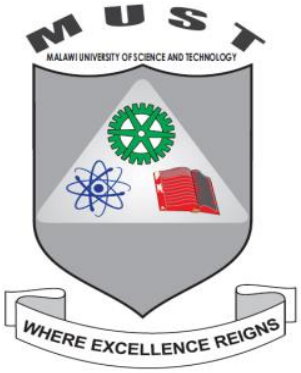


CLASSIFICATION OF MULT-SSPECTRAL DATA TO DISTIGUISH PLANT HEALTHY STATUS(TEA)

Thyolo, Malawi

BEYARD KAPIDA(Gis-022-17)

Dissertation submitted to Ndata School of Climate and Earth Sciences of the Malawi University of Science and Technology in partial fulfilment of the requirements for the Bachelor of Science degree in earth sciences.

DATE

23, May 2023

DECLARATION

I BEYARD KAPIDA declare that this research project represents my work and that it has never been submitted to this institution or any other institution for any academic purpose. All sources of information have been appropriately acknowledged.

Signature 

Date 23-05-2023

DISSERTATION APPROVED BY

Mr. Jabulani Nyengere Signature: 

ASSESSOR:

Title, Initial, Name Signature:

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ABSTRACT

This research aimed at comparing tea healthy status of satemwa tea field. Earth observation data downloaded on united states geological survey has been used which include Landsat 7 images from which Land surface temperature, Normalized difference vegetation index, soil adjusted vegetation index, spectral signatures and classified maps were generated, Study area polygon obtained on google earth which helped to delineate the study area, soil and precipitation data obtained on cru. Data website and earth map respectively. Training areas from the Landsat 7 images were generated using supervised approach to come up with spectral signature plots which has indicate decrease in reflectance of tea plants across the study period. NDVI, SAVI and Land surface temperature results has also shown decrease across the study periods. Results of annual precipitation shows increase across the study period. The results of the research would prompt farm managers to go into tea fields to see what has contributed to decrease in healthy status in the case that the biophysical factors under assessment shows little variation. For the purpose of this study only Land surface temperature, soil and precipitation were assessed but the methodologies can be simulated to assess other factors such as humidity and moisture.

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ACCRONYMS/ABREVIATIONS

NDVI: Normalized difference vegetation index

SAVI: Soil Adjusted vegetation index

VIR: Visible infrared

LST: Land Surface Temperature

LDCM: Landsat Data Continuity Mission

ETM: Enhanced Thematic Mapper

TM: Thematic Mapper

MSS: Multispectral Scanning System

MODIS: Moderate Imaging Spectroradiometer

NASA: National Aeronautics and Space Administration

LAI: Leaf Area Index

RS: Remote Sensing

GIS: Geographical Information Sciences

ERP: Enterprise Resource and Planning

OLI: Operational Land Imagery

EOS: Earth Observation Satellite

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CHAPTER 1: INTRODUCTION

1.1: BACKGROUND

Stress is a major focus of agricultural research, due to the vast economic losses caused to cash crops (Miltler, 2012). The relationship between stress and plant yield affects economic decisions as well as practical development. The impact of biotic injury on crop yield impacts population dynamics, plant-stressor coevolution, and ecosystem nutrient cycling. Malawi is the second largest tea producer in Africa after Kenya and produces approximately 10% of African tea. Export of tea is the third most important agricultural product by export value of Malawi (FAO, 2015). The biggest export destinations are the UK and South Africa. The color and brightness of Malawi tea is a key factor in blending of leading British tea brands. Malawi has an annual rainfall rate of 750 to 1,600 mm (World Bank, 2016), 80% of the tea is produced within the summer season from December to April. In the winter season only 20% is produced. Tea in Malawi is mostly produced in the districts of Mulanje and Thyolo in the Southern regions of the country as well as in Nkhatabay in the North (Tea Research Foundation of Central Africa, 2013).

The presence of diseases or insect feedings on plants or canopy surface causes changes in pigment, chemical concentrations, cell structure, nutrient, water uptake, and gas exchange. These changes result in differences in color and temperature of the canopy, and affect canopy reflectance characteristics, which can be detectable by remote sensing. Therefore, remote sensing provides a harmless, rapid, and cost-effective means of identifying and quantifying crop stress from differences in the spectral characteristics of canopy surfaces affected by biotic and abiotic stress agents.

1.2 PROBLEM STATEMENT

Traditional methods of predicting crop yields throughout the growing season include models that assimilate climate, soils and other environmental data as response functions to describe development, photosynthesis, evapotranspiration and yield for a specific crop (Wiegand and Richardson 1990). Though based on strong physiological and physical concepts, these models are poor predictors when spatial variability in soils, stresses or management practices are present (Wiegand 1984, Wiegand and Richardson 1990). In

addition to that this method is limited in the scale of monitoring and cannot give historical field information on Tea healthy over a period of time to help in its effective management. However, remote sensing of crop canopies has been promoted as a potentially valuable tool for agricultural monitoring because of its synoptic coverage and ability to 'see' in many spectral wavelengths (Hinzman et al. 1986, Quarmby et al. 1993). Numerous studies have recognized that plant development; stress and yield capabilities are expressed in the spectral reflectance from crop canopies and could be quantified using spectral vegetation indices (Jackson et al. 1986, Malingreau 1989, Weigand and Richardson 1990). Vegetation indices (VI), such as the Normalized Difference Vegetation Index (NDVI), are typically a sum, difference or ratio of two or more spectral wavelengths. Remote sensing technology can provide spatial distribution information of stressing agents in its early stage and over a large area with relatively low cost overcoming the problem of late identification of stressing agent.

1.3: MAIN OBJECTIVE

The main objective of this research is to compare the health status of Tea plantation using GIS & RS

1.4: SPECIFIC OBJECTIVE

- To produce land use and land cover maps of the study area for selected times.
- To extract and produce Land surface temperature, NDVI and SAVI from the land use and land cover maps.
- To conduct spectral analysis for all images from the study period to assess band signatures and reflectance curves.

1.5: RESEARCH QUESTIONS

- Can tea plants be realistically identified automatically from satellite images like LANDSAT?
- Is there any relationship between NDVI and tea leaf yield at critical period?
- What are some of the main steps to consider when conducting spectral analysis of images?

- How can the results obtained be helpful in overcoming the problems of conventional tea practicing methods?

1.6: SCIENTIFIC SIGNIFICANCE

The main significance of this study is that it will provide and offer an efficient and reliable means of collecting information on the structure and health of tea bushes required, in order to map tea type and acreage. The spectral reflectance of a tea field always varies with respect to the phenology, stage type and crop health and these could be well monitored and measured using the multispectral sensors. Information from remotely sensed data can be inputted to a Geographic Information System (GIS) and other cropping system which can then be combined with ancillary data to provide information of ownership and management practices. This study will also help planters to detect early stress and crop infestations that are associated with tea and provide them with an opportunity to mitigate diseases and ensure good tea productivity.

