit area. These subjective results are usually extrapolated to estimate the national crop volumes. A more subjective, but tedious approach is the collection of crop area estimates from ward level, to district and provincial levels before final compilation of national crop area statistics, followed by use of the long-term average yield to get the expected volume.

The limitations of these methods are in the lack of emphasis on random selection of the samples (Craig and Atkinson, 2013). Also, some inaccessible areas can easily be left out leading to underestimations. The Department of Agriculture and Extension (AGRITEX) in the Ministry of Agriculture, Mechanisation and Irrigation Development has the mandate to carry out tobacco crop forecasts but is generally, poorly equipped in terms of transport. This could compromise the representativeness of the selected samples. The visual assessors of the selected samples may be inadequately experienced to relate the qualitative results from their observations to the actual yields. A large number of assessors often with different levels of experience with the crop are
involved in forecasting, making it difficult to standardise the approach. The hyperinflationary period of 2008-2009 led to a brain-drain in Government, leaving a large number of new and inexperienced officers. Routinely, there is more emphasis on crop area alone, and less detail on varieties, planting date, fertilizer management levels, plant population, and the farmers’ management capabilities, which all combined, have an effect on the final yield. The need for a more objective approach thus becomes critical.

There are many challenges in the estimation of crop size by the conventional survey methods. The area planted for harvest of a given crop may change throughout the growing season due to abandonment, weather damage, or unusual economic conditions leading to the neglect of the crop (Craig and Atkinson, 2013). It is usually necessary to make estimates at least three times throughout the crop season even for a given crop and there could be a need to measure prospective or intended plantings before they actually take place (Vogel, 1985).

The application of the regression approaches is based on the fact that the reflectance in the red spectral region decreases while that in the near-infrared (NIR) region increases when the vegetation density increases (Jackson and Huete, 1991). A large number of measurements is, however, needed for a regression model for biomass estimation to be derived and, the relationship is vegetation-type dependent (Toulios et al., 1998) while noise from such factors as soil substrate effect, atmospheric effect, and bidirectional properties of the vegetation can pose a challenge (Weigand et al., 1991).

The general basis of the study was that a reliable model for estimating crop yield depends on the correct selection of a suitable spectral index for assessing the general crop status in response to management in the field. The most suitable index could then be used to separate crop varieties, different planting dates and fertilizer management levels. Through the use of a suitable index the most suitable temporal windows for spectral data collection are then identified.

Using the in-season spectral indices, the volume of the area under crop and the yield/unit area would be estimated. Two approaches can then be applied to estimate the final crop yield: (1) the final yield can be estimated through fitting the remotely-sensed crop area into the long-term
yield-area model or (2) relate the canopy average maximum satellite derived NDVI to the final yield, and multiply the result by either remotely sensed or crop survey crop area estimate to get the final yield.

However, the established optimum temporal windows for collecting satellite data for purposes of tobacco yield forecasting (Chapters 4, 6) may shift due to climate change. Climate records demonstrate that Zimbabwe is already beginning to experience the effects of climate change, notably rainfall variability and extreme events (Manyeruke et al., 2013). These conditions, combined with warming trends, are expected to render land increasingly marginal for agriculture (IIED, 2013). Climatic characteristic in the Agro-ecological zones, as described by Vincent and Thomas (1960), have long since changed and several researchers have established through modern technologies like remote sensing, that the boundaries have long since shifted (Chikodzi et al., 2013), with a reported decrease of Natural Region II by 49% for example (Mugandani et al., 2012). Zimbabwe’s climatic conditions are drifting towards relatively arid conditions that are not favourable for agriculture and the dry regions, that is, region IV and V have expanded by 5.6% and 22.6% respectively (Manyeruke et al., 2013).

8.2 From a suitable reflectance index to above-ground biomass estimation

In this study the spectral indices for assessing tobacco in the field were confirmed (Chapter 3). Using the multispectral radiometer, all the five channels of the radiometer, NDVI and the SRI had a strong relationship with fertilizer application level, with both NDVI and SRI for the T66 variety being greater than those for K RK26 and KE1. Although the SRI had a stronger relationship with the biophysical parameters of above-ground dry mass, plant count/unit area and plant height than NDVI, the NDVI was selected for later activities because of a stronger relationship the index showed with total N than the SRI. The minimum threshold SRI and NDVI values for optimum growth (100% fertilizer) were 6.1 and 0.72 respectively, meaning that any crop that showed values less than these would not be optimally growing and would also produce less than optimum yields. All other conditions affecting crop production were optimum.

The results in Chapter 4 confirmed that the different planting dates, crop varieties and fertilizer application levels could be spectrally separated. The assessment of the influence of these factors
on crop yield can, therefore, be done separately. The September, October, and November-planted crops showed significant variety and fertilizer treatment differences from 10 weeks after planting, with the varieties T 66 and KRK26 showing similar reflectance values that were greater than those for KE1. The 100% and the 150% fertilizer application levels were similar and both had greater reflectance values than the 50% fertilizer application levels. All of the fertilizer and variety treatments in the December-planted crops had similar reflectance characteristics, which were lower than for the September and October plantings.

At 9-12 weeks after planting which were the optimal times for separating the varieties, planting dates and fertilizer application effect coincided with the 3rd to 4th week of November, up to the 4th week of February. The 3rd to 4th week of November was optimal for separating the irrigated September-October-planted crop from the rainfed November and December-planted crops, while the later period was important for separating the December from the November-planted crop. One can, therefore, focus on collecting satellite imagery for the two temporal windows, and calculate the reflectance values for use in estimating the whole crop area, leading to savings in time and costs reduction in data collection. There is, however, a possibility for error in separating the November from December-planted crops due to spectral confusion arising from interference of adjacent vegetation and other field crops like cotton, soybeans and maize, which could also be dominant during this later time of the growing season. However, using a combination of NDVI temporal profiles and instantaneous NDVI values as suggested by Rembold et al. (2013), this problem of spectral confusion can easily be overcome.

