THE EFFECTIVENESS OF USING A SPECTRORADIOMETER IN DETECTING COFFEE DISEASES: A CASE STUDY OF CHIPINGE COFFEE RESEARCH INSTITUTE, ZIMBABWE

BY

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DECLARATION

I declare that this is my own work and all the information from the other sources was fully acknowledged.

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APPROVAL FORM

The undersigned certify that they have read and recommended to the Midlands State University for the acceptance of a dissertation entitled:

THE EFFECTIVENESS OF USING A SPECTRORADIOMETER IN DETECTING COFFEE DISEASES: A CASE STUDY OF CHIPINGE COFFEE RESEARCH INSTITUTE, ZIMBABWE.

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Submitted in partial fulfilment of the requirements of a BSc Honours Degree in Geography and Environmental Studies.

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DEDICATION

This research is dedicated to the Creator of everything, and to my father Mr D. Magada who supported me in all my education endeavours.

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May God Bless You All.

ABSTRACT

Major economic losses in Agriculture worldwide are reported to be caused by plant diseases, therefore diseases management in an accurate and timely manner is of great importance. This study assessed the effectiveness of using a spectroradiometer in detecting coffee diseases (cercospora, CLR). Healthy and diseased plants were used to compare effectiveness of different indices using a spectroradiometer. Results from this study showed that original data from a spectroradiometer does not show pronounced reflectance differences between the healthy coffee plants and the diseased plants. Twenty two known vegetation indices were used to evaluate the reflectance on healthy and diseased coffee plants (plants infected with cercospora, CLR). These indices were evaluated using ANOVA in Genstat 14th Edition and seventeen indices were found to be effective in detecting coffee diseases. The highest significant difference of $p<0.001$ was found in ten indices. Two sample t-test was performed (on reflectance on healthy plants vs. cercospora, healthy vs. CLR infected plants and CLR vs. cercospora), the indices that were found to be effective, to evaluate their potential in detecting reflectance differences in all the 3 plant states. Results have shown that out of the sixteen indices only six indices were able to detect changes in all the three plant states at ($p=0.05$) with the highest probability of $p<0.001$. Indices that were able to differentiate the reflectance of all the three states were regarded as the most effective indices in coffee diseases detection in this study. Results from interviews have also indicated that cercospora and CLR have many detrimental effects on coffee plant growth, yield and quality of coffee product. It is recommended that CORI should adopt the use of remote sensing in the management of coffee diseases, so as to control these diseases before it's dire.

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ACRONYMS

ANOVA	Analysis of Variance
ARI	Anthocyanin Reflectance Index
CLR	Coffee leaf rust
CORI	Coffee Research Institute
ENVI	Environment for visualising Image
ICO	International Coffee Organisation
MCARI	Modified Chlorophyll Absorption Reflectance Index
MNDVI	Modified Normalised Difference Vegetation Index
MSR	Modified Simple Ratio
NDVI	Normalised Difference Vegetation Index
NPCI	Normalised Pigment Chlorophyll Index
SIPI	Structured Insensitive Pigment Chlorophyll
SR	Simple Ratio
TCARI	Transformed Chlorophyll Absorption Ratio
TVI	Triangular Vegetation Index

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CHAPTER ONE: INTRODUCTION

1.1Background to the study

Coffee production is an important economic activity in more than 70 countries worldwide, with an estimated annual trade value of over 20 billion US dollars and employing millions in the value chain (ADBG, 2010). The livelihood of an estimated 25 million families worldwide depend on coffee, the world's most valuable tropical export and second most traded commodity after to oil (International Coffee Council, 2014). More than 90% of the world's coffee is grown in the developing countries where the crop is a main source of revenue for these governments (FAO, 2011). The agricultural sector is at great risk from climate change with a projected average global yield loss of up to 50% by 2050. The incidents of severity of some coffee diseases and pests such as coffee leaf rust are projected to increase, reducing yields, quality and increasing production costs worldwide (Kutywayo et al, 2013). Central America and Mexico account for 15% of the world's coffee production and coffee leaf rust continues to hamper output for most of the countries. The increase in coffee diseases and pests has contributed to low crop yields that are threatening the livelihoods of coffee growers, for example between 2002 and 2012 Indian, and Columbian coffee production declined by nearly 30%. Coffee leaf rust and cercospora diseases are devastating to coffee plantations (Schumann, 2014). Coffee leaf rust is a fungicidal disease that can reduce crop harvest by 40% or more affecting both quality and quantity of coffee (International Coffee Council, 2014). On the other hand cercospora (leaf spot) lesions on leaves begins as chlorotic spots that expand to become deep brown and necrotic on the upper leaf surface, and the disease account for 15% yield losses annually throughout the world (International Coffee Council, 2014).

Coffee is a very important commodity in Africa; Uganda being the biggest exporter, the majority is produced by smallholder farmers in the highlands of south-western Ethiopia, South Sudan and Northern Kenya (Central Coffee Research Institute, 2011). In Africa weather is encouraging the spread of diseases that makes coffee production more difficult leading to a reduction in profits. Coffee yields have declined by a significant percentage, to an extent that many farmers in Tanzania, South Africa, Kenya and Zimbabwe have given up on coffee production completely (Craparo, 2010).The highland areas of coffee-producing countries such as Kenya, Rwanda, Uganda and Zimbabwe are particularly at risk. Rust attack leaves of coffee and inhibits the cherry from ripening, thus compromising coffee production

(International Coffee Council, 2014). In Zimbabwe coffee is regarded the second most profitable crop after tobacco. Coffee in Zimbabwe is mainly grown in the Eastern Highlands districts of Chipinge, Chimanimani, Mutare and Mutasa and in the Northern parts of the country in Guruve, Harare and Mhangura (CORI, 2010), Chipinge being the largest producer of coffee. Zimbabwe's coffee production is also being affected by the increasing coffee diseases, and this is evidenced by a significant loss in yields and a number of farmers who are giving up on coffee production especially in Chipinge District. Coffee Leaf Rust is effectively managed using fungicides and host plant resistance (Zambolin, et al., 2005).

The use of fungicides has become the major practice in Coffee Leaf Rust and cercospora control in the corporate farms and smallholder farms (Chidoko, 2013; Subramani, et al, 2012). The use of chemicals to control pests and diseases is expensive and pollutes the environment (Coelho, et al., 2009; Rainforest Alliance, 2009). To reduce the pollution caused, there should be implementation of better diseases monitoring methods for precision farming.

Early detection of coffee plant disease and the accuracy in the collection of disease survey data are the most important in the success of crop protection and management methods. Coffee disease monitoring methods that are currently used rely on occasional field scouting and surveying by experienced people and the results are confirmed once the disease has already damaged the crop.

Remote sensing offers opportunities for immediate, spatially clear objective assessment of plant condition (Sankaran et al., 2010). This can increase productivity, reduce production costs and labour in disease assessment and reduce environmental contamination from over-application of pesticides by providing information for precision crop protection. It has been demonstrated that remote sensing approaches can be used in detection of plant diseases in many crops (Huang et al, 2007) Remote sensing applications for disease detection rely of identifying specific wavebands in hyperspectral scanners that correlate to disease presence in plant leaves that can be used to discriminate and/or quantify disease presence. The majority of the wavebands and vegetation indices used in disease detection are in the narrow contiguous parts of red-edge and Near Infrared regions of the electromagnetic spectrum (Coops et al., 2003). Reflectance in these regions is able to detect any changes in the quality and quantity of chlorophyll and chemical properties of affected leaves caused by pests and diseases when compared to the unstressed counterparts (Mutanga and Skidmore, 2007). It is

against this background that this study seeks to assess the effectiveness of a spectroradiometer in detecting coffee diseases at Chipinge Coffee Research Institute, so as to improve on the methods used for coffee diseases detection and monitoring in order to improve coffee yields and quality.

1.2 Statement of the problem

Climate change and poor soil fertility promote an increase in pest and disease attack on coffee plants leading to yield losses. Crop protection from pests and diseases is a major challenge in the coffee farming sector. Coffee diseases are a threat to coffee production in both smallholder and large scale farms (International Coffee Council, 2014). If the diseases are left unchecked, they can lead to premature defoliation, which results in die-back and reduction of yields, quality and eventually tree mortality. There are several diseases that affect plants with a potential to cause devastating economic, social and ecological losses. In coffee, cercospora, leaf rust and leaf miner are the major diseases that lead to reduced yields. Coffee Leaf Rust is the most devastating coffee disease in almost all coffee growing areas worldwide (Arneson, 2000; Schumann, 2014). Production losses have been recorded in agricultural industries worldwide due to poor methods of analysing crop health status (Sankram et al, 2010). In Zimbabwe, the major problem in coffee diseases management is of the methods that are used to detect and identify diseases. These methods identify diseases when they are severe, require more labour and also a lot of human errors are encountered. Therefore, accuracy of the data is compromised and it becomes difficult to deal with diseases. Current monitoring methods for coffee diseases rely on occasional field scouting by trained and experienced personnel. In this context, diagnosing diseases in an accurate and timely way is of ultimate importance and the success of potential crop protection methods is highly dependent on early detection of the disease. Spectral anomalies and diseases in the field can be detected using remote sensing earlier and can be used in the decision making process to safeguard yields. Remote sensing offers opportunities for immediate, spatially clear objective assessment of plant condition (Sankaran et al., 2010). This can improve productivity, reduce costs in disease assessment and reduce environmental contamination from over-application of pesticides by providing information for precision crop protection. This study seeks to assess the effectiveness of a spectroradiometer in detecting coffee diseases.

1.3.1 General objective

- To assess the effectiveness of a spectroradiometer in detecting coffee diseases at Chipinge Coffee Research Institute

1.3.2 Specific objective

- **x** To determine the capability of a spectroradiometer in distinguishing the infected coffee plants from healthy ones at Chipinge Coffee Research Institute
- x To identify spectral indices which are more effective in detecting cercospora coffee leaf rust in coffee at Chipinge Coffee Research Institute
- x To evaluate the effectiveness of using a spectroradiometer in detecting cercospora and coffee leaf rust coffee diseases at Chipinge Coffee Research Institute
- x To assess the effect of coffee diseases in coffee production at Chipinge Coffee Research Institute

1.4 Hypothesis

H_0 The spectroradiometer is not capable of detecting coffee diseases (cercospora and coffee leaf rust).

H_1 The spectroradiometer is capable of detecting coffee diseases (cercospora and coffee leaf rust).

1.5 Justification of the study

Worldwide and particularly in Zimbabwe, coffee diseases management is of great concern and therefore good coffee disease management practices are part of sustainable coffee production. Little has been done in the country to improve coffee diseases detection and monitoring methods, so as to improve coffee yields and quality. The study will help in the management of coffee diseases and will give information for immediate action to be taken to deal with coffee diseases. The research findings will help enhance the socio economic life of smallholder coffee farmers who depends on coffee farming and tend to have little resources to manage their farms. The farmers will benefit in that the study will be used as a guideline to detect and monitor coffee plant health status before its dire, which allows for immediate actions to safeguard yields there- by ensuring good revenues. The cost of production, labour and time needed for diseases survey will be less, due to precise and accurate provision of information from the use of a spectro-radiometer. There is a significant reduction of coffee yields in Zimbabwe, especially due to climate change which increases diseases and pest manifestations in coffee. This study will help in the provision of information on diseases so as to take immediate actions to safeguard coffee yields, through precise management of coffee diseases. Coffee research Institute will benefit from this study, since it is the one which does disease surveys in different coffee growing areas. The methods they use are time

consuming, that is they need more time to incubate the samples, of which the disease will be becoming more severe at the farm during that time. With the use of remote sensing there is provision of information at the right time, and remedial action is taken before diseases become severe, thereby enhancing coffee yields and quality. Coffee is a very important crop in the economy of Zimbabwe, and so this study is very important in that when better yields are guaranteed, the economy of the country will be boosted since coffee contributes greatly to the country's revenue.