1.7 STUDY GEOGRAPHICAL AREA

The field of research is Satemwa Tea Estate which is located in Thyolo district, which is nestled in the shire highlands in the country's south. The tropical climate is moderated by Blantyre's elevation of 3409 feet (1039 meters). It has three seasons: a wet season (December to March), a cold season (April to August), and a hot season (September to November) (September to November). Figure 1 and 2 below shows rainfall and temperature variations (2010-2020)

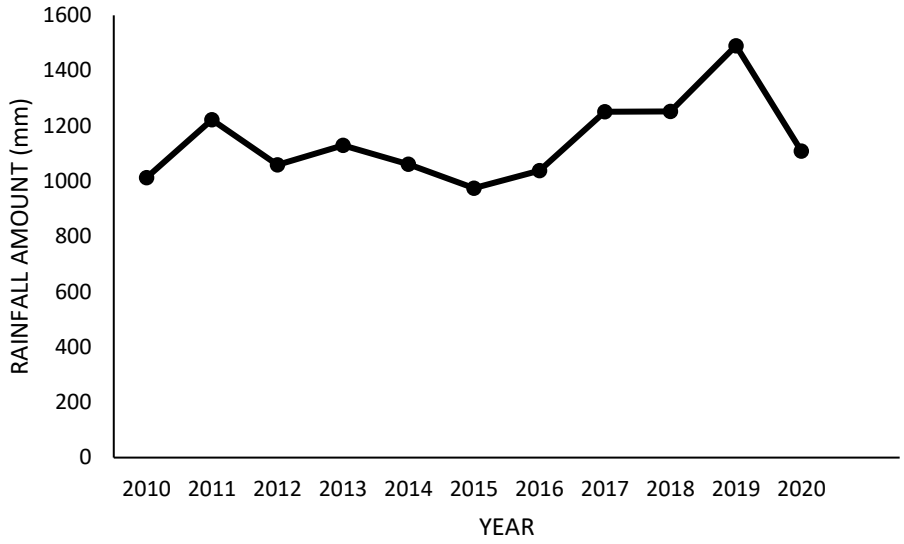


Figure 1:Rainfall variation

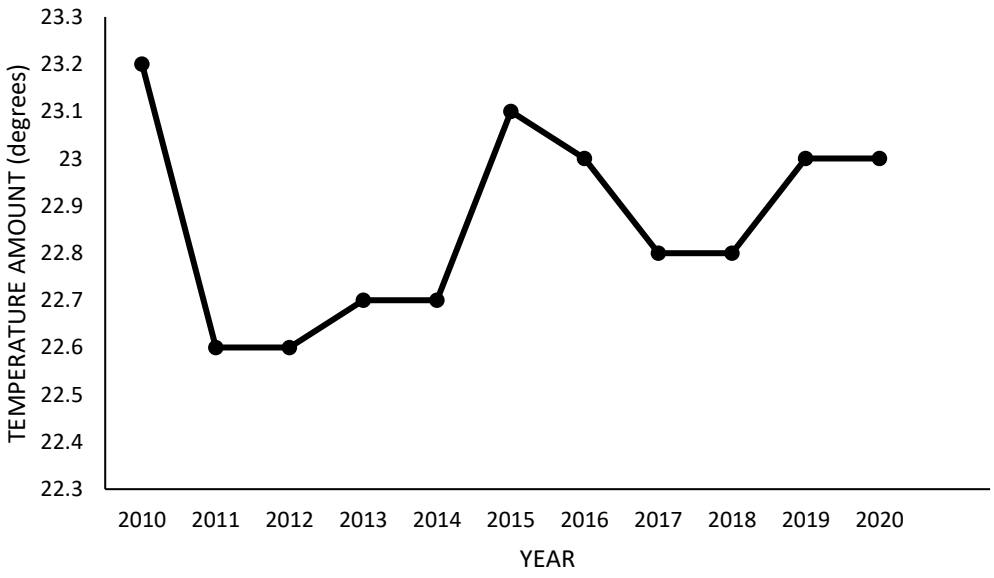


Figure 2: temperature variations

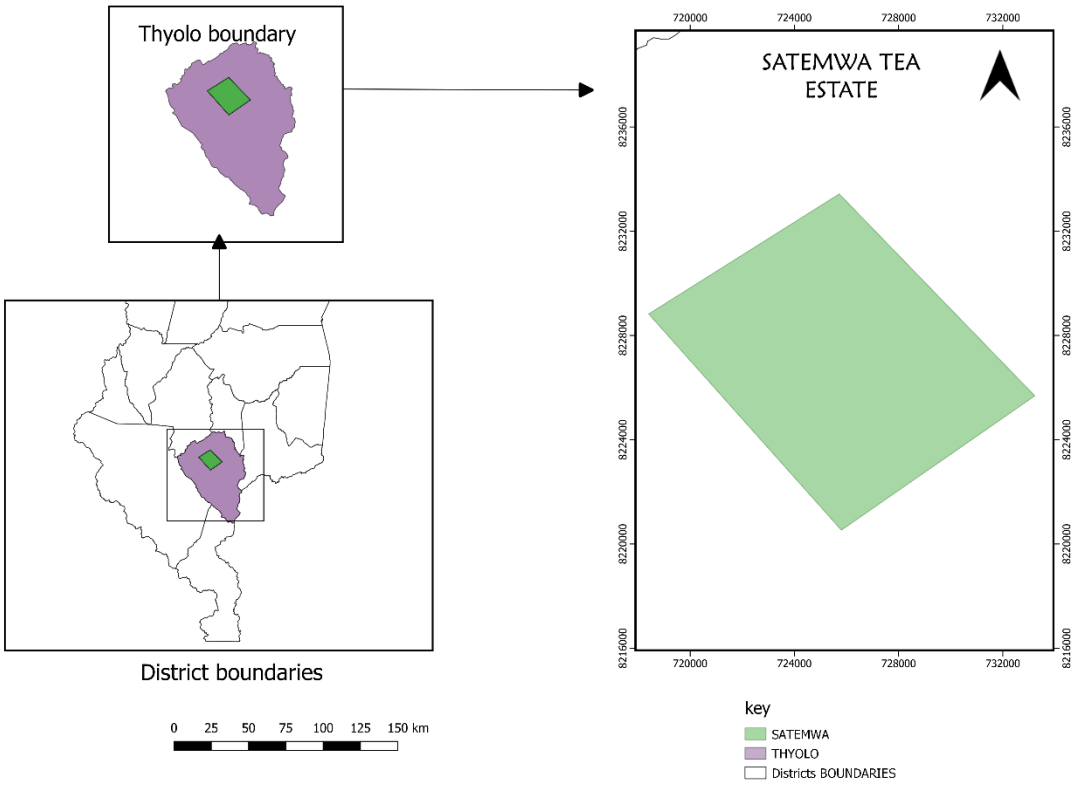


Figure 3 study area map

CHAPTER 2: LITERATURE REVIEW

2.1 OPTICAL REMOTE SENSING FOR CROP MONITORING

Assessment of the health of a crop, as well as early detection of crop infestations, is critical in ensuring good agricultural productivity. Stress associated with, for example, moisture deficiencies, insects, fungal and weed infestations, must be detected early enough to provide an opportunity for the farmer to mitigate. This process requires that remote sensing imagery be provided on a frequent basis (at a minimum, weekly) and be delivered to the farmer quickly, usually within 2 days. Remote sensing has a number of attributes that lend themselves to monitoring the health of crops. One advantage of optical (VIR) sensing is that it can see beyond the visible wavelengths into the infrared, where wavelengths are highly sensitive to crop vigor as well as crop stress and crop damage. Remote sensing imagery also gives the required spatial overview of the land. Recent advances in communication and technology allow a farmer to observe images of his fields and make timely decisions about managing the crops. Remote sensing can aid in identifying crops affected by conditions that are too dry or wet, affected by insect, weed or fungal infestations or weather-related damage. Images can be obtained throughout the growing season to not only detect problems, but also to monitor the success of the treatment.

2.2 LAND SURFACE TEMPERATURE

Land Surface Temperature (LST) is the temperature of the surface which can be measured when the land surface is in direct contact to the measuring instrument.