In Chapter 5 the relationship between tobacco canopy reflectance, leaf dry mass and cured leaf yield was investigated and the results largely confirmed the hypothesis that crop canopy spectral reflectance characteristics are directly related to biomass and final yield; and that the strength of the relationship between in-season dry mass and yields expressed as mass at untying with NDVI was not affected by tobacco variety, planting date, and fertilizer application level. The best fitting curves for the yield-NDVI regressions were quadratic. At 9–12 weeks after planting, with the highest dry mass-NDVI coefficient of determination was the optimum stage for collecting spectral data for tobacco yield estimation was the weeks after planting, thus confirming the findings of Chapter 4.
From the results in Chapter 5, NDVI can be deployed to assess crop status and the October-November crops can be combined, while the November and December-planted crops can also be combined and estimated separately. The yield and NDVI regression models for the September and the October-planted crops were statistically similar slopes ($p = 0.4238$), making it possible to come up with one regression model relating tobacco yield and NDVI for the two crops. The yield and NDVI regression models for the November and the December planted crops were also statistically similar slopes ($p = 0.5409$), making it possible to come up with one regression model relating tobacco yield and NDVI for the two crops. The slopes for the mass at untying versus NDVI curves for the three varieties, K RK 26, T 66 and K E1 ($p = 0.2198$) and slopes for the mass at untying versus NDVI curves for three fertilizer levels (50%, 100% and 150%) ($p = 0.1666$) statistically similar. This made it is possible to pool all the fertilizer levels and varieties for the mass at untying versus NDVI regression analysis without compromising the accuracy of the forecast.

8.3 A new approach to area and yield forecast

Using a suitable index, NDVI (Chapter 3), it was established that although the varieties and fertilizer application levels could be spectrally separated. The two agronomic factors had no influence on the Yield-NDVI relationship (Chapter 5). It was established that planting date effect could be separated and, the levels of accuracy of the Yield-NDVI regression models for the September-October were comparable, but different from those for the November and the December-planted crops (Chapter 5). The optimum times for collecting the imagery for such assessments were the 4th week of November to the 3rd week of March (Chapters 4 and 5).

The cloud free MODIS images covering the period September to end of March between 2010 and 2013 were downloaded and georeferenced, and NDVI from the sampled tobacco field was estimated (Chapter 6). The results of this study confirmed that, based on the MODIS derived NDVI data, the third to fourth week of November and the third to fourth week of February are the optimal times for discriminating the irrigated from the non-irrigated tobacco crops. The crop areas for the three studied seasons were estimated and yield estimates calculated from the long-term yield- area regression model. The three-season average yield estimates were 98.8 %
accurate (Chapter 6). The approach assumed that the yield-NDVI response was not affected by variety, fertilizer and planting date as established in Chapter 4 and 5.

8.4 The tobacco yield-NDVI model

In Chapter 7, an attempt to establish a direct yield NDVI model was made through up-scaling the multispectral radiometer based yield-NDVI models using MODIS satellite imagery. The tobacco yield-NDVI$_{\text{MODIS}}$ relationship was finally developed using NDVI’s extracted from the freely downloaded images from 38 randomly selected tobacco fields. A linear regression of the observed versus predicted tobacco yield was highly significant ($p <0.05$).

8.5 Contribution of the study

8.5.1 Crop science and Agronomy

This study identified NDVI as the most suitable spectral index for assessing plant canopy development in response to fertilizer management. The index was highly correlated with such biophysical parameters as plant height and stem thickness as well as total nitrogen, which are also measures of crop status and quality in the field. A rapid assessment of optimum plant canopy development and an assessment of fertilizer needs can be done using spectral techniques, with information from remote sensing being used as base maps in variable rate applications of fertilizers. This could allow stakeholders, including farmers, to focus on affected areas of the field, district or province. Problems within fields or districts can be identified remotely and remedial measures can be taken before the crop is negatively affected.

The study also established a strong relationship between crop canopy reflectance to plant growth stage and density, thus providing a rapid and reliable method for assessing plant phenology and plant population in the field. NDVI increased with progression of vegetation growth up to 9 -12 weeks, where it plateaued before a decline. The highest relationship of NDVI with tobacco leaf yield was found at between 9 -12 weeks after planting. From a standard NDVI seasonal profile, comparison of specific profiles for crops under study can be made to ascertain the management interventions required, thus providing a fast method for assessing fertilizer, crop maturity rate and planting date differences.
The study also established temporal windows for collection of satellite imagery for use in yield estimation using remote sensing. Models were developed, which showed that the vigour of the crop canopy, observed in the spectral remote sensing data, is directly related to the yield of the given crop. The models are relatively simple to routinely adopt for practical use because the remote sensing data–yield relations derived were expressed in formulae, facilitating wider application.

The study established a rapid method of assessing cropped area and for crop yield estimation. Remote sensing technology is non destructive, with data obtained systematically and repeatedly over very large geographical areas rather than just single point observations, enabling the acquisition of information from sites and fields that are not easily inaccessible.

### 8.6 Future Research

The current study has highlighted a number of possible aspects for further research. First, there is a lack of observational studies on inventory and mapping of agricultural lands using remote sensing. Future studies could focus on mapping agricultural lands and determining changes in the proportion of the arable land under different cash and food crops. The information would be useful for food security assessment and would generate more accurate national statistics for policy and planning purposes.

Assessments for the changes in the use in agricultural land would be quick and enable detection of expansion of a particular crop into agro-ecological zones where it was previously not grown. Second, national soil categorization and mapping, are recommended research areas that would assist in identifying areas for potential expansion for production of crops of economic interest.

Third, the investigation of the applicability of other spectral indices in the discrimination of crops can improve the accuracy of crop monitoring and yield estimation for Zimbabwe and the region. These include the Blue Normalized Difference Vegetation Index (BNDVI), Green Normalized Difference Vegetation Index (GNDVI) (Wang et al. (2007), Nitrogen Reflectance Index (NRI) (Penuelas et al., 1994), Chlorophyll Index (CI) (Gitelson et al., 2001), Soil Adjusted
Vegetation Index (SAVI) and Transformed Soil Adjusted Vegetation Index (TSAVI) (Ricky et al., 1998).

Fourth, further study is required on the applicability of other choices of temporal NDVI integration, ranging from maximum NDVI value of the season, the average of the peak values (plateau) to the sum of the NDVI values of the total crop cycle. Instead of using a fixed value from instantaneous measurements, the integral could be computed between the start of the growing period and the beginning of the descending phase.

Fifth, research on the use of remote sensing for routine crop production management and crop condition assessment is recommended as part of the ultimate goal in crop yield estimation. Such studies should include use of remotely sensed images to identify nutrient deficiencies, diseases, water deficiency or surplus, weed infestations, insect damage, hail damage, wind damage, herbicide damage, and plant populations as well as estimation of agro meteorology parameters. The final yield estimate would then pool the effects of all these factors.
REFERENCES


Boegh, E., H. Soegaard, N. Broge et al. (2002). Airborne multispectral data for quantifying leaf


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Kyllo, K. P. (2003). NASA funded research on agricultural remote sensing, Department of Space Studies, University of North Dakota.


http://www.a-a-r-s.org/aars/proceeding/ACRS1994/Papers/AGS94-3.htm

Accessed on 19 November, 2008


National Aeronautics and Space Administration (NASA), 2013. MODIS.


Tobacco Research Board (TRB) (2012). Annual report and Accounts for the Year
   Ended 30 June, 2011. TRB, Harare

   satellite images and cotton yield maps to evaluate field variability inprecision farming.