1.6 Study Area

1.6.1 Map of study area

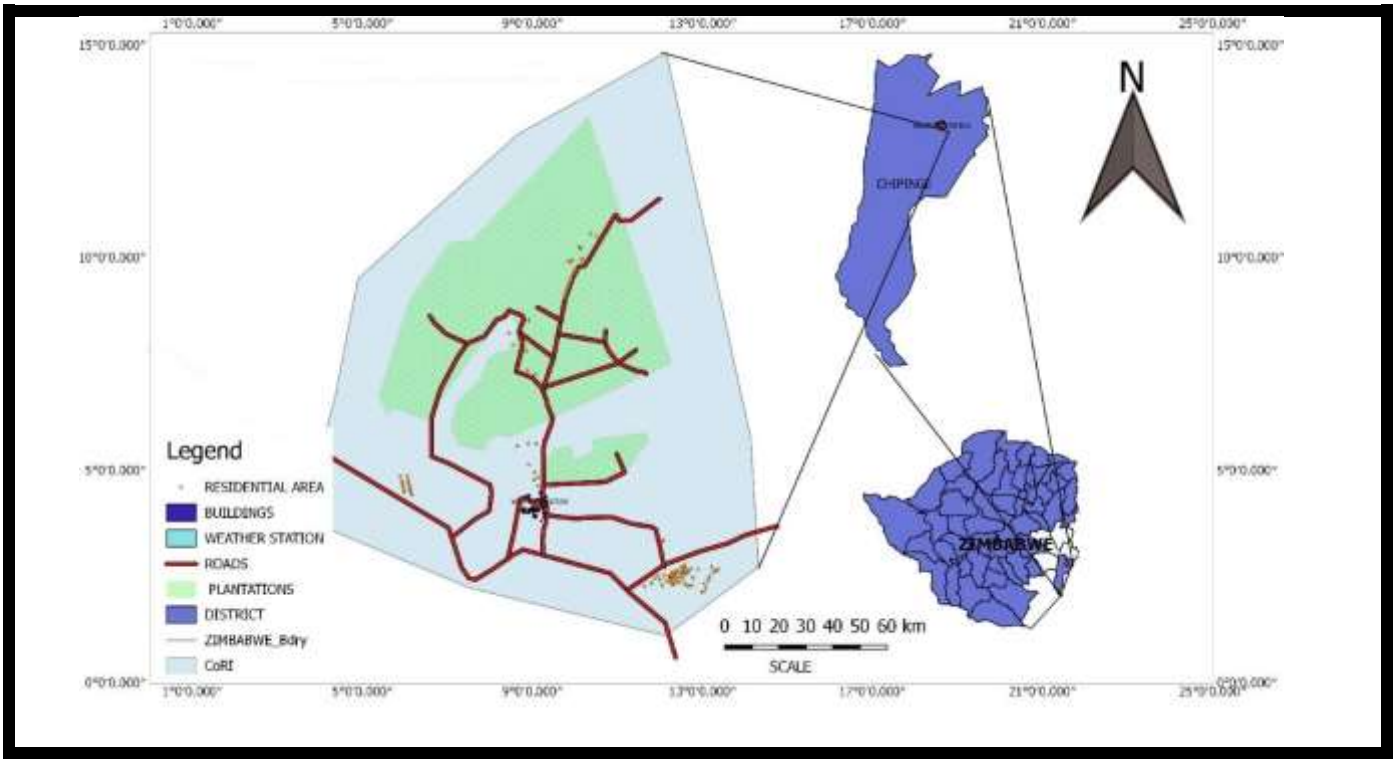

Figure 1.1 Map showing Chipinge Coffee Research Institute (CoRI)

Source: Department of Geography and Environmental Studies, Midlands State University

1.6.2 Physical description of the area

Coffee Research Institute is situated 8km South West of Chipinge town. Its GIS position is ($20^0 21^1$S and $32^0 37^1$E) and it is lies at an altitude of between 1060 and 1290 meters above sea level. It is in Natural Region 1 in terms of Agro- ecological classification used in Zimbabwe. Its mean maximum temperature is 20 degrees Celsius and its mean minimum temperature is 14 degrees Celsius (Chemura, et al. 2014). The Annual rainfall of the area varies from 800 to

1300mm. A large portion of the soils at Coffee Research are derived from quartzite which forms the *orthoferallitic* group and another portion is made of sandstones that are leached and strongly weathered (FAO, 2006). The area is mainly characterized by Eucalyptus and *Brachystegia Spiciformis* (msasa) and *Julbenadia globiflora* tree species.

1.6.3 Socio-economic description of the study area

Agriculture is the main economic activity done at the institute. This includes coffee production, piggery, growing of maize, vegetables and the production of citrus fruits, granadillas, macadamia nuts, eucalyptus seedlings, among others. There are four main sections at coffee research institute, Plant pathology, entomology, agronomy and farm section. Pathology section deals with disease management in coffee and other crops (fungal, nematodes, viral and bacterial). The Entomology section deals with insect and pest management. The Agronomy section deals with soil and crop management. The Farm section deals with crop production. The seasonal activities done at the institute include coffee harvesting, pulping, and drying of coffee. The institute transports its coffee to Zimbabwe Coffee Mills and Grain Marketing Board. Coffee Research Institute has approximately 129 employees. There is a government primary school, Madziwa, which is under Coffee research, where the workers' children go to. The area has a good road network, which makes it easy for the people to travel to and from town and also easy for the transportation of the institute's products. This road network also helps the workers children who travel to town for their secondary education and also to Madziwa secondary which is to the south of the institute. The institute provides its workers with accommodation and thus there is a very big compound, which is electrified and well serviced, for example, ZINWA supply adequate water for the people. There are three shops in the area where these workers can buy what they want. The workers produce their own food through farming on the institute's land currently not being utilised by the institute.

CHAPTER TWO: LITERATURE REVIEW

2.1 Importance of coffee

According to Rutherford (2006) coffee is produced in more than 50 countries around the world, and although it is not a food crop (Muller 2010) it is a major source of revenue in most coffee-growing countries. According to FAO (2011) statistics it was indicated that in 2011 alone a total amount of seven billion dollars was generated through coffee trading in the World and thus it has led to improved economies, landscapes and societies through trade in over 70 countries (Masaka and Khumbula 2007). According to Baker (2011) the global annual export of coffee exceeds US $9 billion and the sector employs more than 25 million people globally at different stages of the production.

The majority of the people working in the coffee production sector are small holder farmers in Latin America Asia and Africa (FAO 2011), and this shows that coffee production improves the quality of life of these smallholder farmers. In 2009 and 2010 Africa contributed 12% of the coffee global production and it is mainly produced in Kenya, Ethiopia, Uganda, Ivory Coast, Cameroon and Zimbabwe (ADBG 2010).More than half of the export earnings in countries such as Burundi and Uganda were accounted for by coffee exports (Prasad et.al 2011). Coffee production mainly contributes in creation of employment, poverty alleviation, rural development and food security, for example, it contributes 30% to the Kenyans GDP by employing the population directly or indirectly. According to CORI (2010), coffee is mainly produced in the Eastern highlands of Zimbabwe, that is, in Chipinge, Mutasa, Chimanimani and Mutare, it is also produced in the northern part in Mhangura, Guruve and Harare. 50 000 families are supported from coffee employment and coffee is grown by 3000 smallholder farmers in Zimbabwe (ICO 2009). This indicates that coffee production is contributing significantly in the livelihoods of the country's population.

2.2 Capability of a spectroradiometer in detecting plant diseases

According to Doraiswamy et.al (2003) many researchers have shown the capability of remote sensing techniques in the area of agriculture, crop production and plant disease detection. Remote sensing techniques and studies have indicated the potential to discriminate disease and other plant stress in their early stages (Gazala 2013).

De Jong and Van der Meer (2006) defined remote sensing as a technique for obtaining information on an object by measuring the electromagnetic energy reflected or emitted by the Earth's surface without physical contact. Since remote sensing is a non- contact technique,

spectral measurements acquired by portable instruments such as handheld spectroradiometer and spectrometers are analysed to retrieve information on the object observed, that is, plant health in this case. In the annex of principles relating to remote sensing of the earth from space, United Nations (2002) in their definition of remote sensing, included the purpose of remote sensing and indicated that it is for the improvement of natural resources management, land use and the protection of the environment.

A spectroradiometer is a remote sensing machine designed to measure spectral radiance or irradiance across various spectral ranges. These are also ideal for use in the field where accurate measurements need to be taken under real world conditions (Konica Minolta Sensing America, 2006). Recent researches have shown that remote sensing has potential to direct detection of plant diseases under field conditions and these researches show that it is simple to distinguish one object from the other because each object has its special reflectance property (Bock et al 2010; Laudien et al 2003). Thus it can distinguish infected plants from healthy ones.

Rumpf et al (2010) has indicated that a spectroradiometer measure hyperspectral reflectance with a difference of up to 97% accuracy. For example, healthy leaves of sugar beet from those infected with *C.beticola, Uromyces befface* causing cercospora leaf spot, sugar beet rust and powdery mildew were differentiated at up to 97% accuracy (Rumph et.al 2010). In wheat, stripe rust is a major obstacle to stable and high yields, it has, however been monitored successfully by using remote sensing at different platforms such as single leaf, ground, airborne and space platform (Mahlein, 2010). Meron et.al (2010) also suggested that stressed plants react with protection mechanisms that lead to suboptimal growth which show up as changes in variables such as chlorophyll content, surface temperature and leaf area index (LAI). These changes due to plant stress produce a spectral signature that is different from the signature of a healthy and unstressed plant. This shows that remote sensing is able to detect plant diseases and can differentiate them due to the different spectral signatures provided by different infections.

Furthermore, West et al (2003) stated that when plants are exposed to pathogens or fungi, they react to the presence of these pathogens with physiological mechanisms such as reduction of photosynthesis rate and this induces an increase of fluorescence and heat emissions and thus the spectral signatures of an infected plant becomes different from the healthy ones. For example, the spectral reflectance measurements for an early diagnosis of

symptoms in *Nicotian*a *debney* have shown changes between the health and infected plants. A decrease in leaf reflectance due to a reduction of chlorophyll content was observed in the infected plants as compared to healthy ones (Polischuk et al 1997).

According to Gazala (2013) spectral reflectance of soybean leaves due to mung bean, yellow mosaic India virus infection was examined and the spectral measurements indicated significant changes in reflectance in the infected as compared to healthy soybean. He indicated that the reflectance of the infected increased in the visible region and decreased in near infrared region of the spectrum. Gazala (2013) had indicated that viral infection causes changes in leaf pigment, biochemical components and metabolic alterations in infected leaves, and also characteristic changes in reflectance spectrum has been observed in many plants, for example, due to potatoes yellow vein virus infection in potatoes (Chavez 2011) infection of sugarcane with sugarcane yellow leaf virus (Grisham 2010) and grapevine leaf roll associated with virus in grape (Gazala 2013). These changes in the reflectance show the capability of a spectroradiometer in detecting plant disease and also the potential of spectral sensor systems for the detection of fungal diseases (Mahlein et al 2010; 2013 and Steddon et al 2005).

Table: 2.1 Some of the studies on plant diseases detection using spectroscopic techniques

Plant	Disease	Statistical method	Reference
Citrus	Citrus canker	_	Belasque et al (2005)
Rice	Row plant hopper	_	Yang and Chen (2001)
Wheat	Powdery mildew	ANOVA, correlation and regression analysis	Graeff et al (2006)
Kiwi fruit	Gray mould, sclerotinia rot	PCA	Coast e tal (2007)
Tomato	Leaf minor	_	Xu et al (2007)
Grapevine	Grapevine leaf roll	Discriminant Analysis	Naidu et al (2009)

Source: Sankaran et al (2010)

2.3 Advantages of using remote sensing techniques in detecting plant disease

Major economic losses in the agriculture industry worldwide are caused by plant diseases (Kobayashi et al. 2001) and these diseases also cause social and ecological losses. Diagnosis of diseases in an accurate and timely manner is therefore of utmost importance. Remote sensing methods, such as hyper- and multi-spectral sensors have multiple opportunities in increasing productivity of agriculture production systems (Oerke et al 2006; Steiner et al 2008).