Over the past several decades in Remote Sensing community, land surface temperature (LST) is found to be one of the most important parameters in the physical processes of surface energy and water balance at local through global scales (Anderson et al. 2008; Brunsell and Gillies 2003; Karnieli et al. 2010; Kustas and Anderson 2009; Zhang et al. 2008). In more general terms LST can be defined as hotness of surface of earth, from RS satellite's perspective, the surface is whatever it sees when it looks through the atmosphere to the ground. LST estimation provides information about temporal and spatial variations of the surface equilibrium state and is of fundamental importance in

many applications. LST is being used in a variety of areas such as evapotranspiration, climate change, hydrological cycle, vegetation monitoring, urban climate and environmental studies, among others (Arnfield 2003; Bastiaanssen et al. 1998; Hansen et al. 2010; Kalma et al. 2008; Kogan 2001; Su 2002; Voogt and Oke 2003; Weng 2009; Weng et al. 2004). Since the launch of the Landsat-8 satellite (also known as Landsat Data Continuity Mission, LDCM) in February 2013 continuity of remote sensing data at high spatial resolution acquired by instruments on board previous Landsat satellites such as the multispectral scanner system (MSS), the thematic mapper (TM), and the enhanced thematic mapper plus (ETM+). Landsat-8 carries two sensors, i.e., the operational land imager (OLI) and the thermal infrared sensor (TIRS). OLI collects data at a 30 m spatial resolution with eight bands located in the visible and near-infrared and in the shortwave infrared regions of the electromagnetic spectrum, plus an additional panchromatic band at 15 m spatial resolution. TIRS sensor measures the TIR radiance at 100 m spatial resolution using two bands located in the atmospheric window between 10 and 12 lm (Irons et al. 2012). Since Satellite-based thermal infrared (TIR) data is directly linked to the LST through the radiative transfer equation. The retrieval of the LST from remotely sensed TIR data has attracted much attention, specially from Landsat-8 TIR bands. Direct estimation of LST from the radiation emitted in the TIR spectral region is difficult to perform with that accuracy, because radiances measured by the radiometers onboard satellites depend not only on surface parameters (temperature and emissivity) but also on atmospheric effects. Therefore, besides radiometric calibration and cloud screening, the determination of LSTs from space-based TIR measurements requires atmospheric corrections (Vidal 1991). In past many studies have been carried out to estimate LST from satellite derived TIR data, by using different approaches and methods (Jiménez-Muñoz and Sobrino 2003). Before the invention of earth observation satellites (EOS), it was hard to estimate the LST of an area. Generally, it was calculated for a particular set of sample points and interpolated into isotherms to generalize the point data into area data. But now a day's remotely sensed data is being used for LST estimation by using thermal data. LST greatly affected by the increasing greenhouse gases in the atmosphere. As it rises, it melts the glaciers and ices sheets in the polar region, it also increases flood

and sea level, Increase in LST also affects the climatic condition of the monsoon countries leading to unpredictable rainfall hence vegetation in the entire Earth surface will be affected by this (Rajeshwari and Mani 2014). Land use/Land cover (LU/LC) of an area can be used for estimating the amount of LST. The natural and anthropogenic activities change the LU/LC of an area. It also influences LST of that area. As its value changes the local climate of the area also changes, this draws attention of many researchers to calculate the amount of LST for any particular region. In literature it has been found that many methods of LST estimation are developed and adopted some of the most widely used methods are as follow: split-window (SW), SC algorithm, Dual-Angle, Sobrino, Mao, and Submao. Most of the studies were done for urban areas and arid and semi-arid regions and in many of the studies, single thermal band was used. LST products are routinely generated from moderate-resolution satellite data (e.g., moderate resolution imaging spectroradiometer (MODIS) on the National Aeronautics and Space Administration's (NASA) Terra and Aqua platforms, Advanced Along-Track Scanning Radiometer on the European Space Agency's Environmental Satellite) because they indicate the surface energy that is available at the land–atmosphere interface (Norman and Becker 1995).

2.3 NDVI-LAI RELATIONSHIP

Several studies have shown that Normalized Difference Vegetation Index (NDVI) and Leaf Area Index (LAI) have been used for yield estimation and prediction. Both these parameters give the vegetation status of the area. It has been observed that NDVI and LAI provide the relation with yield that predicts the yield fluctuations. Many models have been tried in this regard. The LAI is an important vegetation canopy characterization. It is one parameter for crop growth models. The major interest of remote sensing LAI retrievals took place since the launch of earth observation satellite. It is indeed difficult to build accurate and robust retrieval models due to the complexity of relationship between retrieved signal and LAI. But MODIS LAI could be developed and validated (Guissard, 2005). Since NDVI and LAI are obtained from satellite data (Gardner et.al., 1991), the distinction of vegetation and quantitative assessment for growth has

become possible. Since plant canopy is composed of leaves, which is a direct source of the energy matter interactions that are observed by earth-observing remote sensing systems, LAI has been an attractive variable of interest in vegetative remote sensing. However, large portion of such studies to estimate LAI using NDVI were dealing with semi-arid vegetation and agricultural systems where the canopy closure is less than 100%. Studies have also been carried out where the linear models were evaluated using NDVI and field LAI. Cross validation procedure was used to assess the prediction power of the regression models. The study demonstrates that for hyperspectral image data, linear regression models can be applied to quantify LAI with good accuracy (Clement et.al, 2004). LAI – NDVI relationship was also used for estimating the evapotranspiration where the relationships between the NDVI – LAI were adjusted by potential model. 57 – 72% variance of NDVI was explained by the LAI (Xavier et.al, 2004). Research has also been done where the correlation has been developed between remote sensing data and strawberry growth and yield. Regression analysis was then used to determine the relationship between canopy size and the NDVI from the aerial image. The results showed positive correlation between the two sets of data (r2 =0.918). Studies have also been carried out to find the correlation between the maximum latewood density of annual tree rings and NDVI based estimates of forest productivity (Darrigo et.al., 2000). This study showed positive correlations between maximum latewood density data and NDVI based net primary productivity (NPP). Remote sensing from satellite and aerial platforms has been used to detect nutrient status of plants (Blackmer et al., 1996; Wright et al., 2000) and estimate yield (Shanahan et al., 2001; Labus et al., 2002). Some experiments have already been carried out on wheat plants. Most of the yield prediction estimates on larger scales use a simple linear regression model derived from the normalized difference vegetation index (NDVI) with imagery collected during the wheat grain filling period (Benedetti and Rossini, 1993; Doraiswamy and Cook, 1995). Correlation coefficients derived from remote sensing range between 0.7 to 0.83 (r2) in uniform crop patterns (Raun, et al., 2000) with the expectation of better correlation as spatial and spectral resolution increases and algorithms improve. From the above discussion it is quite clear that correlation and regression between NDVI and LAI could

help in linear model development which could further help in estimating and predicting yield.

2.4 APPLICATION OF REMOTE SENSING IN TEA SECTOR

Remote sensing has been in used for quite a long time. Remotely sensed data helps in identifying the vegetation status and allows the users to take appropriate actions at the appropriate time. Lot of research work has also been carried out in the agricultural sector from crop monitoring to damage assessment. But it was observed that very less work has been done in the tea sector. As such few research works have been carried out in the tea sector using remote sensing and GIS. As tea is a very important beverage, from both management and commercial point of view, an attempt has been made to predict tea yield using remote sensing and GIS and other key parameters in the GIS environment (Tripathy et.al). Leaf area index (LAI) is one main key factor useful in crop growth models that may be derived from optical remote sensing data. LAI plays an important role in both the processes of crop growth and canopy reflectance (Clevers et. al., 1994). The normalized difference vegetation index (NDVI) is used as a measure of plant productivity (Sellers, 1985). It has also been considered as a measure of LAI for most of crops (Gong, et. al., 1995). So NDVI-LAI could be used to study the vegetation status of the crop. There have been many attempts to estimate LAI using various types of remote sensing data since the early stage of space remote sensing (Badwhar et al., 1986; Peterson et al., 1987; Turner et al., 1999). Remote sensing estimation of LAI has been primarily based on the empirical relationship between the field-measured LAI and sensor observed spectral responses (Curran et al., 1992; Peddle et al., 1999). As a single value to represent the remotely sensed spectral responses of green leaves, spectral vegetation indices, such as normalized difference vegetation index (NDVI) or simple ratio, are frequently used to indirectly estimate LAI. Normalized difference vegetation index (NDVI) has been a popular index with which to estimate LAI across diverse ecosystems. Recent studies have shown that the NDVI may not be very sensitive to values of LAI in particular at the forest ecosystem having the close canopy condition that the LAI value is relatively high (Chen and Cihlar 1996, Turner et al. 1999). Since NDVI and are obtained from satellite data