Trocaire, 2013. Climate change hitting Zimbabwe's farmers hard. Reliefweb.


   National Agricultural Statistics Service and Office of the Chief Economist, World
   Agricultural Outlook Board Miscellaneous Publication Number 1554, Washington DC, 20250

   spectroscopy to study ecosystem processes and properties. BioScience. Volume 54,
   Number 6: Pages 523–534.

   yield maps. ASAE Annual International Meeting. Toronto, Ontario, Canada. ASAE, St.
   Joseph, MI.

   of vegetation indices from multi-angular Chris/PROBA data. International Archives of
   Photogrammetry, Remote Sensing and Spatial Information Sciences (ISPRS) Commission
   VII Mid-term symposium, Enschede, Netherlands: 677-683.


### Appendix 3.1: Analysis of the relationship between channel 1 (450 – 520nm) reflectance for K RK 26, T 66 and K E1 and the fertilizer application level

<table>
<thead>
<tr>
<th>Reflectance (%)</th>
<th>Reflectance (%)</th>
<th>Reflectance (%)</th>
<th>Pooled (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Best-fit values</strong></td>
<td><strong>K RK 26</strong></td>
<td><strong>T 66</strong></td>
<td><strong>K E1</strong></td>
</tr>
<tr>
<td>Slope</td>
<td>-0.01133 ±</td>
<td>-0.01347 ±</td>
<td>-0.01510 ±</td>
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<tr>
<td>Y-intercept when X=0.0</td>
<td>12.47 ± 0.5935</td>
<td>13.04 ± 1.110</td>
<td>13.47 ± 0.2734</td>
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<td>1/slope</td>
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<td>95% Confidence Intervals</td>
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<td></td>
</tr>
<tr>
<td>Slope</td>
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<td>-0.03196 to -0.005027</td>
<td>-0.01965 to -0.01054</td>
</tr>
<tr>
<td>Y-intercept when X=0.0</td>
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<td>8.269 to 17.82</td>
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</tr>
<tr>
<td>X-intercept when Y=0.0</td>
<td>672.2 to 7243</td>
<td>506.2 to +infinity</td>
<td>728.1 to 1193</td>
</tr>
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<td>Goodness of Fit</td>
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<tr>
<td>R square</td>
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<td>Sy.x</td>
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<td>Is slope significantly non-zero?</td>
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<td>1.000, 2.000</td>
<td>1.000, 2.000</td>
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<td>Equation</td>
<td>Y = -0.01133*X</td>
<td>Y = -0.01347*X</td>
<td>Y = -0.01510*X</td>
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Appendix 3.2: Analysis of the relationship between channel 2 (520-600nm) reflectance for K RK 26, T 66 and K E1 and the fertilizer application level

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<th>Best-fit values</th>
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<th>Reflectance (%)</th>
<th>Pooled</th>
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<td></td>
<td>K RK 26</td>
<td>T 66</td>
<td>K E1</td>
<td></td>
</tr>
<tr>
<td>Slope</td>
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<td>-0.01365 ±</td>
<td>-0.01510 ±</td>
<td>-0.01336 ±</td>
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<td>Y-intercept when X=0.0</td>
<td>12.47 ± 0.5935</td>
<td>13.08 ± 1.034</td>
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<tr>
<td>Equation</td>
<td>Y = -0.01133*X</td>
<td>Y = -0.01365*X</td>
<td>Y = -0.01510*X</td>
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<td>+ 12.47</td>
<td>+ 13.08</td>
<td>+ 13.47</td>
<td>+ 13.00</td>
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Appendix 3.3: Analysis of the relationship between channel 3 (630 – 690 nm) reflectance for K RK 26, T 66 and K E1 and the fertilizer application level

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<th>Best-fit values</th>
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<td></td>
<td>K RK 26</td>
<td>T 66</td>
<td>K E1</td>
<td></td>
</tr>
<tr>
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<tr>
<td>95% Confidence Intervals</td>
<td>-0.05603 to 0.01433 to 0.01348 to 0.01529</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slope</td>
<td>0.02218 ±</td>
<td>0.02578 ±</td>
<td>0.02294 ±</td>
<td></td>
</tr>
<tr>
<td>Y-intercept when X=0.0</td>
<td>13.21 ± 2.387</td>
<td>14.00 ± 0.7381</td>
<td>13.11 ± 0.8858</td>
<td></td>
</tr>
<tr>
<td>X-intercept when Y=0.0</td>
<td>595.4</td>
<td>543.0</td>
<td>571.6</td>
<td></td>
</tr>
<tr>
<td>1/slope</td>
<td>45.08</td>
<td>38.78</td>
<td>43.60</td>
<td></td>
</tr>
<tr>
<td>95% Confidence Intervals</td>
<td>0.02578 ± to 0.0294 ±</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slope</td>
<td>0.02578 ±</td>
<td>0.02294 ±</td>
<td>0.02294 ±</td>
<td></td>
</tr>
<tr>
<td>Y-intercept when X=0.0</td>
<td>14.00 ± 0.7381</td>
<td>13.11 ± 0.8858</td>
<td></td>
<td></td>
</tr>
<tr>
<td>X-intercept when Y=0.0</td>
<td>543.0</td>
<td>571.6</td>
<td>571.6</td>
<td></td>
</tr>
<tr>
<td>1/slope</td>
<td>38.78</td>
<td>43.60</td>
<td>43.60</td>
<td></td>
</tr>
<tr>
<td>95% Confidence Intervals</td>
<td>0.02294 ± to 0.02578 ±</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R square</td>
<td>0.7648</td>
<td>0.7422</td>
<td>0.9760</td>
<td>0.8172</td>
</tr>
<tr>
<td>Sy.x</td>
<td>2.523</td>
<td>2.853</td>
<td>0.8822</td>
<td>1.834</td>
</tr>
<tr>
<td>Is slope significantly non-zero?</td>
<td>Not Significant</td>
<td>Not Significant</td>
<td>Significant</td>
<td>Significant</td>
</tr>
<tr>
<td>F</td>
<td>6.502</td>
<td>5.757</td>
<td>81.34</td>
<td>44.69</td>
</tr>
<tr>
<td>DFn, DFd</td>
<td>1.000, 2.000</td>
<td>1.000, 2.000</td>
<td>1.000, 2.000</td>
<td>1.000, 10.00</td>
</tr>
<tr>
<td>P value</td>
<td>0.1255</td>
<td>0.1385</td>
<td>0.0121</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Deviation from zero?</td>
<td>Not Significant</td>
<td>Not Significant</td>
<td>Significant</td>
<td>Significant</td>
</tr>
<tr>
<td>Equation</td>
<td>Y = -0.02085*X</td>
<td>Y = -0.02218*X</td>
<td>Y = -0.02578*X</td>
<td>Y = -0.02294*X</td>
</tr>
<tr>
<td></td>
<td>+ 12.13</td>
<td>+ 13.21</td>
<td>+ 14.00</td>
<td>+ 13.11</td>
</tr>
</tbody>
</table>
Appendix 3.4: Analysis of the relationship between channel 4 (760 – 900 nm) reflectance for K RK 26, T 66 and K E1 and the fertilizer application level