Currently the most common methods used in disease detection and management are visual disease and damage quantification methods (Steddom, 2005). However, according to Gazala (2013) these traditional methods used have several limitations in assessment of the plant diseases in that, they are time consuming, labour intensive and according to Turner et.al, (2004) these methods are subject to bias and they can be inaccurate. The methods can be inaccurate in that they are mostly subjected to human errors, since they are tiresome and time consuming people end up making numerous mistakes.

According to Yang et al (2013) to prevent diseases spread with the least damage to crop production, early detection of disease is of key importance and Kobayashi et.al (2001) indicated that remote sensing with the use of spectrometers and lateral flow devices deliver instantaneous results and can effectively detect early infections directly in the field. More timely and useful information, spatial and clear objective assessment of plant condition is offered by remote sensing (Sankaran et.al.2010). This can improve and increase productivity in agriculture (Oerke et al 2006; Steiner et al; 2008), render agriculture more sustainable and safe, avoiding expensive use of chemicals in crop production (Kobayashi et al 2001), and reduce environmental contamination.

Remote sensing techniques are useful in monitoring a large crop area at a single time point, something not possible by visual observations alone (Gazala 2013). However some researchers have shown that DNA based and serological methods can now provide essential tools for accurate diagnosis of plant diseases, but Kobayashi (2001) argues that although the methods have revolutionised plant disease detection, they are not reliable at asympiotic stage, are labour intensive and are time consuming. For example, there is need for sample harvest, processing and analysis. This argument also shows the advantage of remote sensing over the DNA methods. According to Hillhutter and Mahlein (2008) an automatic and objective alternative to visual disease assessment can be provided by remote sensing technologies.

2.4 Spectral vegetation indices used in plant disease detection and monitoring

According to Gitelson (2002) spectral vegetation indices are widely used in monitoring, analysing temporal and spartial variations in vegetation and if the ratios of several bands and different ranges of spectrum are calculated the spectral vegetation indices can be useful in effective data analysis for disease discrimination in plants (Steddon 2005).

Researchers have shown that biochemical and biophysical related parameters of plants can be summarised by calculated spectral vegetation indices (Gitelson 2002; Steddon 2005). The indices that were developed have formulas that can be used in further studies and use of remote sensing. The formulas of the most common vegetation indices are as discussed below.

In Environment for Visualising Images (ENVI) the vegetation indices were categorised into broadband greenness, narrowband greenness, light use efficiency and leaf pigment. NDVI, SRI, EVI, ARI, SIPI among other indices form a basis of many remote sensing applications in the management of crops (Burling 2011; Steddon 2005) after being correlated to several biochemical and physical plant parameters indicating plant health. In most studies chlorophyll and thermography related vegetation indices have proven their potential in detection and quantification of plant disease at early stages (Oerke 2006; Steddon 2005).

Indices related to leaf pigments involved in photosynthesis include Simple Ratio (SR), Normalised Difference Vegetation Index (NDVI), and Modified Chlorophyll Absorption Reflectance Index (MCARI). Literature has also shown that NDVI and SR have been used as indicators for plant vitality. NDVI, MCARI, TCARI, PRI AND CAI are able to detect changes in vegetation index value for the infected plants (Burling et al 2011; Oerke 2006) NDVI is the most used and well-known vegetation index which is very effective. Mahlein (2010) has indicated that NDVI is successful in predicting photosynthetic activities in plants, and thus it is able to detect plant disease since they change the photosynthesis characteristics of plants. Literature has also shown that NDVI data obtained from plants and correlation with various factors is able to detect any stress or disease in plants (Kumar et.al 2010).

Spectral vegetation indices in literature have been found to be useful in effective data analysis for disease detection. For example, Chaele (2004) was able to indicate plant virus interaction in tobacco and cercospora *beticola* in sugar beet. Spectral vegetation indices from multispectral data from a sugar beet field were calculated by Steddon (2005) and the indices were compared to disease severity visually related by plant pathologists and it was successful in detecting changes at every stage. Previous researches had shown the ability and

effectiveness of spectral vegetation indices able to detect plant diseases (Laudien et al 2003; Graeff et al 2006; Jing et al 2007). According to Hatfield (2008) several authors have shown that vegetation indices have the potential to detect plant disease since they are related to characteristics of crops. Thus any changes related to plant health can be detected

Table 2.2: Some of the common spectral vegetation indices and their formulas

Name of index	Formula
EVI	2.5*((R800-R670)/(R800-(6*R670)-(7.5*R475)+1) Huete et.al (1992)
TVI	0.5*(120*(R750-R550)-200*(R670-550)) Broge and Leblanc (2000)
Green NDVI	(R800-R550)/(R800+R550) Gitelson et al (1996)
MCARI	((R700-R670)-0.2*(R700-R550))*(R700/R670) Daughtry et.al (2000)
MNDVI	(R800-R680)/(R800+R680-2R445) Sims and Gamon (2002)
MSR	(R800-R445)/(R680-R445) Sims and Gamon (2002)
NDVI1	(R800-R670)/(R800+R670) Gitelson and Merzlyak (1994)
NDVI2	(R750-R705)/(R750+R705) Gitelson and Merzlyak (1994)
NDVI3	(R800-R670)/(R800+R670) Gitelson and Merzlyak (1994)
NPCI	(R680-R430)/(R680+R430) Penualas et al (1994)
ARI	(1/R550)-(1/R700) Gitelson and Merzlyak (1994)
SIPI	(R800-R445)/ (R800-R680) Penuelas et al (1995)
TCARI2	3*((R750-R705)-0.2*(R750-R550)*(R750/R705)) Haboudane et al (2002)
SR1	R750/R700 Gitelson and Merzlyak (1997)

Source: Main et al (2011)

2.5 Impacts of Cercospora and Coffee leaf rust diseases

Coffee farmers in Africa as elsewhere are continuously threatened by a range of plant pests and diseases (Rutherford and Phiri 2006). Most of the diseases have minor damage and effects on yield and quality of coffee. However, some such as Coffee leaf rust, coffee wilt and cercospora can be more serious and have major impacts on both individual farmers and on governments, especially those that heavily depend on coffee production for foreign exchange earnings (Rutherford and Phiri 2006). Cercospora also known as brown eye spot affects leaves and berries, on leaves grey brown spots with a yellow hollow appears and on berries brown lesions appear (Muller et.al, 2004). Coffee leaf rust also affects the leaves, leaving a yellow rusty powder on leaves.

According to Kobayashi (2001) major economic losses in the agricultural industry worldwide are due to plant diseases. Moreover, the most damaging disease agents on global crop production are fungal and pathogens and these are the agents that causes cercospora and leaf rust (Bebber 2016). Defoliation of coffee plants is also caused by coffee leaf rust and cercospora which have more impacts on plant growth (Rutherford 2006). Additionally, these diseases lead to crop losses due to premature leaf shedding, plant defoliation, there-by reducing the plant potential to growth; this occurs after the fungus infection (Rutherford and Phiri 2006). These diseases lead to light and immature coffee beans and premature ripe of coffee, although the pulp seems ripe (Alvelino and Ribeyre 2014) and thus reducing yields and quality of coffee. Furthermore, there is high risk of fermentation, since the pulp is difficult to remove during the wet process (Alvelino and Ribeyre 2014). This leads to poor quality coffee and most of it becomes unsuitable for market purposes.

According to Muller et.al (2004) Coffee leaf rust causes significant losses. For example, in 1860 the disease led to the obliteration of the entire population of coffee in Sri Lanka (Koebler 2013) and in Colombia mean annual production declined by around 40% from 2008 to 2011 and the production decline has been linked to a severe Coffee leaf rust outbreak that had occurred during that period (Bebber et al 2016; Avelino 2015).

To indicate more on the effects of leaf rust of coffee in Columbia, Avelino (2015) argued that the Columbia and Central America coffee rust epidemics had strong social impacts and led to food security issues, as most of the people highly depend on coffee directly or indirectly. For example, the countries had more than 500 000 families growing and depending on coffee crop for their livelihoods (Avelino 2015). This shows that the population's standard of living

was reduced due to coffee leaf rust which had affected production. An excess of 75% yield loss is estimated to be caused by CLR where outbreaks are severe (Rutherford and Phiri 2006) and cercospora disease account for 15% yield losses in coffee annually throughout the world (International Coffee Council, 2014).

According to Rutherford and Phiri (2006) and Rutherford (2015), there are very high costs of controlling these diseases, and the costs are high due to the large reliance on fungicides use. Globally the cost of using the fungicides is estimated to be between US$1 billion ad US$3 billion (Rutherford and Phiri 2006) and due to these high costs and severity of diseases most coffee farmers are abandoning coffee production. Most farmers are neglecting coffee and are now engaged into annual crop production (CORI 2010).

According to Hagga and Schepp (2011), the control of diseases such as CLR, cercospora and wilt using chemicals remains a challenge and the chemicals are beyond reach for many smallholder farmers who dominate the coffee production sector. Bebber (2016) argued that despite the use of chemical controls and plant resistance breeding, it is estimated that about one quarter of global production is losing enough to feed hundreds of millions. Thus plant disease management is still a difficult issue.

Currently CLR and cercospora diseases are controlled by the use of fungicides. According to other researches the use of chemicals helps to improve coffee quality by preventing proliferation of pests and diseases which may affect quality. However, Ribeyre and Avelino (2014) objected that these chemicals have adverse impacts on the environment and that is, the repeated use of these contaminates the soil, plants and the product. For example, toxicity problems could be encountered due to Cu content in the coffee beans which is used in spraying CLR, (Loland and Sigh 2004) and this can be harmful to those consuming the coffee. Avelino and Ribeyre (2014) also advocated that the use of chemicals in controlling plant diseases such as CLR has adverse impacts, as they had alluded that the in appropriate and excessive use of these may have negative impacts on the environment and could lead to potential health problems for consumers and those applying the chemicals.

2.6 Knowledge Gap

The studied literature on the use of remote sensing in detecting plant disease showed that the subject is under researched in the use of remote sensing in coffee diseases detection as compared to other plants such as wheat, soybean and tobacco (*nicotiana*) among others. A research particularly in the use of remote sensing in coffee disease detection, is permitted by the gap in the reviewed literature. Most studies have shown the importance of coffee, effects of coffee diseases and problems associated with the management of these diseases. However, there is scarce literature on the effective solutions to the disease management so as to reduce the great loses being experienced. Little has been done to improve coffee disease detection and monitoring methods so as to improve coffee yields and quality in Zimbabwe and the World as a whole. This study therefore seeks to explore the possible opportunities of remote sensing in coffee disease detection and management by providing immediate information for immediate action to be taken before its dire, so as to reduce losses associated with coffee disease, and also to reduce the environmental effects incurred in dealing with these coffee diseases (cercospora and CLR).

CHAPTER THREE: METHODOLOGY

3.1 Research Design

Research design is a blue print for conducting a study with maximum control over factors that may interfere with the validity of findings (Burns and Groove, 2003). The aim of this research is to assess the effectiveness of a spectroradiometer in detecting coffee diseases at Chipinge Coffee Research Institute. In this case experimental research design was used. According to Robson (1993), experimental research design is the approach for obtaining information about casual relationships, allowing researchers to assess the correlation between one variable and another. Experimental designs are developed to answer hypotheses formulated by the researcher to address specific questions. A principle factor of this design is that one element is manipulated by the researcher to see whether it has any impact upon another (Robson, 1993). The researcher used this research design in order to organise treatments in a manner that allowed valid statistical analysis to be carried out on the resulting data from the spectroradiometer. The researcher also wanted to isolate suspected sources of variations, so that the treatments effects could be evaluated free of extraneous environmental or other influences (Montgomery, 1997). The design was essentially used to measure the reflectance of infected coffee plants and the healthy ones, basing on the numerical figures in terms of reflectance of different infections (cercospora and coffee leaf rust) and the healthy ones. Experimental design also allowed the researcher to have information on spectral indices that were analysed to see their capability in detecting differences in healthy and infected coffee plants.

3.2 Procedure for Data collection

Fifty, six months old coffee seedlings were inoculated with coffee leaf rust and the other fifty with coffee cercospora in a greenhouse. Yellow cartuai coffee variety was used in the inoculation of leaf rust because it is well known to be susceptible to coffee leaf rust. Mundo Novo was also used in the inoculation of cercospora, as it is also known to be more susceptible to cercospora. These varieties were selected because they are popular with farmers since they produce high yields.