(Gardner et.al., 1988 and Baret et.al., 1991) the distinction of vegetation and quantitative assessment for its growth stage and the estimates of its carbon absorption and evapotranspiration (Nimani et.al., 1989 and Ebisu, 2000) become possible (Ogawa, et.al., 2000). Using optical and radar satellite data, crop specific LAI could be obtained for growth monitoring and modelling (Guissard et.al., 2005). It has also been found that spectral characteristics of tea plants are very important for monitoring the tea plantations by remote sensing. A study was carried out in Sri Lanka where LAI of the tea canopy and spectral reflectance of different types of tea clones for different pruning ages were studied in fifty tea fields in the estate and an empirical model between NDVI and LAI of tea canopy was developed (Rajapakse et. al., 2001). An attempt has also been made to develop a GIS anchored web enabled Decision Support System (DSS) for tea enterprises, introduction of precision farming, user friendly IT framework for collection of spatiotemporal data and efficient and smart Enterprise Resource and Planning (ERP) package for decision support at all levels for better management and profitability (Ghosh et.al., 2004). Some work has already been carried out in West Bengal; India where remote sensing has been used for finding the ground water availability in the tea growing areas of Terai Region. The study has revealed that satellite remote sensing combined with other conventional data has great potential for ground water exploration (Duarah et.al. 1993). It is observed that water management is an important factor for augmenting the productivity of perennial crops like tea. A study was carried out on the land use and ground water potential through remote sensing technique in the Darrang and Sonitpur District of Assam (Bordoloi et.al., 1994). Attempt has also been made to use porphyrin derivative, n-tetraphenyl porphine manganese (111) chloride, thin films for detection of tea aroma using optical fibre reflectance with three different colour LED's i.e., red, yellow and green as the light sources (Akrajas et.al., 2000). Researches have also been carried out on determining the tea quality by using neural network based electronic nose. Metal oxide sensor based electronic nose (EN) have been used to analyze five tea samples with different qualities in oven. The metal oxide used has electronic resistance with partial sensitivity to headspace of tea. The data were processed using Principal Components Analysis (PCA) and Fuzzy C Means algorithm (FCM). It was found that EN was able to

discriminate between the flavors of tea manufactured under different processing conditions (Dutta et.al.) The electronic nose (ER) was also applied for aroma characterization of orthodox black tea where orthodox samples were tested using Alpha MOS 2000 Electronic Nose and data obtained from the experimental setup have been classified using PCA and Black-propagation Multi-Layer Perceptron model (Bhattacharyya et.al.). Experiments have also been conducted for the measurement of plural tea information using fibre-optic sensor. Fibre reacts to various signals like temperature and pressure. The plural tea information using the multi-functional technique was measured with optical fibre (Zhu et.al. 2004). Attempts have also been made to model the influence of irrigation on potential yield of tea where the CUPPA Tea model was validated against the yield data from irrigation experiments carried out on contrasting soil types at Siliguri and Tezpore regions of North-East India (Panda et. al., 2002).

CHAPTER 3: METHODOLOGY

3.1 RESEARCH DESIGN

Data used for this study was categorized in two types: Earth Observation Data and Field Survey Data.

Earth Observation Data:

- **LANDSAT-7 ETM+ Image:** The 2 images were taken on 04 march, 2016 and 27 February, 2020. It includes spectral regions of VNIR (bands 1 -4 with 30 m resolution), SWIR (bands 5 and 7 with 30 m resolution and TIR (band 6, with 60 m resolution) and one panchromatic band 8 with 15 m resolutions. The Enhanced Thematic Mapper Plus (ETM+) is the instrument payload on the LANDSAT-7 spacecraft. The ETM+ is a derivative of the Thematic Mapper (TM) instrument on LANDSAT-4 and LANDSAT-5 (Markham, 2003). Landsat 7 was chosen because it has newer features that make it a more versatile and efficient instrument for global change studies, land cover monitoring/assessment and large area mapping.

Table 1: overview of the nominal characteristics of Landsat-ETM+

Band No	Band – pass(μm)	Spatial resolution
1	0.452-0.514	30
2	0.519-0.601	30
3	0.631-0.692	30
4	0.772-0.898	30
5	1.547-1.748	30
6	10.3112.36	120
7	2.065-2.364	30
8	0.515-0.896	15

Field Survey Data

- **Google earth Data Collection**: The coordinates were used for validation. Tea growing areas in the field were identified. Google earth map was used for taking the coordinates of the area from where the study was done.

3.1.1 SOIL

Soil data for the study area was downloaded on the cru. Data website. Soil data was used in this study to know the presence of nutrients and type of soils that are found in the ground. In addition to that soil data was crucial in this study as it help in assessing the properties and the composition of the soil.

3.1.2 PRECIPITATION

Precipitation data was also crucial for this study; this data was taken from the earth map. Precipitation data allowed us to see the variations of rainfall between the 2 years.

3.1.3 LAND SURFACE TEMPERATURE

Land Surface Temperature (LST) is the temperature of the surface which can be measured when the land surface is in direct contact to the measuring instrument. Land surface temperature for the study area was extracted from the Landsat image of different years. The land surface temperature thematic maps were produced in ArcMap which showed the changes or the difference in the land surface temperature of the study area over the years and how it has possibly affected the growth and productivity of the Tea plants.

3.2: MATERIALS

3.2.1 SOFTWARE'S USED

I. Quantum GIS(QGIS) 3.14
II. ARCGIS 10.8
III. Google earth

3.2.2 ACQUISITION OF SATELLITE IMAGE

The 2 Landsat images of different years were downloaded on USGS platform the images were taken in April 2016 and 2020. It includes spectral regions of VNIR (bands 1 -4 with 30 m resolution), SWIR (bands 5 and 7 with 30 m resolution and TIR (band 6, with 60 m resolution) and one panchromatic band 8 with 15 m resolutions. The Enhanced Thematic Mapper Plus (ETM+) is the instrument payload on the LANDSAT-7 spacecraft.

The ETM+ is a derivative of the Thematic Mapper (TM) instrument on LANDSAT-4 and LANDSAT-5 (Markham, 2003).

3.2.3 SATELLITE IMAGE CLSASSIFICATION TECHNIQUE

The basic assumption for image classification is a specific part of the feature space corresponding to a particular class. Classes have to be distinguished in an image and classification needs to have different spectral characteristics. This can be done by comparing spectral reflectance curves. Image classification gives results to certain levels of reliability. The principle of image classification is that a pixel is assigned to a class based on its feature vector by comparing it to predefined clusters in the feature space. Two basic approaches exist for classification: pixel based and object oriented. For this study a pixel-based image analysis was used:

Supervised Classification:

Here the image analyst supervises the pixel categorization process by specifying, to the computer algorithm, numerical descriptors of various landcover types present in the image. Training samples that describe the typical spectral pattern of land cover classes are defined. Pixels in the image are compared numerically to the training samples and are labeled to landcover classes that have similar characteristics.

Accuracy Assessment:

In accuracy assessment the main assumption is that the reference data or field data are correct. Classification accuracy was determined by using three complementary measures which are based on error matrices or confusion matrix derived from independent field data.