<table>
<thead>
<tr>
<th>Best-fit values</th>
<th>Reflectance (%)</th>
<th>Reflectance (%)</th>
<th>Reflectance (%)</th>
<th>Pooled</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>K RK 26</td>
<td>T 66</td>
<td>K E1</td>
<td></td>
</tr>
<tr>
<td>Slope</td>
<td>0.04071 ±</td>
<td>0.04244 ±</td>
<td>0.04419 ±</td>
<td>0.04245 ±</td>
</tr>
<tr>
<td>Y-intercept when X=0.0</td>
<td>0.01365</td>
<td>0.01714</td>
<td>0.004449</td>
<td>0.006025</td>
</tr>
<tr>
<td>X-intercept when Y=0.0</td>
<td>25.77 ± 3.525</td>
<td>24.34 ± 4.424</td>
<td>23.06 ± 1.149</td>
<td>24.39 ± 1.556</td>
</tr>
<tr>
<td>1/slope</td>
<td>24.56</td>
<td>23.56</td>
<td>22.63</td>
<td>23.56</td>
</tr>
<tr>
<td>95% Confidence Intervals</td>
<td>-0.01804 to</td>
<td>-0.03129 to</td>
<td>0.02505 to</td>
<td>0.02902 to</td>
</tr>
<tr>
<td></td>
<td>0.09947</td>
<td>0.1162</td>
<td>0.06333</td>
<td>0.05587</td>
</tr>
<tr>
<td>Y-intercept when X=0.0</td>
<td>10.60 to 40.94</td>
<td>5.302 to 43.37</td>
<td>18.12 to 28.00</td>
<td>20.92 to 27.86</td>
</tr>
<tr>
<td>X-intercept when Y=0.0</td>
<td>-infinity to -116.2</td>
<td>-infinity to -51.08</td>
<td>-1086 to -294.5</td>
<td>-940.9 to -382.0</td>
</tr>
<tr>
<td>Goodness of Fit</td>
<td>R square</td>
<td>0.8164</td>
<td>0.7541</td>
<td>0.9801</td>
</tr>
<tr>
<td></td>
<td>Sy.x</td>
<td>4.213</td>
<td>5.288</td>
<td>1.373</td>
</tr>
<tr>
<td>Is slope significantly non-zero?</td>
<td>F</td>
<td>8.890</td>
<td>6.134</td>
<td>98.66</td>
</tr>
<tr>
<td></td>
<td>DFn, DFd</td>
<td>1.000, 2.000</td>
<td>1.000, 2.000</td>
<td>1.000, 2.000</td>
</tr>
<tr>
<td></td>
<td>P value</td>
<td>0.0965</td>
<td>0.1316</td>
<td>0.0100</td>
</tr>
<tr>
<td>Deviation from zero?</td>
<td>Not Significant</td>
<td>Not Significant</td>
<td>Significant</td>
<td>Significant</td>
</tr>
</tbody>
</table>

Equation
Y = 0.04071*X + Y = 0.04244*X + Y = 0.04419*X + Y = 0.04245*X + 

Equation
25.77          24.34          23.06          24.39
### Appendix 3.5: Analysis of the relationship between channel 5(1550 – 1750 nm) reflectance for K RK 26, T 66 and K E1 and the fertilizer application level

Best-fit values

<table>
<thead>
<tr>
<th>Reflectance (%)</th>
<th>Reflectance (%)</th>
<th>Reflectance (%)</th>
<th>Pooled</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>K RK 26</td>
<td>T 66</td>
<td>K E1</td>
</tr>
<tr>
<td>Slope</td>
<td>-0.01351 ±</td>
<td>-0.01324 ±</td>
<td>-0.01703 ±</td>
</tr>
<tr>
<td></td>
<td>0.007463</td>
<td>0.007110</td>
<td>0.005157</td>
</tr>
<tr>
<td>Y-intercept when X=0.0</td>
<td>17.68 ± 1.927</td>
<td>18.30 ± 1.836</td>
<td>18.86 ± 1.331</td>
</tr>
<tr>
<td>X-intercept when Y=0.0</td>
<td>1309</td>
<td>1382</td>
<td>1108</td>
</tr>
<tr>
<td>1/slope</td>
<td>-74.02</td>
<td>-75.53</td>
<td>-58.74</td>
</tr>
<tr>
<td>95% Confidence Intervals</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slope</td>
<td>-0.04562 to</td>
<td>-0.04383 to</td>
<td>-0.03921 to</td>
</tr>
<tr>
<td></td>
<td>0.01860</td>
<td>0.01736</td>
<td>0.005164</td>
</tr>
<tr>
<td>Y-intercept when X=0.0</td>
<td>9.388 to 25.97</td>
<td>10.40 to 26.20</td>
<td>13.13 to 24.59</td>
</tr>
<tr>
<td>X-intercept when Y=0.0</td>
<td>506.9 to +infinity</td>
<td>538.0 to +infinity</td>
<td>580.8 to +infinity</td>
</tr>
</tbody>
</table>

**Goodness of Fit**

<table>
<thead>
<tr>
<th>R square</th>
<th>Sy.x</th>
<th>Is slope significantly non-zero?</th>
<th>F</th>
<th>DFn, DFd</th>
<th>P value</th>
<th>Deviation from zero?</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.6210</td>
<td>2.303</td>
<td>Not Significant</td>
<td>3.277</td>
<td>1.000, 2.000</td>
<td>0.2120</td>
<td>Not Significant</td>
</tr>
<tr>
<td>0.6342</td>
<td>2.194</td>
<td>Not Significant</td>
<td>3.467</td>
<td>1.000, 2.000</td>
<td>0.2037</td>
<td>Not Significant</td>
</tr>
<tr>
<td>0.8450</td>
<td>1.591</td>
<td>Not Significant</td>
<td>10.90</td>
<td>1.000, 2.000</td>
<td>0.0808</td>
<td>Not Significant</td>
</tr>
<tr>
<td>0.6918</td>
<td>1.646</td>
<td>Not Significant</td>
<td>22.45</td>
<td>1.000, 10.00</td>
<td>0.0008</td>
<td>Significant</td>
</tr>
</tbody>
</table>

Equation

\[
Y = -0.01351X + 17.68 \\
Y = -0.01324X + 18.30 \\
Y = -0.01703X + 18.86 \\
Y = 0.01459X + 18.28
\]
Appendix 3.6: Analysis of variance of (a) NDVI and (b) SRI for 72 days after sowing

a.  