The diseases spores for coffee leaf rust and cercospora diseases were collected from naturally infected coffee plants from the Gene bank coffee field that is maintained at the institute for experiments. The spores from the leaf rust infected leaves were scrapped into petri dishes using a sterilised razor blade. These spores were then used to make a spore. A total of 50 plants were inoculated with coffee leaf rust. The spores were distributed by brushing the

spore suspension at the underside of leaves using pen brushes. Mundo Novo coffee variety was inoculated with cercospora. Strains isolated from common cercospora lesions were used in the inoculation and 50 with coffee cercospora. The inoculated plants were incubated in dark incubation chambers with 100% relative humidity. After completion of inoculation, the plants were put in blocks and each infected plant (the plants infected with cercospora and the others with leaf rust) and healthy ones were replicated 10 times. The coffee plants were scored and grouped by a plant pathologist using visual signs and signs from the microscope, and were grouped into slightly infected, moderately, severely infected and healthy seedlings (no inoculation). Slightly and moderately infected plants were scored using signs from a microscope, since it was not possible by eye visualisation. The researcher used the moderately infected plants for both diseases and a spectroradiometer (300-1000nm) was used to collect the reflectance data for the 3 plant states.

3.2.1 Determining the capability of a spectroradiometer in distinguishing the infected coffee plants from the healthy ones at Chipinge Coffee Research Institute

Reflectance from the moderately infected plants and the health plants was measured using an Apogee VIS-NIR spectrometer with an effective spectral range of 300-1000 nm and a spectral resolution of 0.5 nm. Each reading consisted of an average of three spectral scans, and these averages were re-entered into Microsoft excel sheet in order for the data to be analysed in Genstat 14th edition. The data was analysed in Genstat to find the averages of healthy and infected reflectance which were further analysed using ANOVA to find the significant differences. The reflectance for infected and healthy plants was analysed in Genstat 14th edition in order to determine the capability of a spectro radiometer in distinguishing the infected plants from the healthy ones.

3.2.2 Identifying more effective indices in detecting cercospora and coffee leaf rust at Chipinge Coffee Research Institute

Twenty two vegetation indices related to chlorophyll and plant stress (published) were calculated using data from the spectrometer and evaluated for their ability to detect cercospora and coffee leaf rust. The indices were analysed using ANOVA in Genstat to see their ability in detecting the diseases. Indices that have significant difference between the reflectance of infected and healthy plants were selected. The spectral indices that were able to

differentiate the infected from the healthy plants were determined by examining whether there were statistical differences between the mean reflectance of infected and the healthy ones at each index.

3.2.3 Evaluating the effectiveness of a spectroradiometer in detecting cercospora and coffee leaf rust diseases at Chipinge Coffee Research Institute

The reflectance data for the healthy and infected plants from the spectral indices were analysed using ANOVA in Genstat 14th edition to find the means. These means were analysed using two sample t-test to find the indices that were able to identify the infected plants from the healthy ones. Statistical differences between the mean reflectance of infected and healthy plants were calculated at each index. If some of the indices came up with positive results, it showed that the spectroradiometer was very effective in detecting the diseases and the opposite is true.

3.2.4 Assessing the effects of coffee diseases in coffee production at Chipinge Coffee Research Institute

The researcher used purposive sampling technique in selecting the people she interviewed. Purposive sampling technique is a non-probability sampling method in which the researcher chooses the members of population to participate in the research according to her/ his judgement (Dudovsiky, 2016). The researcher used this technique because she wanted to interview the agronomist, plant pathologist and the AGRITEX Officer, because these were the individuals who had knowledge and experience about the issue of interest. To get information on the effects of coffee diseases in coffee production, the researcher used interviews. Interviews are ways for participants to get involved and express their views. The interviewees are able to discuss their perception and interpretation in regards to a given situation and it is their expression from their point of view (Cohen, et al. 2000). The interviews aimed at collecting data on the effects of coffee disease on yields and quality of coffee, the costs incurred in trying to reduce these effects, constrains faced in managing the diseases and what they think on the introduction of remote sensing in coffee farming. The researcher used interviews so as to attain personalised data from the interviewees.

Table 3.1 Interviewees and rationale for interviewing them

Interviewee	Reasons for selection
Agronomist	x He/ she is the one who manages crop planting, growth and harvesting or yields x They look for signs of disease problems, problem with soils and weeds x Finds out how to improve the crops and foster the use of best management practices for coffee farming techniques x Participates in technology transfer and training activities to coffee farmers
Plant pathologist	x Has the knowledge on the conditions that influence plant health, including environmental conditions, plant diseases and plant nutrients x Finds out causes of plant diseases x Develops ways to combat and control the plant diseases whenever there is infection. x Utilises modern scientific equipment and techniques to control the diseases x Participates in technology transfer and training activities that have to do with diseases management
AGRITEX Officer	x Monitors farm activities x Recommends technologies and advise on how to utilise the technologies x Promotes agricultural programmes that enhance productivity sustainably through training and regulatory services

3.3 Hypothesis testing

The relationship between the spectral signatures of the coffee plants and the spectral indices, was determined by analysing the reflectance data from each index for both the healthy and infected plants in Genstat 14th edition , and changes in the mean reflectance of these different

plant situations for both the diseases determines the relationship. The relationship was found by using t-test in Genstat 14th edition.

3.4 Secondary data

Secondary data refers to the information that is already available, that has been gathered by someone other than the researcher (Zikmund, 2000). Secondary data comprises published reports, internet materials, media reports and analysed data for other purposes other than the needs for the current research (ACAPS, 2012). The researcher had used text books, journals, internet sources and combined annual reports of Coffee research institute, which gave her background information for her study.

3.5 Data analysis and Presentation

Data analysis is the process used to describe and analyse data applying systematic statistics and logical procedures to examine each element of data available (Krishramurthi, 2003). Data in this study was organized according to the objectives of the study, and it was analysed using ANOVA in Genstat 14th edition. Means Calculated in Genstat were used to find association between diseases reflectance and spectral indices. Analysis of variance (ANOVA) with diseases as factors was performed to determine the bands at which the spectra indices can significantly differentiate between health and infected plants using the reflectance data recorded. This was done by examining whether there were statistical difference between the mean reflectance of coffee leaf rust infection and coffee cercospora compared to the mean reflectance of the health plants (using t-test technique) at each of the spectra vegetation indices. Data collected using interviews was analysed using descriptive analysis to assess the major effects of coffee diseases.

Data presentation refers to the main appearances of the data set described in an easily and clear manner representing the data and indicators disseminated (EQAVET, 2010). Graphs were used to present the relationship between reflectance and wavelength of the healthy and infected plants. Tables were used to present data on the statistical differences between the mean reflectance of the healthy plants and infected plants and also to present indices that were able to detect the selected diseases. Data collected using interviews was presented in a discussion manner.

3.6 Research Ethics

Research ethics is the code of morals by a person or group of people of planning, conduct and reporting of the research and this tries to protect the rights of the research participants

(Trochim, 2006). It is the application of moral rules in collecting, reporting and publicising information about research participants in a way acceptable to them. The researcher had already known the area and so she considers the respondents' work time, so as to avoid interruption with their schedules. The data collection was done during Saturdays since it is not their work day and also they do not work in their private fields on this day. When the researcher got to the area of her study, she first approached the Head of the institute to seek for permission to undertake the field study for the project. The researcher explained to the head and all the research participants that the research was for academic purposes only and highlighted the purpose and objectives of the study in order for the participants to know the basis of the research study. The participants were assured that their names and other personal details were not to be published. The researcher told the participants that they were free to withdraw any time they felt to without any penalties for withdrawal. To assure them more the researcher did not collect any personal details, such as phone numbers and addresses for privacy issues. All the participants were asked to sign a consent form. The researcher carried with her a letter from the university which confirms that she is a bonafide student of Geography and Environmental Studies Department at Midlands State University and is doing the research as sanctioned by the university. The researcher gave the participants the address and phone number of the University, so that the participants could confirm anything they were not sure of. The researcher started her field work when she had made sure that all participants had understood everything above.

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Capability of a spectroradiometer in distinguishing the infected coffee plants (cercospora, CLR) from the healthy ones at Chipinge Coffee Research Institute

The following graphs (figure 4.1 to figure 4.10) show the original reflectance results from the spectroradiometer for the detection of healthy (HL), cercospora (CS) and CLR (CL) of all the plants that were under the experiment. Plants 1-10 of all the plant states (healthy, cercospora, CLR) were compared. Reflectance of the 3 plant states for number one plants are presented in Figure 4.1

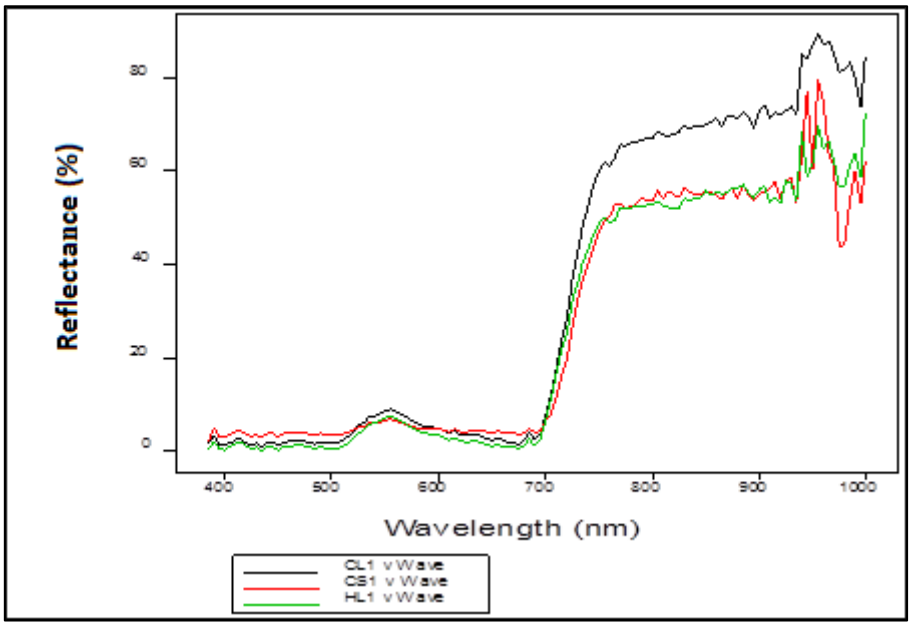

Figure 4.1 Reflectance of the 3 plant states (healthy, cercospora CLR) in number one plants
Source: Field data (2017)

Figure 4.1 shows the reflectance of cercospora, CLR and healthy on plants number ones. It is shown that there is no distinct difference in the reflectance of all the 3 plant states from 400nm to 700nm. Some distinct differences were recognised from 700nm and above. Coffee leaf rust was more distinct from the other 2 plant states. Coffee leaf rust has a higher reflectance as compared to the healthy and cercospora infected plant. There is no pronounced difference between the reflectance of healthy and cercospora on the entire wavelength.