3.3 METHODS

3.3.1 LANDUSE AND LANDCOVER MAP

Land use and land cover thematic map were produced in QGIS environment which showed the land use plan of the area. The classification process was based on the collected ROIs and the spectral signatures. Classification preview was done in order to assess the results influenced by spectral signature before the final classification.

IDW was used because it allows localized adaptability by considering only nearby points for interpolation. Assigns weights based on distance and by adjusting the power parameter it is possible to control the rate of decay of influence with increasing distance. This adaptability made IDW useful for capturing local variations in soil, precipitation and temperature.

3.3.2 SOIL MAP

Soil data for the study area was downloaded on the cru.dat website. Soil data was used in this study to know the presence of nutrients and type of soils that are found in the ground. In addition to that soil data was crucial in this study as it was assessing the properties and the composition of the soil. The soil thematic map was produced through interpolation with inverse distance weighting as type of algorithm used to determine the soil type of the study area.

3.3.3PRECIPITATION MAP

Precipitation data was also crucial for this study; this data was downloaded on Cru. Data Precipitation data allowed us to see the variations of rainfall between the study period. After obtaining the precipitation data the thematic map was produced through the process of interpolation where Inverse Distance Weighting (IDW) was chosen as the type of interpolation. The thematic map showed the annual distribution of rainfall of the study area and how it possibly affected growth and productivity of tea plants.

3.3.4 LAND SURFACE TEMPERATURE

Land Surface Temperature (LST) is the temperature of the surface which can be measured when the land surface is in direct contact to the measuring instrument. Land surface temperature for the study area was extracted from the Landsat image of different years. The land surface temperature thematic maps were produced in ArcMap which showed the changes or the difference in the land surface temperature of the study area over the years and how it has possibly affected the growth and productivity of the Tea plants.

3.3.5 SPECTRAL ANALYSIS

Spectral analysis of all the images of the study period was conducted and analyzed to assess and interpret band signatures and reflectance curves. This was possible with the use of QGIS software which has the capability of conducting spectral analysis. Training samples were manually created by drawing polygons. To increase accuracy of spectral signatures the following issues were observed, many training sites were generated for each class, Training sites were generated throughout the entire image, large polygon for each training area. Signatures for each class were highlighted and merged to calculate average signature for each class. Calculate signatures for highlighted items button was used to calculate the average of the pixels and the average reflectance in each spectral reflectance band and create average spectral signatures. The calculated signatures for each class were plotted then plotted.

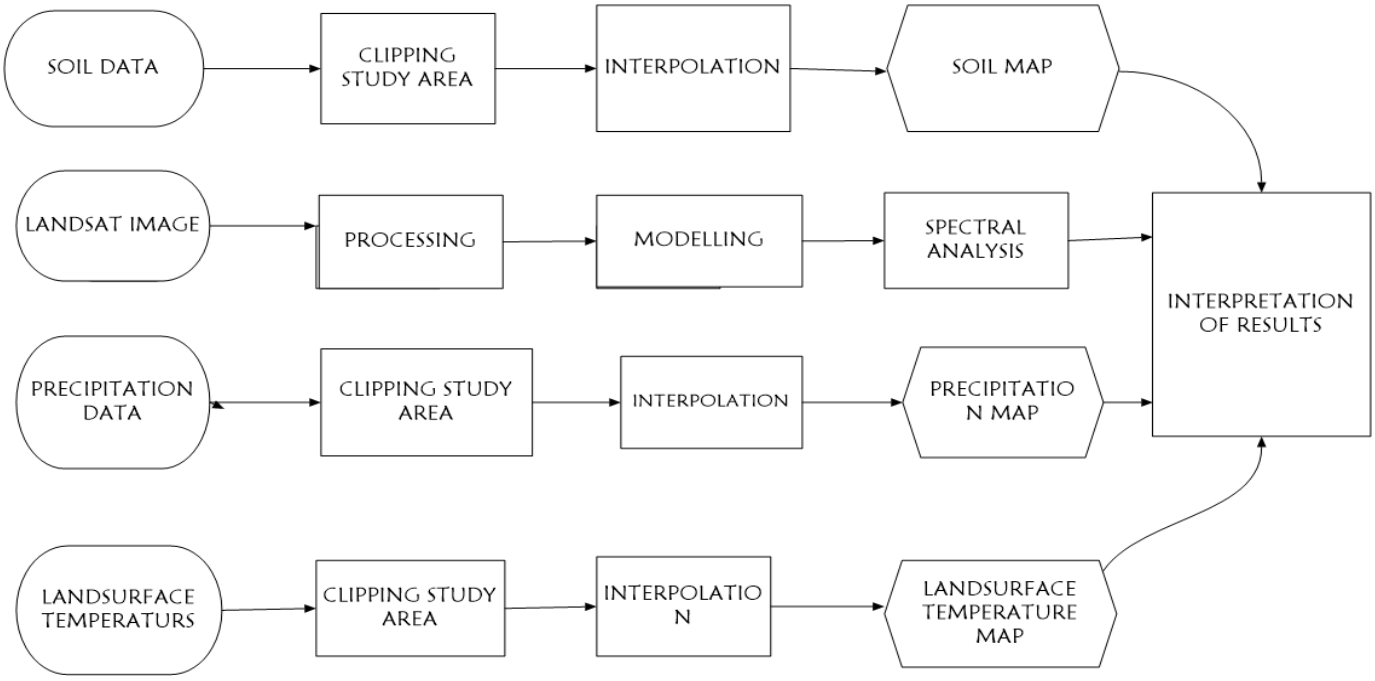


Figure 4 Methodology flow chart

CHAPTER 4: RESULTS AND DISCUSSION

Figure 5 and 6 below shows the plot of reflectance values against wavelength. The doted vertical lines represent band number. Of our interest is spectrum in green which is tea plants. Tea plants is showing high reflectance values in the wavelength region 0.8 which is around 0.37 unlike in figure 6s which is around 0.43. Reflectance in this wavelength region corresponds to high level of chlorophyl which is also directly related to healthiness of plant, therefore 2016 had more healthy tea plants as compared to the year 2020.

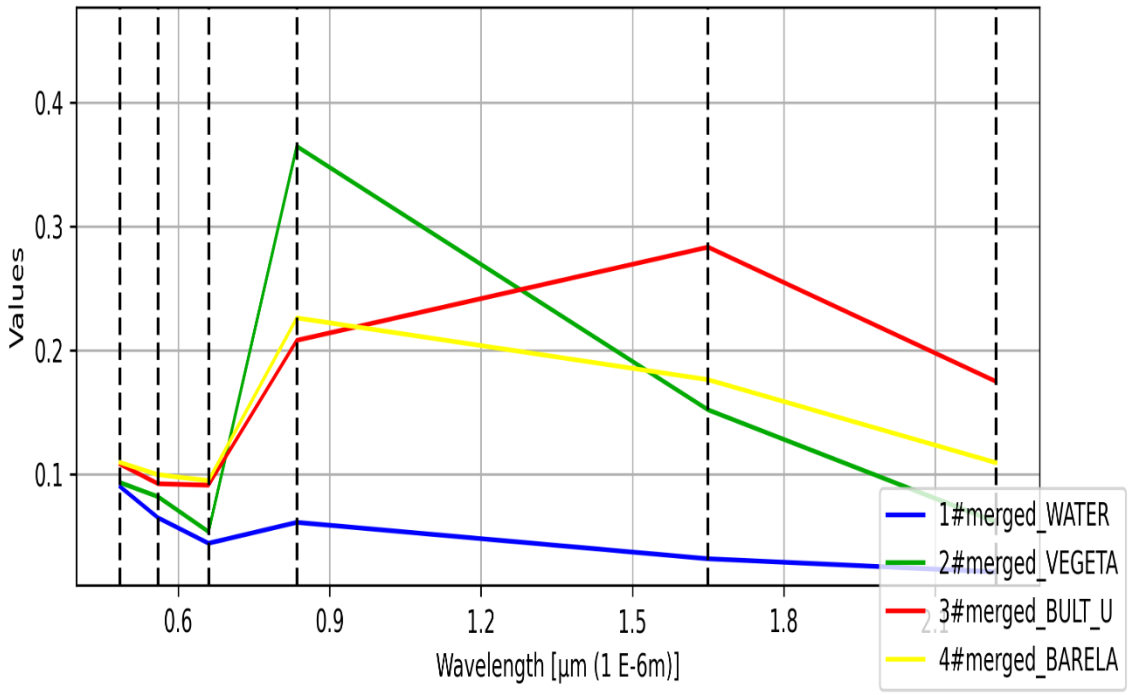


Figure 5; spectral signature plot for land features (2016)