<table>
<thead>
<tr>
<th>Source of variation</th>
<th>d.f.</th>
<th>s.s.</th>
<th>m.s.</th>
<th>v.r.</th>
<th>F</th>
<th>pr.</th>
</tr>
</thead>
<tbody>
<tr>
<td>block stratum</td>
<td>3</td>
<td>0.006864</td>
<td>0.002288</td>
<td>0.29</td>
<td></td>
<td></td>
</tr>
<tr>
<td>block.<em>Units</em> stratum</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>variety</td>
<td>2</td>
<td>0.058759</td>
<td>0.029380</td>
<td>3.74</td>
<td>0.034</td>
<td></td>
</tr>
<tr>
<td>nitrogen</td>
<td>3</td>
<td>3.229603</td>
<td>1.076534</td>
<td>136.94</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>variety x nitrogen</td>
<td>6</td>
<td>0.231805</td>
<td>0.038634</td>
<td>4.91</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>Residual</td>
<td>33</td>
<td>0.259429</td>
<td>0.007861</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>47</td>
<td>3.786459</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

b.  

<table>
<thead>
<tr>
<th>Source of variation</th>
<th>d.f.</th>
<th>s.s.</th>
<th>m.s.</th>
<th>v.r.</th>
<th>F</th>
<th>pr.</th>
</tr>
</thead>
<tbody>
<tr>
<td>block stratum</td>
<td>3</td>
<td>5.244</td>
<td>1.748</td>
<td>0.56</td>
<td></td>
<td></td>
</tr>
<tr>
<td>block.<em>Units</em> stratum</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>variety</td>
<td>2</td>
<td>7.435</td>
<td>3.717</td>
<td>1.19</td>
<td>0.316</td>
<td></td>
</tr>
<tr>
<td>nitrogen</td>
<td>3</td>
<td>696.315</td>
<td>232.105</td>
<td>74.47</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>variety x nitrogen</td>
<td>6</td>
<td>50.029</td>
<td>8.338</td>
<td>2.68</td>
<td>0.032</td>
<td></td>
</tr>
<tr>
<td>Residual</td>
<td>33</td>
<td>102.853</td>
<td>3.117</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>47</td>
<td>861.876</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Appendix 3.7: Summary of NDVI and SRI for all the variety x fertilizer application levels

<table>
<thead>
<tr>
<th>Fertilizer level</th>
<th>Simple ratio index</th>
<th>NDVI</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1.52-1.78</td>
<td>0.21-0.28</td>
</tr>
<tr>
<td>50</td>
<td>1.92-5.16</td>
<td>0.38-0.67</td>
</tr>
<tr>
<td>100</td>
<td>6.10-7.41</td>
<td>0.72-0.76</td>
</tr>
<tr>
<td>150</td>
<td>8.34-10.5</td>
<td>0.79-0.83</td>
</tr>
</tbody>
</table>
### Appendix 4.1: Optimum times for discriminating crops for different planting times

<table>
<thead>
<tr>
<th>Weeks from September 1</th>
<th>Spectrally Dominant Crop</th>
<th>Crop Area (A)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 – 9</td>
<td>September (s)</td>
<td>$A = A_s$ only</td>
</tr>
<tr>
<td>10 - 12</td>
<td>September (s) + October (o)</td>
<td>$A = A_s + A_o$ ($A_s &gt; A_o$)</td>
</tr>
<tr>
<td>13 - 15</td>
<td>September (s), October (o) and November (n)</td>
<td>$A = A_s + A_o + A_n$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$NDVI_o &gt; NDVI_s &gt; NDVI_n$</td>
</tr>
<tr>
<td>16 - 18</td>
<td>October (o), November (n)</td>
<td>$A = A_o + A_n$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$NDVI_o \geq NDVI_n$</td>
</tr>
<tr>
<td>18 - 20</td>
<td>October (o), November (n), December (d)</td>
<td>$A = A_o + A_n + A_d$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$(NDVI_o = NDVI_n) \geq NDVI_d$</td>
</tr>
<tr>
<td>20 - 22</td>
<td>November (n), December (d)</td>
<td>$A = A_o + A_n + A_d$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$NDVI_o = NDVI_n = NDVI_d$</td>
</tr>
<tr>
<td>23 - 26</td>
<td>December (d)</td>
<td>$A = A_d$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$NDVI_d$ only</td>
</tr>
</tbody>
</table>

**Where**

1. $A = $ Crop Area
2. $A_s, A_o, A_n, A_d$ = Areas for the September, October, November and December crops
3. $NDVI_s, NDVI_o, NDVI_n, NDVI_d = NDVI$ for the September, October, November and December crops
Appendix 5.1: Comparison of mass at untying -NDVI relationships for the September, October, November and December planted crops.

<table>
<thead>
<tr>
<th>Best-fit values</th>
<th>September Mass at untying (kg ha⁻¹)</th>
<th>October Mass at untying (kg/ha)</th>
<th>November Mass at untying (kg ha⁻¹)</th>
<th>December Mass at untying (kg ha⁻¹)</th>
<th>Pooled Mass at Untying</th>
</tr>
</thead>
<tbody>
<tr>
<td>B0</td>
<td>1908</td>
<td>2200</td>
<td>1178</td>
<td>826.8</td>
<td>1268</td>
</tr>
<tr>
<td>B1</td>
<td>13932</td>
<td>7577</td>
<td>1402</td>
<td>2624</td>
<td>6909</td>
</tr>
<tr>
<td>Mean X</td>
<td>= 0.8031</td>
<td>= 0.8334</td>
<td>= 0.6906</td>
<td>= 0.6153</td>
<td>= 0.7328</td>
</tr>
<tr>
<td>B2</td>
<td>18166</td>
<td>-97910</td>
<td>-12877</td>
<td>-27803</td>
<td>22305</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Std. Error</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>B0</td>
<td>167.5</td>
<td>90.36</td>
<td>53.66</td>
<td>70.52</td>
<td>61.40</td>
</tr>
<tr>
<td>B1</td>
<td>3030</td>
<td>3259</td>
<td>740.8</td>
<td>1235</td>
<td>437.8</td>
</tr>
<tr>
<td>B2</td>
<td>83603</td>
<td>152544</td>
<td>9227</td>
<td>30798</td>
<td>4958</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>95% Confidence Intervals</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>B0</td>
<td>1498 to 2318</td>
<td>1968 to 2432</td>
<td>1047 to 1309</td>
<td>654.2 to 999.3</td>
<td>1143 to 1393</td>
</tr>
<tr>
<td>B1</td>
<td>6518 to 21345</td>
<td>15955</td>
<td>-411.1 to 3214</td>
<td>-397.6 to 5645</td>
<td>7801</td>
</tr>
<tr>
<td>B2</td>
<td>-186410 to 222741</td>
<td>940010 to 29479</td>
<td>-35455 to 9701</td>
<td>-103165 to 47559</td>
<td>32409</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Goodness of Fit</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Degrees of Freedom</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>32</td>
</tr>
<tr>
<td>R square</td>
<td>0.792</td>
<td>0.639</td>
<td>0.695</td>
<td>0.5160</td>
<td>0.8882</td>
</tr>
<tr>
<td>Absolute Sum of Squares</td>
<td>643799</td>
<td>162686</td>
<td>75815</td>
<td>129736</td>
<td>1.700e+006</td>
</tr>
<tr>
<td>Sy.x</td>
<td>327.6</td>
<td>180.4</td>
<td>112.4</td>
<td>147.0</td>
<td>230.5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Constraints</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean X</td>
<td>Mean X = 0.8031</td>
<td>Mean X = 0.8334</td>
<td>Mean X = 0.6906</td>
<td>Mean X = 0.6153</td>
<td>Mean X = 0.7328</td>
</tr>
<tr>
<td>Number of points Analysed</td>
<td>9</td>
<td>8</td>
<td>9</td>
<td>9</td>
<td>35</td>
</tr>
</tbody>
</table>