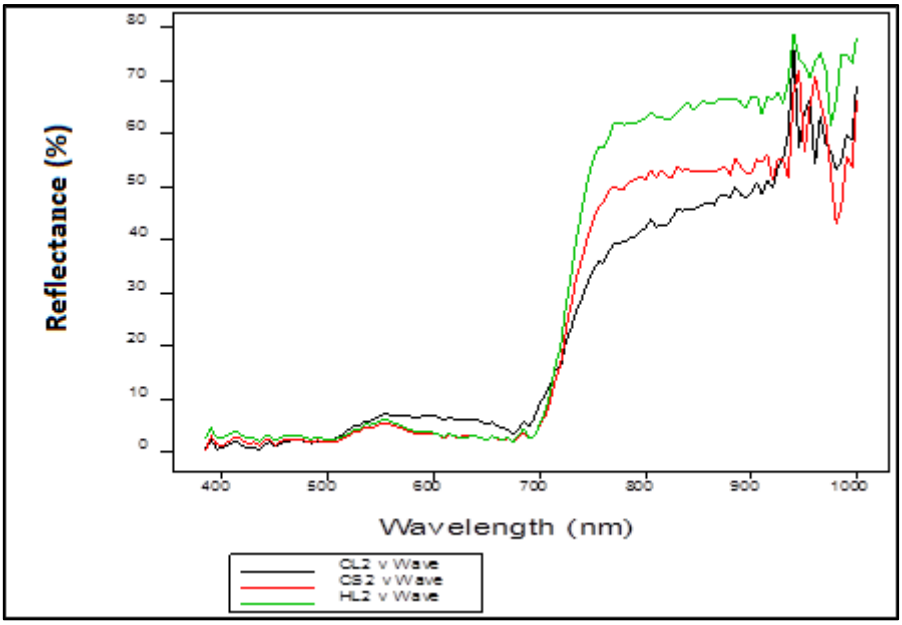

Figure 4.2 Reflectance of the 3 plant states (healthy, cercospora CLR) in number 2 plants
Source: Field data (2017)

Figure 4.2 shows that there were no pronounced differences from 400nm to 700nm in the reflectance of healthy (HL), CLR (CL) and cercospora (CS). All plant states reflectance started to be differentiated at about 710nm and above. The reflectance started to be more visible from 700nm as the wavelength increased.

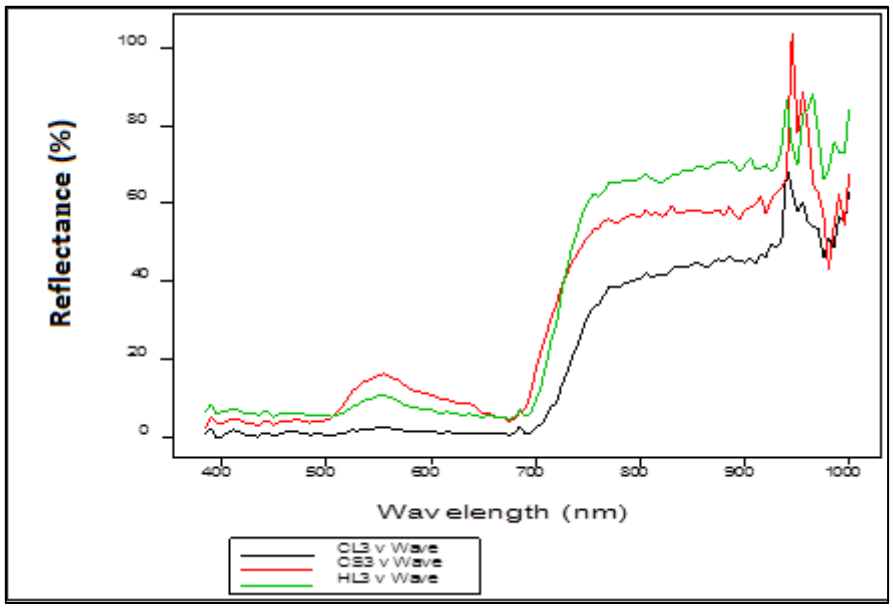

Figure 4.3 Reflectance of the 3 plant states (healthy, cercospora CLR) in number three plants
Source: Field data (2017)

Figure 4.3 shows the reflectance of plants number 3 of the 3 plant states, and the graph shows that pronounced differences in the reflectance of cercospora (CS), healthy (HL) and CLR (CL) started from 500nm to 900nm. Below 500nm and above 900nm there were only some slight differences in the reflectance. More distinct reflectance differences were from 700nm to 900nm, with the highest reflectance in healthy plant and the least in CLR.

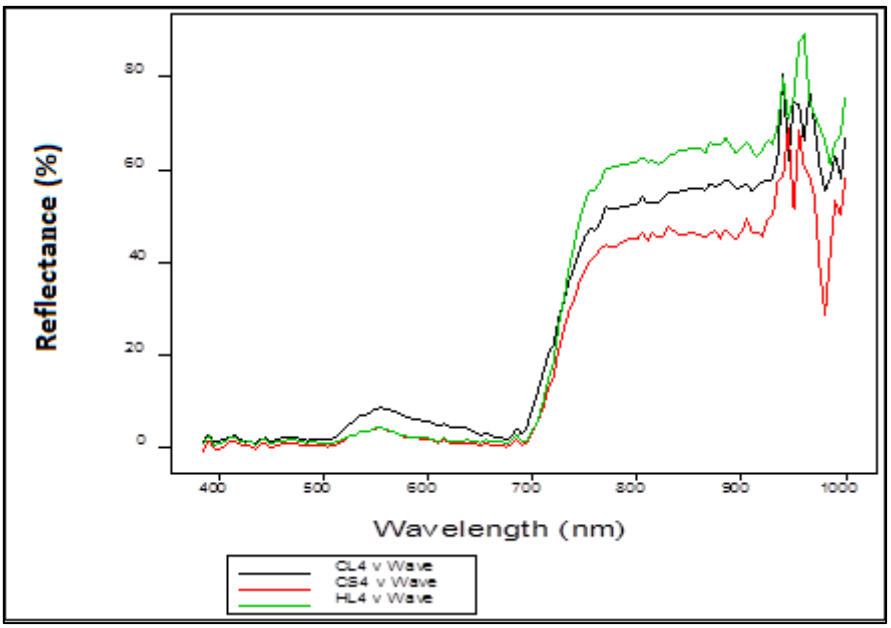

Figure 4.4 Reflectance of the 3 plant states (healthy, cercospora CLR) in number four plants
Source: Field data (2017)

Figure 4.4 shows the reflectance differences on cercospora (CS), CLR (CL) and healthy (HL) on plants 4. The graph shows that there were no distinct differences from 400nm-500nm in the reflectance of the 3 plants (healthy, cercospora and CLR infected plants), and from 710nm more distinct differences are shown among all the 3 plant states with the highest reflectance in healthy plant, and the lowest in cercospora.

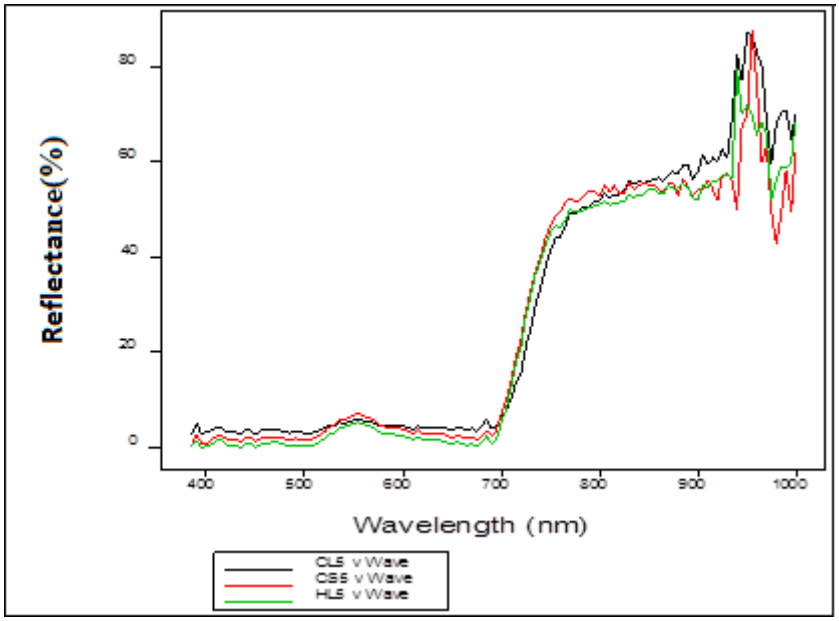

Figure 4.5 Reflectance of the 3 plant states (healthy, cercospora CLR) in number five plants
Source: Field data (2017)

Figure 4.5 shows the original reflectance of plant 5 of the 3 plant states (healthy, cercospora, CLR). The graph shows that there are no pronounced differences on the reflectance of the 3 plant states on all the wavelengths of the spectrometer.

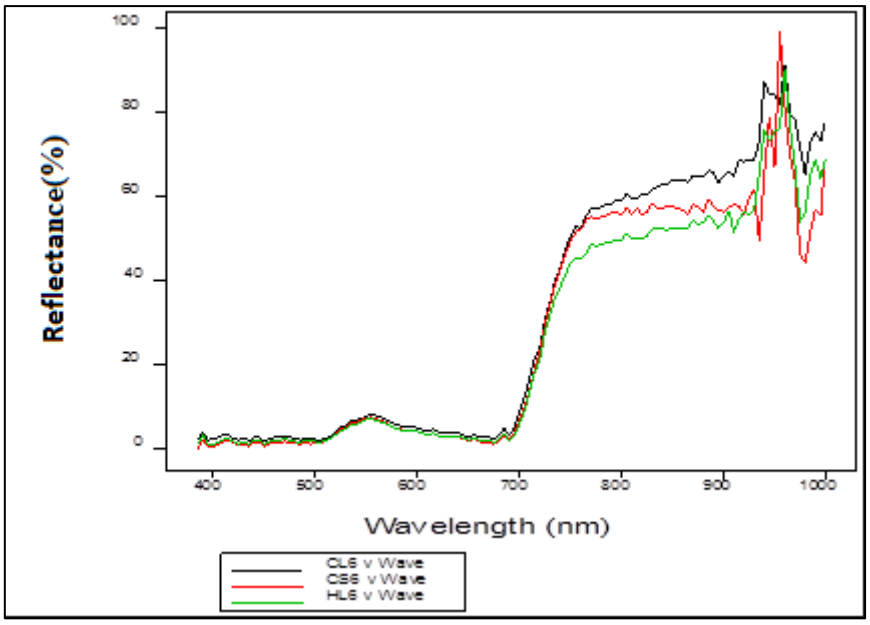

Figure 4.6 Reflectance of the 3 plant states (healthy, cercospora CLR) in number six plants
Source: Field data (2017)

Figure 4.6 shows the reflectance of the number 6 plants on cercospora (CS), healthy (HL) and CLR (CL). The graph shows that there were no reflectance differences among all the 3 plant

states from 400nm -700nm. Some differences are, however, shown from 710nm-900nm, with CLR (CL) having a higher reflectance, and a low in cercospora (CS).

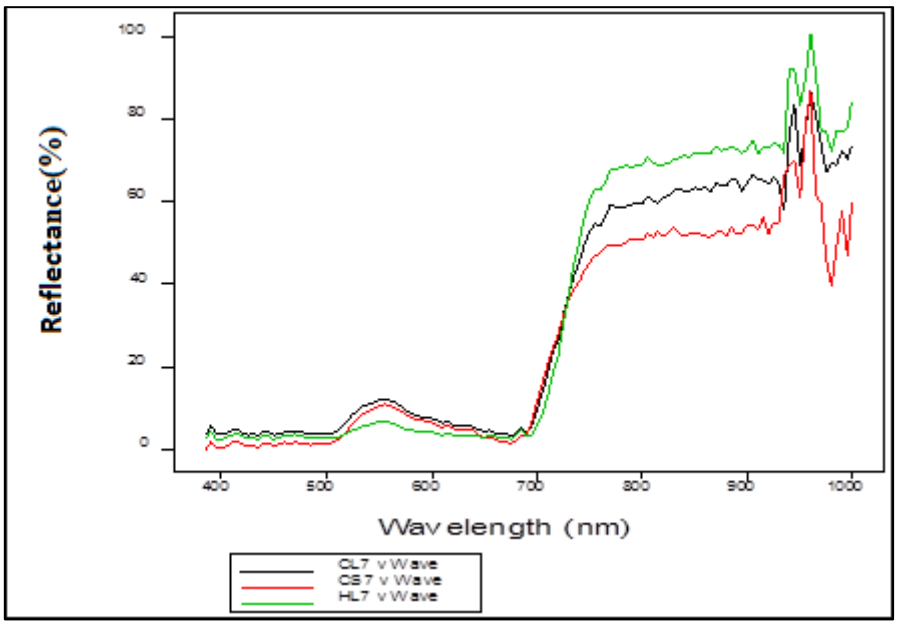

Figure 4.7 Reflectance of the 3 plant states (healthy, cercospora CLR) in number seven plants
Source: Field data (2017)

Figure 4.7 shows the reflectance of plants number 7 on cercospora CLR and healthy, it shows that there were no pronounced differences amongst the reflectance of the 3 plants states from 400nm-750nm, and distinct differences are, however, found from 710nm-940nm with the higher reflectance in healthy plant and a lower reflectance in the cercospora infected plant.