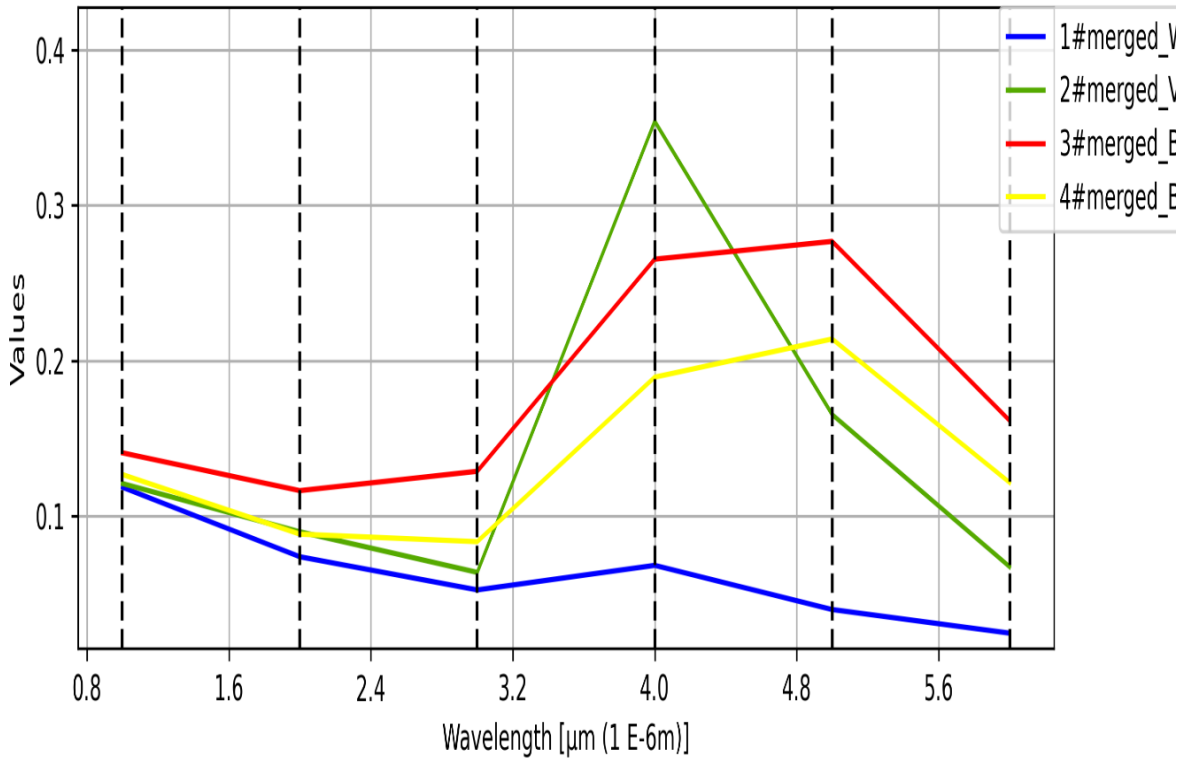


Figure 6:spectral signature plot for land features (2020*)*

Normalized difference vegetation index (NDVI) has been compared by considering their Minimum, maximum and Mean values. Since NDVI also directly corresponds to plant healthiness, from the figure 7 below high values for 2016 means more healthy tea plants than low values of year 2020.

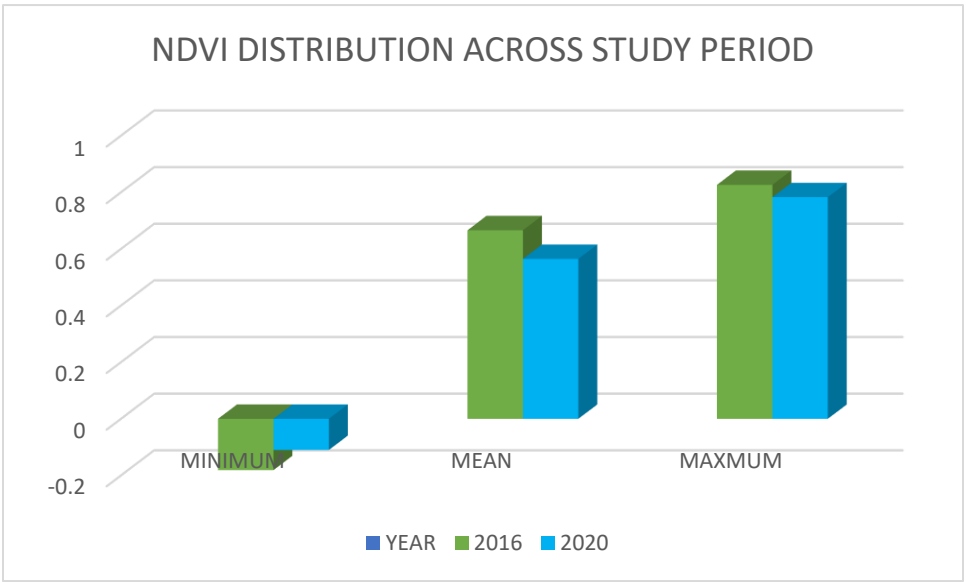


Figure 7:NDVI graphical distribution

NDVI thematic representation in the Figure 8 below shows high values in both maximum and minimum values in the year 2016 than year 2020. Dark green in 2016 means more reflectance than in 2020 which has light green representing less reflectance. Since NDVI directly corresponds to plants healthiness this means 2016 had more healthy tea plants than year 2020.