155
Appendix 5.2: A comparison of Mass at untying -NDVI relationships for the September and the October planted crops.

<table>
<thead>
<tr>
<th>Best-fit values</th>
<th>September mass at untying (t ha(^{-1}))</th>
<th>October mass at untying (t ha(^{-1}))</th>
<th>Pooled mass at untying (t ha(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope</td>
<td>12.60 ± 3.016</td>
<td>8.196 ± 2.953</td>
<td>11.30 ± 1.865</td>
</tr>
<tr>
<td>Y-intercept when</td>
<td>-8.244 ± 2.429</td>
<td>-4.672 ± 2.462</td>
<td>-7.227 ± 1.529</td>
</tr>
<tr>
<td>X=0.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X-intercept when</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y=0.0</td>
<td>0.6541</td>
<td>0.5700</td>
<td>0.6395</td>
</tr>
<tr>
<td>1/slope</td>
<td>0.07935</td>
<td>0.1220</td>
<td>0.08849</td>
</tr>
<tr>
<td>95% Confidence Intervals</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slope</td>
<td>5.223 to 19.98</td>
<td>0.9699 to 15.42</td>
<td>7.299 to 15.30</td>
</tr>
<tr>
<td>Y-intercept when</td>
<td>-14.19 to -2.299</td>
<td>-10.70 to 1.353</td>
<td>-10.51 to -3.947</td>
</tr>
<tr>
<td>X=0.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X-intercept when</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y=0.0</td>
<td>0.4384 to 0.7129</td>
<td>-1.393 to 0.6941</td>
<td>0.5400 to 0.6877</td>
</tr>
<tr>
<td>Goodness of Fit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R square</td>
<td>0.793</td>
<td>0.639</td>
<td>0.7300</td>
</tr>
<tr>
<td>Sy.x</td>
<td>0.3508</td>
<td>0.1711</td>
<td>0.2652</td>
</tr>
<tr>
<td>Is slope significantly non-zero?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>17.46</td>
<td>7.703</td>
<td>36.70</td>
</tr>
<tr>
<td>DFn, DFd</td>
<td>1.000, 6.000</td>
<td>1.000, 6.000</td>
<td>1.000, 14.00</td>
</tr>
<tr>
<td>P value</td>
<td>0.0058</td>
<td>0.0322</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Deviation from zero?</td>
<td>Significant</td>
<td>Significant</td>
<td>Significant</td>
</tr>
<tr>
<td>Overall p = 0.4238</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Appendix 5.3: A comparison of mass at untying -NDVI relationships for the November and the December planted crops.

<table>
<thead>
<tr>
<th>Best-fit values</th>
<th>November mass at untying (t ha(^{-1}))</th>
<th>December mass at untying (t ha(^{-1}))</th>
<th>Pooled mass at untying (t ha(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope</td>
<td>2.045 ± 0.6179</td>
<td>2.854 ± 1.192</td>
<td>3.025 ± 0.5260</td>
</tr>
<tr>
<td>Y-intercept when X=0.0</td>
<td>-0.2880 ± 0.4286</td>
<td>-0.9752 ± 0.7348</td>
<td>-1.023 ± 0.3452</td>
</tr>
<tr>
<td>X-intercept when Y=0.0</td>
<td>0.1408</td>
<td>0.3417</td>
<td>0.3380</td>
</tr>
<tr>
<td>1/slope</td>
<td>0.4889</td>
<td>0.3504</td>
<td>0.3306</td>
</tr>
<tr>
<td>95% Confidence Intervals</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slope</td>
<td>0.5838 to 3.507</td>
<td>0.03556 to 5.672</td>
<td>1.910 to 4.140</td>
</tr>
<tr>
<td>Y-intercept when X=0.0</td>
<td>-1.302 to 0.7256</td>
<td>-2.713 to 0.7627</td>
<td>-1.754 to -0.2908</td>
</tr>
<tr>
<td>X-intercept when Y=0.0</td>
<td>-1.238 to 0.3726</td>
<td>-21.34 to 0.4806</td>
<td>0.1517 to 0.4254</td>
</tr>
<tr>
<td>Goodness of Fit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R square</td>
<td>0.695</td>
<td>0.515</td>
<td>0.685</td>
</tr>
<tr>
<td>Sy.x</td>
<td>0.1196</td>
<td>0.1451</td>
<td>0.1467</td>
</tr>
<tr>
<td>Is slope significantly non-zero?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>10.95</td>
<td>5.735</td>
<td>33.07</td>
</tr>
<tr>
<td>DFn, DFd</td>
<td>1.000, 7.000</td>
<td>1.000, 7.000</td>
<td>1.000, 16.00</td>
</tr>
<tr>
<td>P value</td>
<td>0.0129</td>
<td>0.0478</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Deviation from zero?</td>
<td>Significant</td>
<td>Significant</td>
<td>Significant</td>
</tr>
<tr>
<td>Overall p = 0.5409</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Appendix 5.4: Analyses of the variety yield - NDVI regressions