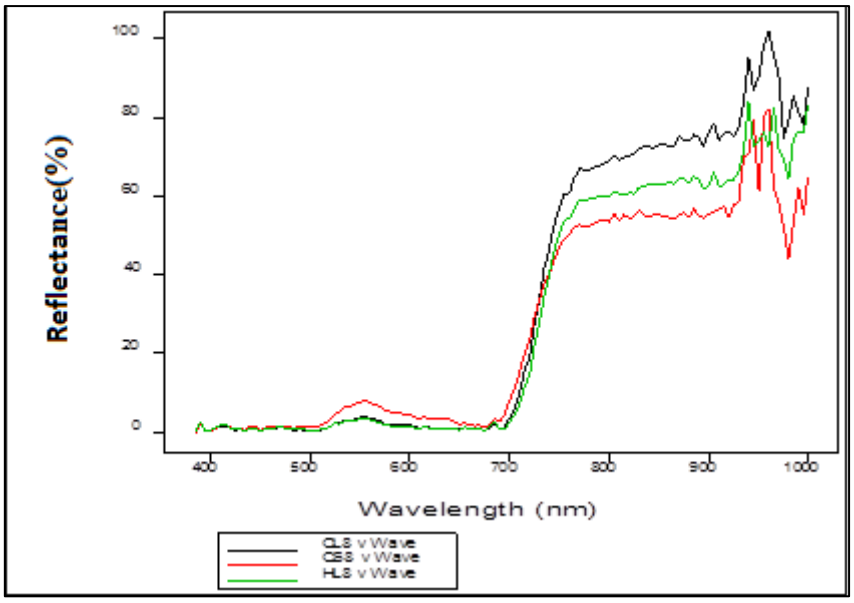

Figure 4.8 Reflectance of the 3 plant states (healthy, cercospora CLR) in number eight plants
Source: Field data (2017)

Figure 4.8 shows the reflectance of number 8 plants on healthy, cercospora and CLR infected plants. The graph shows that there were no pronounced reflectance differences from 400nm-750nm. From 750nm-950nm there were some distinct differences in the reflectance of all the 3 plant states (healthy, cercospora CLR).

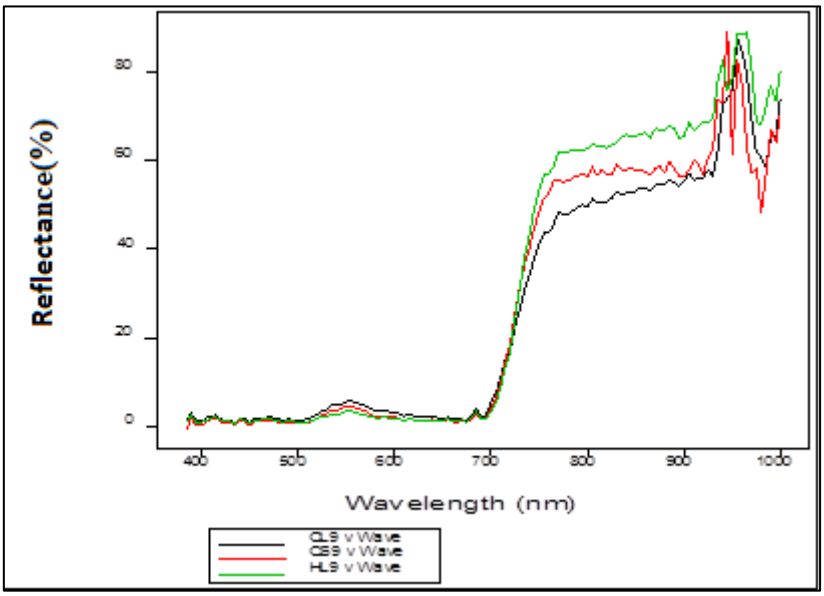

Figure 4.9 Reflectance of the 3 plant states (healthy, cercospora CLR) in number nine plants
Source: Field data (2017)

Figure 4.9 shows the reflectance of plants number 9 on healthy (HL), cercospora (CS) and CLR (CL). The graph shows that there were no differences in the reflectance from 400nm to 730nm. Some distinct differences started to be noticed from 730nm-900nm, with a higher reflectance in the healthy plant and a lowest on CLR infected plant.

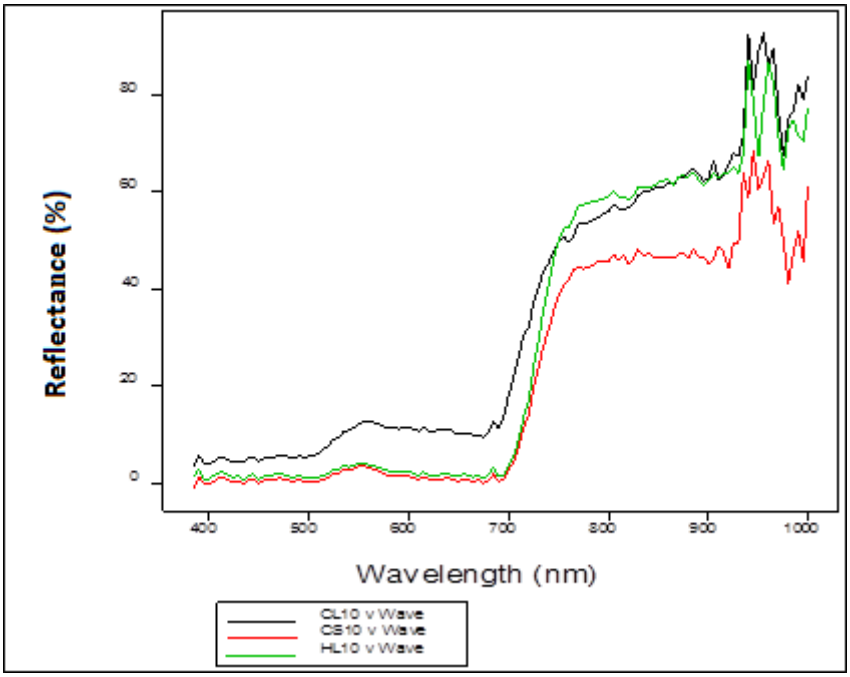

Figure 4.10 Reflectance of the 3 plant states (healthy, cercospora CLR) in number ten plants
Source: Field data (2017)

Figure 4.10 shows the reflectance of plants number 10 on cercospora, CLR and healthy plants. The graph shows that CLR reflectance was differentiated from the other 2 starting from 400nm and there were no distinct reflectance differences between cercospora and the healthy plants from 400nm to 750nm. From 750nm and above there was a difference in the reflectance of cercospora and the other 2 plant states, but no distinct differences between the reflectance of CLR infected plant from the healthy one.

Results from original reflectance of the 30 plants that were under the experiment have shown that there were no distinct differences amongst the three plant states (healthy, cercospora, CLR). For example, in plants number 5, the spectroradiometer was not able to detect changes amongst the 3 plant states. Although there was not a pronounced difference, results from figure 4.1 to 4.10 indicated that the spectro radiometer is capable of detecting the differences from 700nm and above. Although in some plants such as plant 3, differences were observed from 400nm and only on plants number 3 there were more noticeable differences in all the 3 plant states. These results are in line with results found by Yang (2006) when he conducted a study on the use of spectroscopic reflectance (350-2400nm) on Brown plant hoppes on rice plants. His results showed maximum correlation intensity from 420-1450nm and maximum variation in spectral signatures was found from 740-2400nm. Both Yang's (2006) and results

from this study show that changes in plant health are more pronounced as the wave length increases, and there is a certain wavelength where plant health starts to be detected.

4.2 Spectral indices effective in detecting coffee diseases (CLR and cercospora) at Chipinge Coffee Research Institute

Table 4.1 shows the results from ANOVA for each index that was evaluated for its efficacy in detecting cercospora and coffee leaf rust from healthy using the Least Significant Difference (LSD). Mean reflectance on each vegetation index, LSD and the p-values at p=0.05 on all the 3 plant states (cercospora, CLR and healthy) are shown on the table.

Table 4.1 Mean reflectance of healthy, cercospora and CLR (from ANOVA) on each index that was used, the least significant difference (LSD) and p-values on all the 3 plant states

	Mean reflectance				
Indices	**Healthy**	**CLR**	**Cercospora**	**LSD**	**P-value**
ARI	-0.0219**a**	0.0041**b**	0.0316**c**	0.0198	<0.001
Carter1	1.359**a**	2.145**ab**	2.913**b**	0.923	0.007
Carter2	0.0488**a**	0.1000**a**	0.1948**b**	0.067	<0.001
Carter3	0.0531**a**	0.1030**b**	0.1581**c**	0.0492	<0.001
EVI	-41.0**a**	-52.5**a**	-375.0**a**	491.3	0.341
GreenNDVI	0.8230**b**	0.7654**b**	0.7005**a**	0.0596	0.001
MCARI	3.445**a**	4.508**ab**	5.422**b**	1.477	0.037
MNDVI	0.9988**b**	0.9598**b**	0.8840**a**	0.0611	0.002
MSR	563.0**a**	149.6**a**	262.8**a**	685.0	0.452
NDVI1	0.9356**b**	0.8856**b**	0.7962**a**	0.0695	<0.001
NDVI2	0.7406**c**	0.6354**b**	0.47655**a**	0.0191	<0.001
NDVI3	0.9356**b**	0.8856**b**	0.7912**a**	0.0695	<0.001
NPCI	0.1134**a**	0.2423**b**	0.3457**b**	0.1270	0.003
SIPI	1.0032**b**	0.9967**ab**	0.9928**a**	0.0103	0.131
SR1	11.145**c**	7.295**b**	3.915**a**	3.119	<0.001
SR2	10.457**b**	7.816**ab**	5.384**a**	2.898	0.005
SR3	3.121**a**	2.775**a**	2.377**a**	1.065	0.369
TCARI	10.37**a**	13.52**ab**	16.26**b**	4.430	0.037
TCARI2	63.37**a**	65.24**a**	66.64**a**	17.46	0.928
TVI	3156**b**	2746**ab**	2547**a**	520.1	0.067
Vogelmann	0.7477**a**	0.7326**a**	0.8388**b**	0.0445	<0.001
Vogelmann2	3.433**c**	2.604**b**	2.049**a**	0.5533	<0.001

Source: Field data (2017)

*Means followed by the same letter/s in the row are not significant different at p=0.05 using Least Significant Difference (LSD) technique in Fishers protected in GenStat 14th Edition

Results from table 4.1 show that there were significant differences (p=0.05) in the mean reflectance of healthy, cercospora and CLR. Out of the 22 indices that were calculated and evaluated in the experiment, 16 were able to detect differences in either cercospora from

healthy, CLR from healthy and/ or cercospora from CLR. Highest significant differences of ($P<0.001$) were obtained in ARI, Carter 2, Carter 3, Carter 4, NDVI 1, NDVI2, NDVI3, Green NDVI, SR1, SR4, SR5, Vogelmann 1 and Vogelmann 2. Although these indices with ($p<0.005$) show a significant difference, according to the LSD technique, there is no significant differences between the other mean reflectances (means that are followed by the same letter in a row) of other indices. For example, Green NDVI ($p=0.001$) is significant since it was able to detect cercospora from healthy and cercospora from CLR, but it did not differentiate CLR reflectance mean from healthy mean. Thus these indices that were shown as significant were able to detect infected plants from healthy ones in both diseases and or detected cercospora from CLR, but some did not differentiate all the three plant states. There were no significant differences in the mean reflectance of EVI (0.341), MSR (0.452), SIPI (0.131), SR3 (0.369), TCARI2 (0.928) and TVI (0.06). These indices with the $p > 0.05$ did not significantly differentiate any changes in any of the 3 states of plants (healthy, cercospora and CLR) at $p=0.05$.