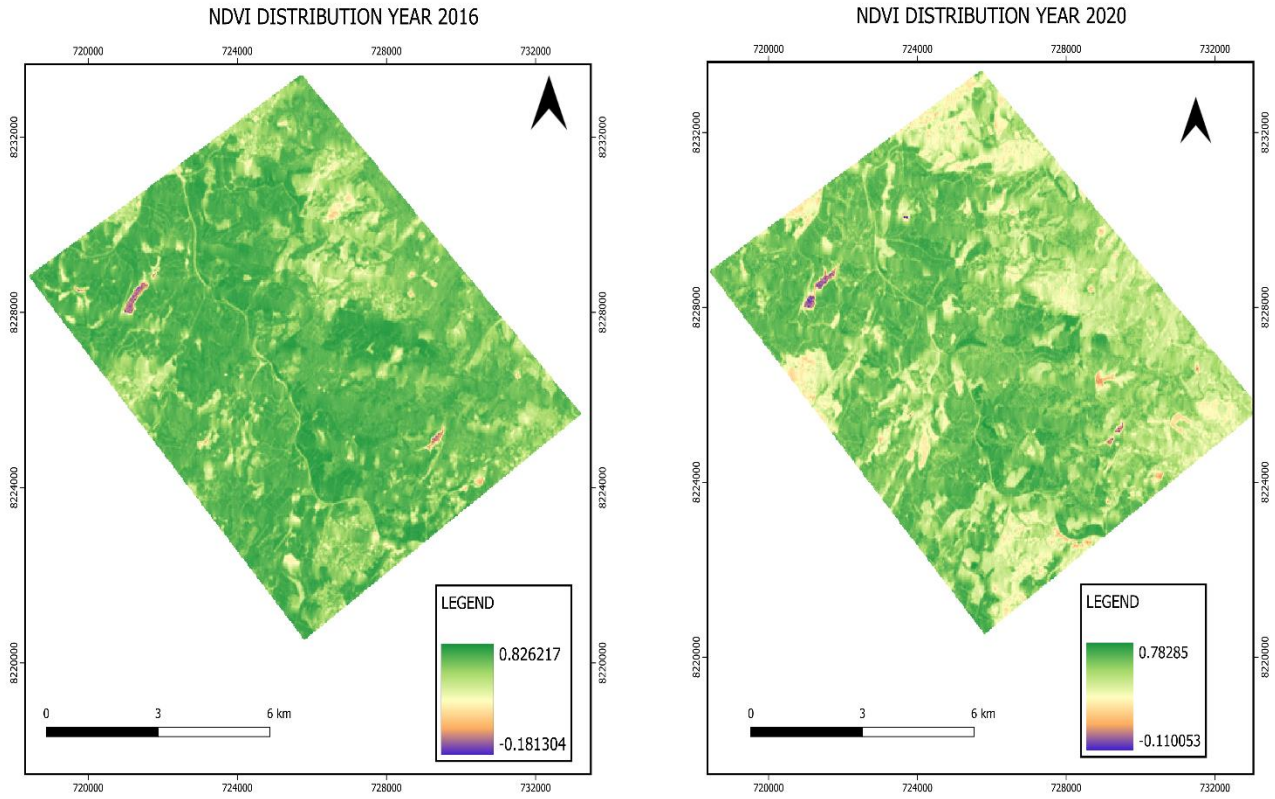


Figure 8:NDVI thematic representations

The results in figure 9 shows that minimum, mean and maximum values for year 2016 are slightly higher than that of 2020.Since SAVI is NDVI with a corrected soil brightness, high values also indicate more healthy tea plants in year 2016 than year 2020.

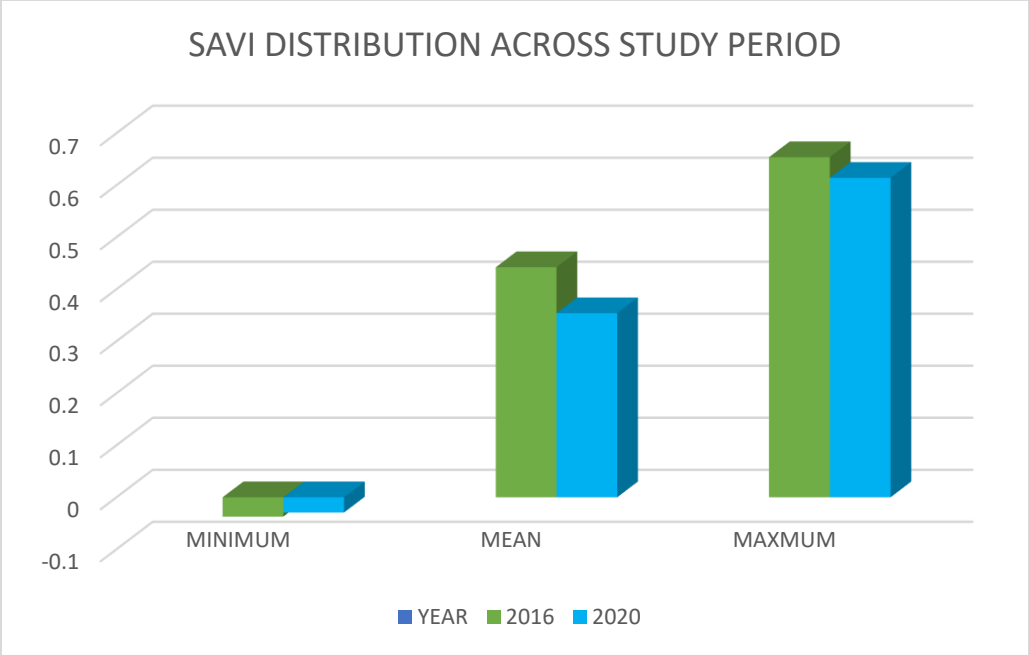


Figure 9:SAVI graphical representations

SAVI thematic representation in the Figure 10 below shows high values in both maximum and minimum values in the year 2016 than year 2020. Dark green means more reflectance therefore 2016 has more healthy tea plants than in 2020 which has light green representing less reflectance.

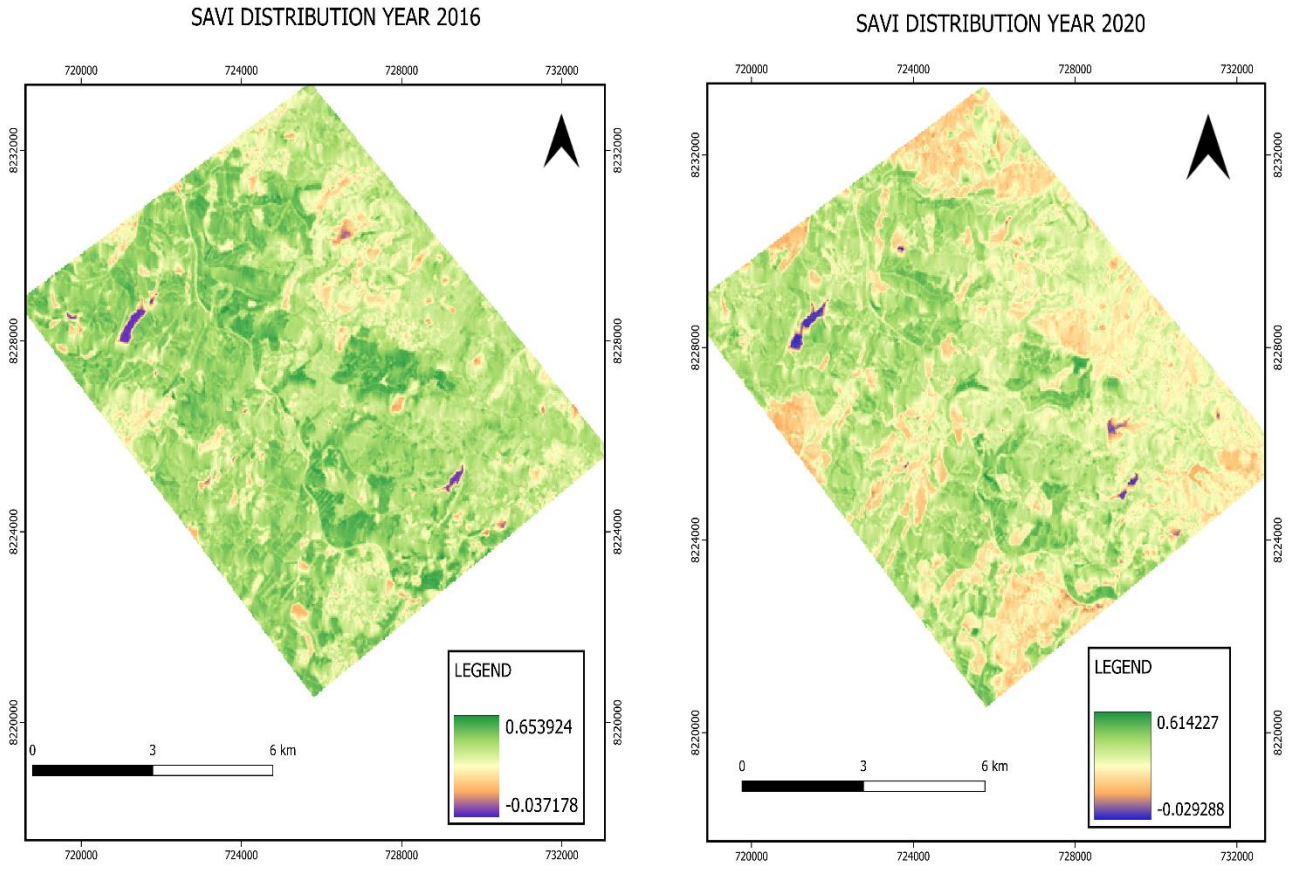


Figure 10:SAVI thematic representation

Land use and landcover thematic maps for the study area have been generated to enhance interpretation. It can be clearly seen from the Figure 11 below that the year 2016 had most of the land covered with tea plants as compared to year 2020.