<table>
<thead>
<tr>
<th>Best-fit values</th>
<th>K RK 26 mass at untying (kg ha(^{-1}))</th>
<th>T 66 mass at untying (kg ha(^{-1}))</th>
<th>K E1 mass at untying (kg ha(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope</td>
<td>4566 ± 923.9</td>
<td>7223 ± 1435</td>
<td>4944 ± 847.3</td>
</tr>
<tr>
<td>Y-intercept when X=0.0</td>
<td>-1697 ± 667.5</td>
<td>-3722 ± 1071</td>
<td>-2301 ± 619.0</td>
</tr>
<tr>
<td>X-intercept when Y=0.0</td>
<td>0.3717</td>
<td>0.5153</td>
<td>0.4653</td>
</tr>
<tr>
<td>1/slope</td>
<td>0.0002190</td>
<td>0.0001385</td>
<td>0.0002023</td>
</tr>
</tbody>
</table>

95% Confidence Intervals

| Slope           | 2476 to 6656                            | 3978 to 10468                          | 3056 to 6832                           |
| Y-intercept when X=0.0 | -3207 to -187.1                        | -6145 to -1298                         | -3680 to -921.6                        |
| X-intercept when Y=0.0 | 0.07470 to 0.4875                      | 0.3232 to 0.5929                      | 0.2986 to 0.5440                      |

Goodness of Fit

<table>
<thead>
<tr>
<th></th>
<th>K RK 26</th>
<th>T 66</th>
<th>K E1</th>
</tr>
</thead>
<tbody>
<tr>
<td>R square</td>
<td>0.748</td>
<td>0.773</td>
<td>0.860</td>
</tr>
<tr>
<td>Sy.x</td>
<td>350.1</td>
<td>419.6</td>
<td>298.1</td>
</tr>
<tr>
<td>Is slope significantly non-zero?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>24.42</td>
<td>25.35</td>
<td>34.04</td>
</tr>
<tr>
<td>DFn, DFd</td>
<td>1.000, 9.000</td>
<td>1.000, 9.000</td>
<td>1.000, 10.00</td>
</tr>
<tr>
<td>P value</td>
<td>0.0008</td>
<td>0.0007</td>
<td>0.0002</td>
</tr>
<tr>
<td>Deviation from zero?</td>
<td>Significant</td>
<td>Significant</td>
<td>Significant</td>
</tr>
<tr>
<td>Overall p value</td>
<td>=0.2198</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Appendix 5.5: Analyses of the variety fertiliser level - NDVI regressions

<table>
<thead>
<tr>
<th>Best-fit values</th>
<th>50 % fert mass at untying (kg ha(^{-1}))</th>
<th>100 % fert mass at untying (kg ha(^{-1}))</th>
<th>150 % fert mass at untying (kg ha(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope</td>
<td>5009 ± 544.6</td>
<td>6819 ± 483.9</td>
<td>6607 ± 1061</td>
</tr>
<tr>
<td>Y-intercept when X=0.0</td>
<td>-2076 ± 376.6</td>
<td>-3523 ± 362.2</td>
<td>-3389 ± 810.6</td>
</tr>
<tr>
<td>X-intercept when Y=0.0</td>
<td>0.4144</td>
<td>0.5166</td>
<td>0.5129</td>
</tr>
<tr>
<td>1/slope</td>
<td>0.0001996</td>
<td>0.0001466</td>
<td>0.0001513</td>
</tr>
<tr>
<td>95% Confidence Intervals</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slope</td>
<td>3777 to 6241</td>
<td>5741 to 7897</td>
<td>4244 to 8970</td>
</tr>
<tr>
<td>Y-intercept when X=0.0</td>
<td>-2928 to -1224</td>
<td>-4330 to -2716</td>
<td>-5195 to -1583</td>
</tr>
<tr>
<td>X-intercept when Y=0.0</td>
<td>0.3214 to 0.4730</td>
<td>0.4715 to 0.5502</td>
<td>0.3698 to 0.5841</td>
</tr>
<tr>
<td>Goodness of Fit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R square</td>
<td>0.9039</td>
<td>0.9521</td>
<td>0.7951</td>
</tr>
<tr>
<td>Sy.x</td>
<td>207.8</td>
<td>146.0</td>
<td>355.6</td>
</tr>
<tr>
<td>Is slope significantly non-zero?</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>84.61</td>
<td>198.6</td>
<td>38.81</td>
</tr>
<tr>
<td>DFn, DFd</td>
<td>1.000, 9.000</td>
<td>1.000, 10.00</td>
<td>1.000, 10.00</td>
</tr>
<tr>
<td>P value</td>
<td>&lt; 0.0001</td>
<td>&lt; 0.0001</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>Deviation from zero?</td>
<td>Significant</td>
<td>Significant</td>
<td>Significant</td>
</tr>
<tr>
<td>Overal p = 0.16666</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Appendix 6.1: The final area (ha) and yield (mkg) estimates for the 2010-13 seasons, after applying a long-term crop yield-area relationship

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>2010-2011</td>
<td>72944</td>
<td>57180</td>
<td>130718</td>
<td>160000</td>
<td>133000</td>
<td>98.3</td>
<td>120.3</td>
</tr>
<tr>
<td>2011-2012</td>
<td>76712</td>
<td>67318</td>
<td>141438</td>
<td>170000</td>
<td>143886</td>
<td>98.3</td>
<td>118.1</td>
</tr>
<tr>
<td>2012-2013</td>
<td>86586</td>
<td>107000</td>
<td>165600</td>
<td>170000</td>
<td>166000</td>
<td>99.8</td>
<td>102.4</td>
</tr>
<tr>
<td>Average</td>
<td>78747</td>
<td>77166</td>
<td>145919</td>
<td>163333</td>
<td>147629</td>
<td>98.8</td>
<td>112.9</td>
</tr>
</tbody>
</table>
Appendix 7.1: Analyses of the Cropscan versus THE MODIS upscaling regressions for the September, October, November and December planted crops.

<table>
<thead>
<tr>
<th>Best-fit values</th>
<th>September planted crop</th>
<th>October planted crop</th>
<th>November planted crop</th>
<th>December planted crop</th>
<th>Combined</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope</td>
<td>2.125 ± 0.3004</td>
<td>1.905 ± 0.3027</td>
<td>1.557 ± 0.2992</td>
<td>1.145 ± 0.2293</td>
<td>1.531 ± 0.1487</td>
</tr>
<tr>
<td>Y-intercept when X=0.0</td>
<td>-0.1945 ± 0.1311</td>
<td>-0.05662 ± 0.1284</td>
<td>0.1054 ± 0.08150</td>
<td>-0.06493 ± 0.06410</td>
<td></td>
</tr>
<tr>
<td>X-intercept when Y=0.0</td>
<td>0.1993</td>
<td>0.1021</td>
<td>0.03636</td>
<td>-0.09207</td>
<td>0.04242</td>
</tr>
<tr>
<td>1/slope</td>
<td>0.4706</td>
<td>0.5249</td>
<td>0.6421</td>
<td>0.8731</td>
<td>0.6533</td>
</tr>
</tbody>
</table>