Results have indicated that some spectral vegetation indices can detect a certain plant disease but can fail to detect another. This is supported by the results found by Groll et al (2006) who did their study on the use of vegetation indices to detect plant diseases at the University of Hohenheim. They found out that TCARI2 indicated that there was a significant difference between healthy wheat plants and winter wheat powdery mildew infected plants, but on cercospora and CLR in coffee it had failed. In this study indices that were able ($p=0.05$) to detect any difference in the reflection of these plant states (healthy, cercospora, CLR) are regarded as effective in detecting these coffee diseases.

4.3 The effectiveness of a spectroradiometer in detecting cercospora and coffee leaf rust diseases at Chipinge Coffee Research Institute

Table 4.2 shows results from Two sample t-test that was performed in Genstat 14th Edition. T-test was done to show the vegetation indices that are able to detect differences in all the 3 plant states (healthy, cercospora, CLR). Table 4.2 shows the probabilities on healthy vs. cercospora, healthy vs. CLR and CLR vs. cercospora on all the 16 vegetation indices that were found to be effective in table 4.1.

Table 4.2 Probability levels from two sample t-test in Genstat 14th Edition of the three states of plants (healthy, cercospora, CLR) on the indices that were able to detect at least one of the states from another.

	t-test probability (p=0.05)		
Index	**Healthy vs. CLR**	**Healthy vs. Cerco**	**CLR vs. Cercos**
ARI	**0.016**	**0.010**	**0.042**
Carter1	**0.123**	**<0.001**	**0.151**
Carter2	**0.050**	**<0.001**	**0.029**
Carter3	**0.039**	**<0.001**	**0.037**
Green NDVI	**0.093**	**<0.001**	**0.046**
MCARI	**0.182**	**0.006**	**0.249**
MNDVI	**0.086**	**0.004**	**0.050**
NDVI1	**0.098**	**<0.001**	**0.030**
NDVI2	**0.042**	**<0.001**	**0.010**
NDVI3	**0.098**	**<0.001**	**0.030**
NPCI	**0.050**	**<0.001**	**0.147**
SR1	**0.047**	**<0.001**	**0.030**
SR2	**0.137**	**0.002**	**0.089**
TCARI	**0.182**	**0.006**	**0.015**
Vogelmann	**0.091**	**<0.001**	**0.062**
Vogelmann2	**0.009**	**<0.001**	**0.001**

Source: field data (2017)

Results from Two sample t-test on table 4.2 show that only seven indices out of 16 indices that were regarded as effective (Table 4.2) using the LSD technique were able to detect differences among the three states of the plant health (healthy, cercospora and CLR infected plants). These indices have probability values which are less than 0.05 among all the 3 plant states (healthy vs. cercospora and CLR, Cercospora vs. CLR) and these are ARI, Carter2, Carter3, NDVI2, SR1 and Vogelmann2. The rest of the vegetation indices were only able to detect either one or two states from the other, but not all the 3. These results in table 4.2 are in contrast to results that were found by Groll et al (2006) when they conducted their experiment on winter wheat powdery mildew using Fieldspec measurement from spectroradiometer, using TCARI, MCARI and NPCI indices in detecting mildew from

healthy plants at Experimental Station "Ihinger Hof" of Hohenheim University in 2006. All the 3 indices had indicated that there were significant differences between healthy and diseased plants. Although these indices were found to detect differences in healthy and diseased plants, results in table 4.2 shows that not all plant diseases can be detected using these three indices, since they did not detect all changes in the 3 coffee plant states (healthy, cercospora, CLR). Indices that were able to detect all the 3 states (healthy, cercospora, CLR) from one another are regarded as the most effective in detecting these coffee diseases in this study. Results on table 4.2 also show that most indices were able to detect cercospora from healthy as compared to CLR from healthy plants.

Hypothesis testing

$H_{0:}$ the spectroradiometer is not capable of detecting coffee disease (cercospora, CLR)

$H_{1:}$ the spectroradiometer is capable of detecting coffee diseases

T-test performed in Genstat (Table 4.2) shows that with the use of some indices (indices with a p-value less than or equal to (0.05), a spectroradiometer is capable of detecting coffee diseases, although not all indices were found to be effective in all the diseases that were studied.

4.4 Effects of coffee disease on coffee production

Results from interviews indicated that coffee diseases have critical impacts on coffee production that reduces the yields, quality of coffee and having adverse impacts on the environment. Cercospora and CLR coffee diseases affect leaves of the plant, plant growth and also coffee berries and this leads to the die-back of the plants, there by affecting yield and quality of coffee. These results concurred with Rutherford and Phiri's (2006) results when they conducted a study on Pests and diseases of coffee in Eastern Africa in 2006 in Nairobi where they concluded that coffee leaf rust affects yield and quality due to premature shedding of leaves which leads to reduced plant growth. Plant agronomists and pathologists have indicated that most coffee producers are abandoning coffee to annual crop production such as maize, due to the effects of these diseases. Results have also shown that coffee diseases (cercospora and CLR) have environmental effects. The continuous use of the chemicals to control these diseases pollutes the environment in many ways. For example, the pathologist indicated that some insects can be seen dead after the spray of *cu*, of which these insects will not be the target. The effects on the environment as shown by the results concurred with Avelino and Ribeyre's findings when they did their study on coffee rust crisis in Columbia

and Central America from 2008-2013, and they found out that the use of chemicals in controlling plant diseases such as CLR has adverse impacts. They indicated that inappropriate and excessive use of these chemicals may have negative impacts on the environment and could lead to potential health problems for consumers and those applying the chemicals.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The use of a spectroradiometer and spectral vegetation indices in coffee disease (cercospora, CLR) detection, and also the effects of coffee diseases (cercospora, CLR) are presented in this study. Results have shown that the original data from a spectroradiometer did not show pronounced differences between the coffee diseased plants and the healthy ones in all the plants that were under the experiment, so it is not perfect to use the original data from the spectroradiometer to detect these diseases.

Twenty two vegetation indices (published) related to leaf chlorophyll and stress were calculated using data from the spectroradiometer and they were analysed in Genstat 14th Edition using ANOVA for their efficacy in coffee disease (cercospora, CLR) detection. Sixteen of these vegetation indices were found to have significantly detected any reflectance differences in the three plant states (healthy, cercospora. CLR) at $p=0.05$. Some indices that are effective in detecting diseased from the healthy plants, but did not detect differences between the two diseases are difficult to use, since there will be no clarity.

Two sample t-test was done (healthy reflectance vs. cercospora, healthy vs. CLR, Cercospora vs. CLR) in Genstat 14th Edition to find indices that were able to differentiate all reflectance differences ($p=0.05$) among the 3 plant states. Six vegetation indices out of the sixteen (effective) were found to be able to detect the reflectance differences in all the plant health states, with the highest significant difference of $p<0.001$ in some of the reflectance. Results have shown that most indices were able to detect cercospora from healthy and cercospora from CLR as compared to CLR from healthy plants.

Results have indicated that cercospora and CLR diseases in coffee plants have detrimental effects on the coffee plant growth, yield and quality of coffee produced. It has also shown that there are also other effects such as environmental pollution due to over application of chemicals used in the management of these diseases, and also much labour and money is required in coffee diseases management, there-by straining resources of the coffee farmers. Results has also shown that these diseases are leading to the reduction in the production of coffee since most coffee farmers are now abandoning coffee farming to annual crop production.

5.2 Recommendations

From the results and conclusion of this study the following recommendations are suggested.

- CORI has to test the vegetation indices (found effective in this study and others that were not tested) in the coffee field, before remote sensing is recommended for use in coffee diseases management, because in this study vegetation indices were tested in a greenhouse.

- AGRITEX in coffee growing areas have to advice coffee farmers to plant healthy seedlings provided by CORI, and also to rely on CORI to tell them when and where to apply chemicals, when Remote sensing is in use, so as to reduce the impacts of these coffee diseases, since information on coffee plants health will be provided earlier before its dire.

- In the management of coffee plant health, CORI have to use satellite image data and image classification techniques data such as ENVI program, Spectral Feature Fitting among other methods in analysing the remotely sensed data, so as to cover a larger area. This will provide accurate information for immediate action to coffee farmers in Zimbabwe, thus accurate information on when and where to apply chemicals to the fields will be provided.

- CORI has to adopt remote sensing in coffee diseases management and use it with some of the current methods such as the use of microscopes for most successful results in coffee disease management. This reduces the error that might be brought by remote sensing. For example, some different effects on the plant (different diseases infections) may have the same reflectance.

- The government has to sponsor remote sensing education to all the people involved in coffee disease management, especially the plant pathologists and the Agronomist, so as to achieve precision and sustainable agriculture. Results from interviews have shown that they do not have much knowledge on what remote sensing is and the methods currently used in coffee diseases management have a lot of disadvantages.

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APPENDICES

Appendix:1

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GenStat Fourteenth Edition
GenStat Procedure Library Release PL22.1

ARI

Two-sample t-test

Variates: healthy, leaf_rust.

Test for equality of sample variances

Test statistic F = 1.96 on 9 and 9 d.f.

Probability (under null hypothesis of equal variances) = 0.33

Summary

Sample	Size	Mean	Variance	Standard deviation	Standard error of mean
healthy	10	-0.02187	0.0006348	0.02520	0.007968
leaf_rust	10	0.00409	0.0003242	0.01801	0.005694

Difference of means:	-0.02596
Standard error of difference:	0.00979

95% confidence interval for difference in means: (-0.04654, -0.005386)

Test of null hypothesis that mean of healthy is equal to mean of leaf_rust

Test statistic t = -2.65 on 18 d.f.

Probability = 0.016

Two-sample t-test

Variates: healthy, Cerco.

Test for equality of sample variances

Test statistic F = 1.21 on 9 and 9 d.f.

Probability (under null hypothesis of equal variances) = 0.78

Summary

Sample	Size	Mean	Variance	Standard deviation	Standard error of mean
healthy	10	0.6354	0.01693	0.1301	0.04114
Cerco	10	0.4765	0.01403	0.1184	0.03746

Difference of means:	0.1589
Standard error of difference:	0.0556

95% confidence interval for difference in means: (0.04204, 0.2758)

Test of null hypothesis that mean of healthy is equal to mean of Cerco

Test statistic t = 2.86 on 18 d.f.

Probability = 0.010

Two-sample t-test

Variates: CLR, Cerco.

Test for equality of sample variances

Test statistic F = 2.79 on 9 and 9 d.f.

Probability (under null hypothesis of equal variances) = 0.14

Summary

Sample	Size	Mean	Variance	Standard deviation	Standard error of mean
CLR	10	0.6354	0.01693	0.1301	0.04114
Cerco	10	0.7406	0.00606	0.0778	0.02461

Difference of means:	-0.1052
Standard error of difference:	0.0479

95% confidence interval for difference in means: (-0.2059, -0.004480)

Test of null hypothesis that mean of CLR is equal to Cerco

Test statistic t = -2.19 on 18 d.f.

Probability = 0.042

CARTER 2

Two-sample t-test

Variates: healthy, Cerco.

Test for equality of sample variances

Test statistic F = 19.44 on 9 and 9 d.f.

Probability (under null hypothesis of equal variances) < 0.001

Note: strong evidence of unequal sample variances -
variances estimated separately for each group.

Summary

Sample	Size	Mean	Variance	Standard deviation	Standard error of mean
healthy	10	0.0448	0.000520	0.02280	0.00721
Cerco	10	0.1948	0.010109	0.10054	0.03180

Difference of means:	-0.1500
Standard error of difference:	0.0326

95% confidence interval for difference in means: (-0.2227, -0.07730)

Test of null hypothesis that mean of healthy is equal to mean of Cerco

Test statistic t = -4.60 on approximately 9.92 d.f.

Probability < 0.001

Two-sample t-test

Variates: CLR, healthy.

Test for equality of sample variances

Test statistic F = 11.12 on 9 and 9 d.f.

Probability (under null hypothesis of equal variances) = 0.00

Note: strong evidence of unequal sample variances -
variances estimated separately for each group.

Summary

Sample	Size	Mean	Variance	Standard deviation	Standard error of mean
CLR	10	0.10002	0.005781	0.07603	0.02404
healthy	10	0.04475	0.000520	0.02280	0.00721

Difference of means: 0.0553
Standard error of difference: 0.0251

95% confidence interval for difference in means: (-0.0002363, 0.1108)

Test of null hypothesis that mean of CLR is equal to mean of healthy

Test statistic t = 2.20 on approximately 10.61 d.f.

Probability = 0.050

Two-sample t-test

Variates: CLR, Cerco.

Test for equality of sample variances

Test statistic F = 1.75 on 9 and 9 d.f.

Probability (under null hypothesis of equal variances) = 0.42

Summary

Sample	Size	Mean	Variance	Standard deviation	Standard error of mean
CLR	10	0.1000	0.005781	0.07603	0.02404
Cerco	10	0.1948	0.010109	0.10054	0.03180

Difference of means: -0.0948
Standard error of difference: 0.0399

95% confidence interval for difference in means: (-0.1785, -0.01100)

Test of null hypothesis that mean of CLR is equal to mean of Cerco

Test statistic t = -2.38 on 18 d.f.

Probability = 0.029

CARTER 3

Two-sample t-test

Variates: healthy, Cerco.

Test for equality of sample variances

Test statistic F = 6.22 on 9 and 9 d.f.

Probability (under null hypothesis of equal variances) = 0.01

Note: evidence of unequal sample variances -
variances estimated separately for each group.

Summary

Sample	Size	Mean	Variance	Standard deviation	Standard error of mean
healthy	10	0.0531	0.000645	0.02539	0.00803
Cerco	10	0.1581	0.004009	0.06332	0.02002

Difference of means:	-0.1050
Standard error of difference:	0.0216

95% confidence interval for difference in means: (-0.1521, -0.05790)

Test of null hypothesis that mean of health is equal to mean of Cerco

Test statistic t = -4.87 on approximately 11.82 d.f.

Probability < 0.001

Two-sample t-test

Variates: CLR, Cerco.

Test for equality of sample variances

Test statistic F = 1.01 on 9 and 9 d.f.

Probability (under null hypothesis of equal variances) = 0.99

Summary

Sample	Size	Mean	Variance	Standard deviation	Standard error of mean
CLR	10	0.1030	0.003958	0.06291	0.01989
Cerco	10	0.1581	0.004009	0.06332	0.02002

Difference of means: -0.0551
Standard error of difference: 0.0282

95% confidence interval for difference in means: (-0.1144, 0.004178)

Test of null hypothesis that mean of CLR is equal to mean of Cerco

Test statistic t = -1.95 on 18 d.f.

Probability = 0.037

Two-sample t-test

Variates: CLR, healthy.

Test for equality of sample variances

Test statistic F = 1.01 on 9 and 9 d.f.

Probability (under null hypothesis of equal variances) = 0.99

Summary

Sample	Size	Mean	Variance	Standard deviation	Standard error of mean
CLR	10	0.1030	0.003958	0.06291	0.01989
healthy	10	0.1581	0.004009	0.06332	0.02002

Difference of means: -0.0551
Standard error of difference: 0.0282

95% confidence interval for difference in means: (-0.1144, 0.004178)

Test of null hypothesis that mean of CLR is equal to mean of healthy

Test statistic t = -1.95 on 18 d.f.
Probability = 0.039

NDVI2

Two-sample t-test

Variates: CLR, healthy.

Test for equality of sample variances

Test statistic F = 2.79 on 9 and 9 d.f.

Probability (under null hypothesis of equal variances) = 0.14

Summary

Sample	Size	Mean	Variance	Standard deviation	Standard error of mean
CLR	10	0.6354	0.01693	0.1301	0.04114
healthy	10	0.7406	0.00606	0.0778	0.02461

Difference of means: -0.1052
Standard error of difference: 0.0479

95% confidence interval for difference in means: (-0.2059, -0.004480)

Test of null hypothesis that mean of CLR is equal to mean of healthy

Test statistic t = -2.19 on 18 d.f.

Probability = 0.042

Two-sample t-test

Variates: Cerco, healthy.

Test for equality of sample variances

Test statistic F = 2.32 on 9 and 9 d.f.

Probability (under null hypothesis of equal variances) = 0.23

Summary

Sample	Size	Mean	Variance	Standard deviation	Standard error of mean
Cerco	10	0.4765	0.01403	0.11845	0.03746
healthy	10	0.7406	0.00606	0.07784	0.02461

Difference of means: -0.2641

Standard error of difference: 0.0448

95% confidence interval for difference in means: (-0.3583, -0.1700)

Test of null hypothesis that mean of Cerco is equal to mean of healthy

Test statistic t = -5.89 on 18 d.f.

Probability < 0.001

Two-sample t-test

Variates: CLR, Cerco.

Test for equality of sample variances

Test statistic F = 1.21 on 9 and 9 d.f.

Probability (under null hypothesis of equal variances) = 0.78

Summary

Sample	Size	Mean	Variance	Standard deviation	Standard error of mean
CLR	10	0.6354	0.01693	0.1301	0.04114
Cerco	10	0.4765	0.01403	0.1184	0.03746

Difference of means: 0.1589
Standard error of difference: 0.0556

95% confidence interval for difference in means: (0.04204, 0.2758)

Test of null hypothesis that mean of CLR is equal to mean of Cerco

Test statistic t = 2.86 on 18 d.f.

Probability = 0.010

SR1

Two-sample t-test

Variates: CLR, healthy.

Test for equality of sample variances

Test statistic F = 1.00 on 9 and 9 d.f.

Probability (under null hypothesis of equal variances) = 1.00

Summary

Sample	Size	Mean	Variance	Standard deviation	Standard error of mean
CLR	10	7.295	16.25	4.032	1.275
healthy	10	11.145	16.21	4.026	1.273

Difference of means: -3.851
Standard error of difference: 1.802

95% confidence interval for difference in means: (-7.636, -0.06514)

Test of null hypothesis that mean of CLR is equal to mean of healthy

Test statistic t = -2.14 on 18 d.f.

Probability = 0.047

Two-sample t-test

Variates: Cerco, healthy.

Test for equality of sample variances

Test statistic F = 7.35 on 9 and 9 d.f.

Probability (under null hypothesis of equal variances) = 0.01

Note: strong evidence of unequal sample variances -
variances estimated separately for each group.

Summary

Sample	Size	Mean	Variance	Standard deviation	Standard error of mean
Cerco	10	3.915	2.206	1.485	0.4696
healthy	10	11.145	16.210	4.026	1.2732

Difference of means: -7.230
Standard error of difference: 1.357

95% confidence interval for difference in means: (-10.20, -4.256)

Test of null hypothesis that mean of Cerco is equal to mean of healthy

Test statistic t = -5.33 on approximately 11.40 d.f.

Probability < 0.001

Two-sample t-test

Variates: CLR, Cerco.

Test for equality of sample variances

Test statistic F = 7.37 on 9 and 9 d.f.

Probability (under null hypothesis of equal variances) = 0.01

Note: strong evidence of unequal sample variances -
variances estimated separately for each group.

Summary

Sample	Size	Mean	Variance	Standard deviation	Standard error of mean
CLR	10	7.295	16.255	4.032	1.2749
Cerco	10	3.915	2.206	1.485	0.4696

Difference of means: 3.380
Standard error of difference: 1.359

95% confidence interval for difference in means: (0.4018, 6.357)

Test of null hypothesis that mean of CLR is equal to mean of Cerco

Test statistic t = 2.49 on approximately 11.40 d.f.

Probability = 0.030

VOLGMANN 2

Two-sample t-test

Variates: CLR, healthy.

Test for equality of sample variances

Test statistic F = 2.56 on 9 and 9 d.f.

Probability (under null hypothesis of equal variances) = 0.18

Summary

Sample	Size	Mean	Variance	Standard deviation	Standard error of mean
CLR	10	2.604	0.5864	0.7658	0.2422
healthy	10	3.433	0.2293	0.4788	0.1514

Difference of means:	-0.829
Standard error of difference:	0.286

95% confidence interval for difference in means: (-1.429, -0.2288)

Test of null hypothesis that mean of CLR is equal to mean of healthy

Test statistic t = -2.90 on 18 d.f.

Probability = 0.009

Two-sample t-test

Variates: Cerco, healthy.

Test for equality of sample variances

Test statistic F = 1.18 on 9 and 9 d.f.

Probability (under null hypothesis of equal variances) = 0.81

Summary

Sample	Size	Mean	Variance	Standard deviation	Standard error of mean
Cerco	10	2.049	0.1949	0.4415	0.1396
healthy	10	3.433	0.2293	0.4788	0.1514

Difference of means:	-1.384
Standard error of difference:	0.206

95% confidence interval for difference in means: (-1.817, -0.9513)

Test of null hypothesis that mean of Cerco is equal to mean of healthy

Test statistic t = -6.72 on 18 d.f.

Probability < 0.001

Two-sample t-test

Variates: CLR, Cerco.

Test for equality of sample variances

Test statistic F = 3.01 on 9 and 9 d.f.

Probability (under null hypothesis of equal variances) = 0.12

Summary

Sample	Size	Mean	Variance	Standard deviation	Standard error of mean
CLR	10	2.604	0.5864	0.7658	0.2422
Cerco	10	2.049	0.1949	0.4415	0.1396

Difference of means:	0.555
Standard error of difference:	0.280

95% confidence interval for difference in means: (-0.03214, 1.142)

Test of null hypothesis that mean of CLR is equal to mean of Cerco

Test statistic t = 1.99 on 18 d.f.

Probability = 0.001

Appendix 2:

Interview administered to Coffee Research pathologist

I am R137865P, a student at Midlands State University studying Geography and Environmental Studies. I'm hereby appealing for your assistance in responding to the interview, which is part of my research work in partial fulfilment of the requirement of the BSc Honors Degree in Geography and Environmental Studies. The research topic is centred on the effectiveness of using a spectroradiometer in detecting coffee diseases at Coffee Research Institute. All given information from the interview will be treated as private and highly confidential and used for research purposes only.

1. What are the major diseases in coffee?
2. Who is responsible for disease management?
3. How do you identify and manage these diseases
4. What are the challenges faced in disease identification and management
5. Have you ever heard about remote sensing? If yes what do you understand?
6. Is remote sensing effective in overcoming these challenges? Support your answer
7. What are the impacts of coffee diseases to coffee production?
8. What are the environmental effects of these diseases?

Thank you for your cooperation.

Appendix 3:

Interview administered to the Chipinge Coffee Research Agronomist

I am R137865P, a student at Midlands State University studying Geography and Environmental Studies. I'm hereby appealing for your assistance in responding to the interview, which is part of my research work in partial fulfilment of the requirement of the BSc Honours Degree in Geography and Environmental Studies. The research topic is centred on the effectiveness of using a spectroradiometer in detecting coffee diseases at Coffee Research Institute. All given information from the interview will be treated as private and highly confidential and used for research purposes only.

1. What are the major diseases in coffee plants?
2. Who is responsible for identifying and managing the diseases?
3. Are there any constraints you know, that are faced in managing these diseases?
4. What are the impacts of coffee diseases
5. What are the effects of coffee diseases on coffee plant growth?
6. Are there any significant changes in the yields and quality of coffee due to the diseases?
7. What do you think can be done to reduce the impacts of the coffee diseases

Thank you for your cooperation.

Appendix 4:

Interview administered to AGRITEX Officer

I am R137865P, a student at Midlands State University studying Geography and Environmental Studies. I'm hereby appealing for your assistance in responding to the interview, which is part of my research work in partial fulfilment of the requirement of the BSc Honors Degree in Geography and Environmental Studies. The research topic is centred on the effectiveness of using a spectroradiometer in detecting coffee diseases at Coffee Research Institute. All given information from the interview will be treated as private and highly confidential and used for research purposes only.

1. What are the major diseases in coffee?

2. Who is responsible for coffee disease management?

3. What are the challenges faced in managing these diseases

4. What are the major effects of these diseases to coffee production?

5. What are the impacts faced by coffee farmers you interact with?

6. What have you done to reduce these impacts?

7. What do you think can be done to reduce the impacts of coffee diseases?

Thank you for your cooperation.