95% Confidence Intervals

| Slope                    | 1.446 to 2.805         | 1.231 to 2.580       | 0.8807 to 2.234       | 0.5843 to 1.706       | 1.230 to 1.831  |
| Y-intercept when X=0.0   | -0.7488 to -0.09837    | -0.4865 to 0.09760   | -0.3470 to 0.2337     | -0.09398 to 0.3049    | -0.1945 to 0.06461 |
| X-intercept when Y=0.0   | 0.06698 to 0.2712      | -0.07813 to 0.1914   | -0.2593 to 0.1589     | -0.5038 to 0.05704    | -0.05197 to 0.1073 |

Goodness of Fit

| R square                 | 0.813                  | 0.801                | 0.747                 | 0.818                 | 0.726           |
| Sy.x                     | 0.1145                 | 0.1140               | 0.1311                | 0.09514               | 0.1283          |

Is slope significantly non-zero?

| F                        | 50.04                  | 39.62                | 27.10                 | 24.95                 | 106.0           |
| DFn, DFd                 | 1.000, 9.000           | 1.000, 10.00         | 1.000, 9.000          | 6.000                 | 40.00           |
| P value                  | < 0.0001               | < 0.0001             | 0.0006                | 0.0025                | < 0.0001        |

Deviation from zero?       | Significant            | Significant          | Significant           | Significant           | Significant      |
Appendix 7.2: Regression analysis of the observed versus predicted tobacco yields (t ha⁻¹)

<table>
<thead>
<tr>
<th>Best-fit values</th>
<th>Observed tobacco yield (t ha⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope</td>
<td>0.7840 ± 0.07141</td>
</tr>
<tr>
<td>Y-intercept when X=0.0</td>
<td>0.9133 ± 0.2056</td>
</tr>
<tr>
<td>X-intercept when Y=0.0</td>
<td>-1.165</td>
</tr>
<tr>
<td>1/slope</td>
<td>1.276</td>
</tr>
</tbody>
</table>

95% Confidence Intervals

| Slope           | 0.6391 to 0.9289                |
| Y-intercept when X=0.0 | 0.4961 to 1.331                |
| X-intercept when Y=0.0 | -2.059 to -0.5400              |

Goodness of Fit

| R square | 0.7700 |
| Sy.x     | 0.5075 |

Is slope significantly non-zero?

| F         | 120.5  |
| DFn, DFd  | 1.000, 36.00 |
| P value   | < 0.0001 |

Deviation from zero?

| Significant |

Data

| Number of X values | 38 |
| Maximum number of Y replicates | 1 |
| Total number of values | 38 |
| Number of missing values | 0 |

Runs test

| Points above line | 21 |
| Points below line | 17 |
| Number of runs?? [X not in order]. | 10 |

Equation

\[ Y = 0.7840X + 0.9133 \]
CURRICULUM VITAE

Ezekia Svitwa was born on 2 September 1964 in the then City of Umtali (now Mutare) in the Manicaland Province of Zimbabwe. He started his primary education in 1972, only to complete the seven year course in 1981 after a three year disturbance between 1976 -1979 due to the war of liberation. He joined St Patrick’s Nyanyadzi Secondary School, in the Chimanimani District of Manicaland and successfully completed the University of Cambridge Ordinary level examinations in 1985. After enrolling for the Advanced level studies in 1986 at Mutare Boys High School in Mutare in 1986, he completed the University of Cambridge Advanced level in 1987.

In 1988 he registered with the University of Zimbabwe in Department of Crop Science to study for the Bachelor of Science in Agriculture and graduated with Honours in 1990. In 1991 he joined the Ministry of Education where, between 1991 and 2002, he taught Agriculture and Mathematics at Pafiwa Secondary School in Manicaland. Within this period, he was granted a study leave twice: in 1993 to study for a Graduate Certificate in Education in the Faculty of Education at the University of Zimbabwe and between 1999 and 2001, to study for a Master of Science in Agricultural Meteorology in the Department of Physics at the University of Zimbabwe.

While in the Ministry of Education, he rose through the ranks to the post of a Head the Department of Agriculture, and was involved in the review of secondary school agriculture curriculum and in the writing of the Advanced level Agriculture Syllabi. He became the first National Chief Examiner for Advanced level agriculture in 2001 and was involved in examination item writing and training of assistant examiners between 2001 and 2008.

In 2002 he joined Esigodini College of Agriculture to lecture agronomy related courses. At Esigodini he was responsible for commercial cabbage, potato and green melies production for one year. He joined Mutare Polytechnic in 2003 to lecture agronomy related courses for the National Diploma in Horticulture. Again at Mutare Polytechnic he was involved in commercial Amenity Horticulture and Oleiriculture activities for 1 year.
In 2004 he joined Chinhoyi University of Technology as a lecturer for *Crop Production Technology* and *Introduction to Soil Science*. He also taught other courses that include Agricultural Safety and Agricultural Economics. While at Chinhoyi University, he successfully published a secondary school text book “*O Level Agriculture Today*” that was co-authored with a fellow Agriculture College lecturer and curriculum developer, and was awarded the First Prize in the Best Designed text book category by the Zimbabwe Book Publishers Association at the Zimbabwe International Book Fair of 2004. He also represented Chinhoyi University for Technology at several research workshops and international conferences, notably the *Second International Conference on Appropriate Technology* (2006) in Bulawayo and the *Environmental Education Association of Southern Africa conference* (2006) in Harare.

He also represented Chinhoyi University of Technology in the writing of Advanced Level Agriculture modules in *Integrated Soil Management, Integrated Water Management, Biodiversity, Agro forestry, Wildlife Management* and *Advanced Level Agriculture Teaching Methodology*, an activity sponsored by the Participatory Agricultural Curriculum for the Environment, Zimbabwe (PACE).

He joined the Tobacco Research Board on 2 January 2008 as an Assistant Coordinator of the Crop Production Division (now Crop Productivity Services), responsible for research in various aspects of tobacco agronomy and, was promoted to be substantive Head of Division on June 1 of 2008. In August 2008, he was given an additional responsibility of coordinating activities for the United Nation Industrial Development Organization (UNIDO) sponsored project on ‘*Phasing out methyl bromide from tobacco seedlings in Zimbabwe*’. The project was successfully completed on 31 December 2009.

Between 2008 and 2009 he developed a research proposal for DPhil studies on the “Development of Tobacco (*Nicotiana tabacum*) yield estimation models using agronomic and remote sensing techniques”. The registration process with the University of Zimbabwe delayed because of the economic challenges during this period. However, in March 2010, he registered for DPhilAg studies.