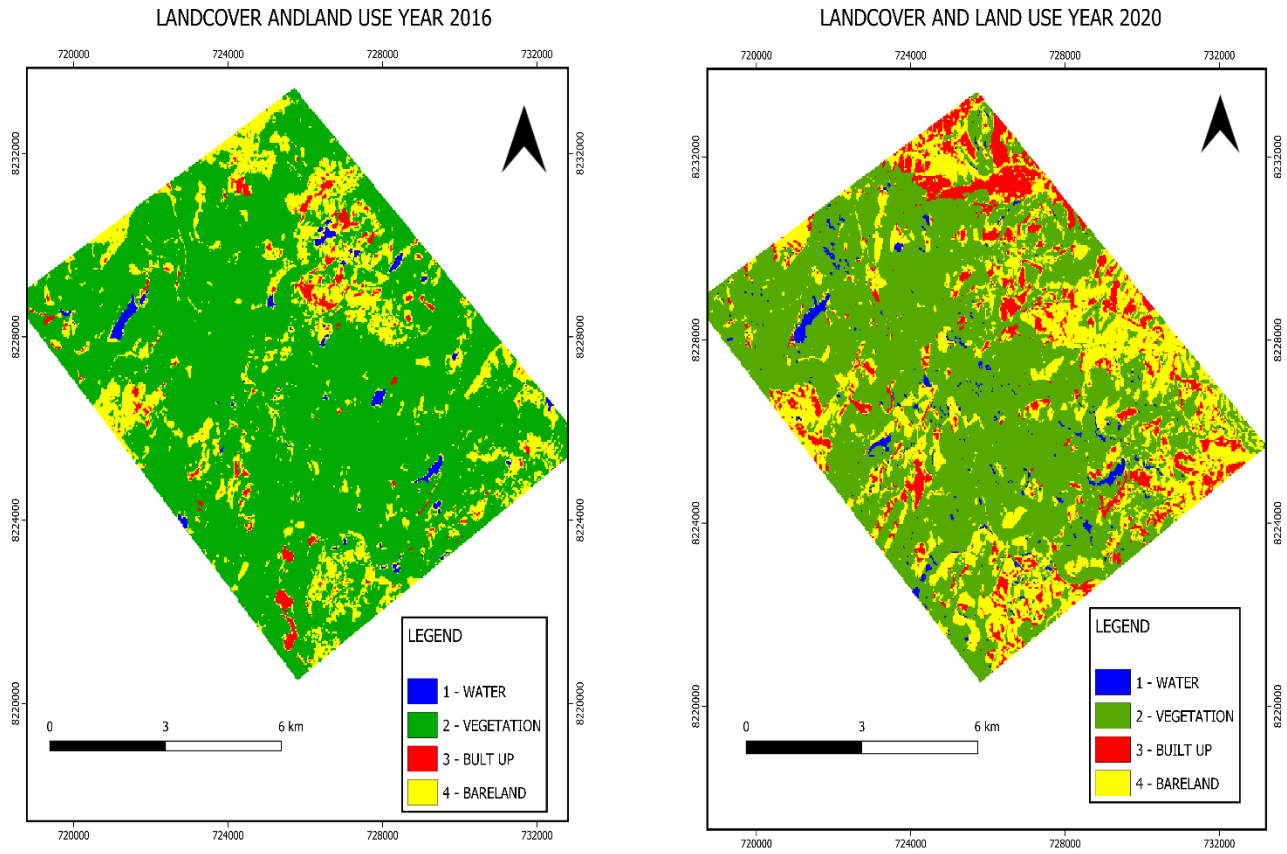


Figure 11:landcover and land use map

The results figure 12 below shows there is slight decrease in Land surface temperature between the study periods as can be seen from Land surface temperature thematic maps. This is portraying negative correlation with tea spectral signature, Normalized difference vegetation index and soil adjusted vegetation index. This decrease in land surface temperature may have contributed to the change in tea healthy status.

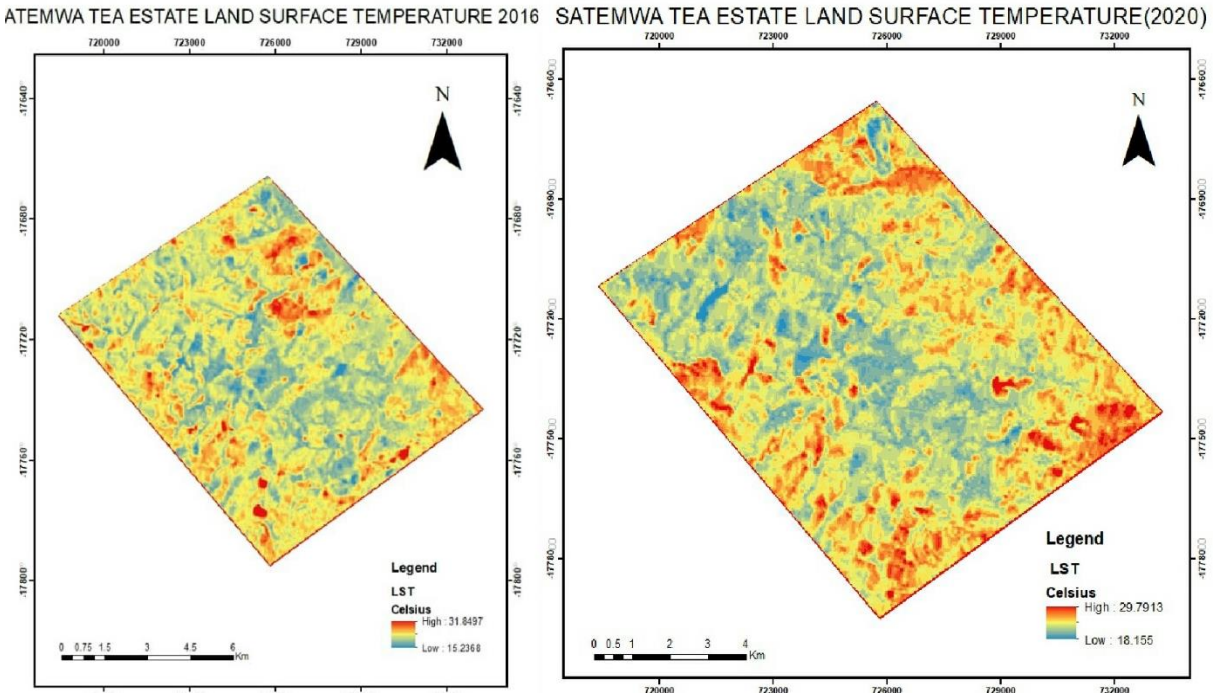


Figure 12:Land surface temperature distribution

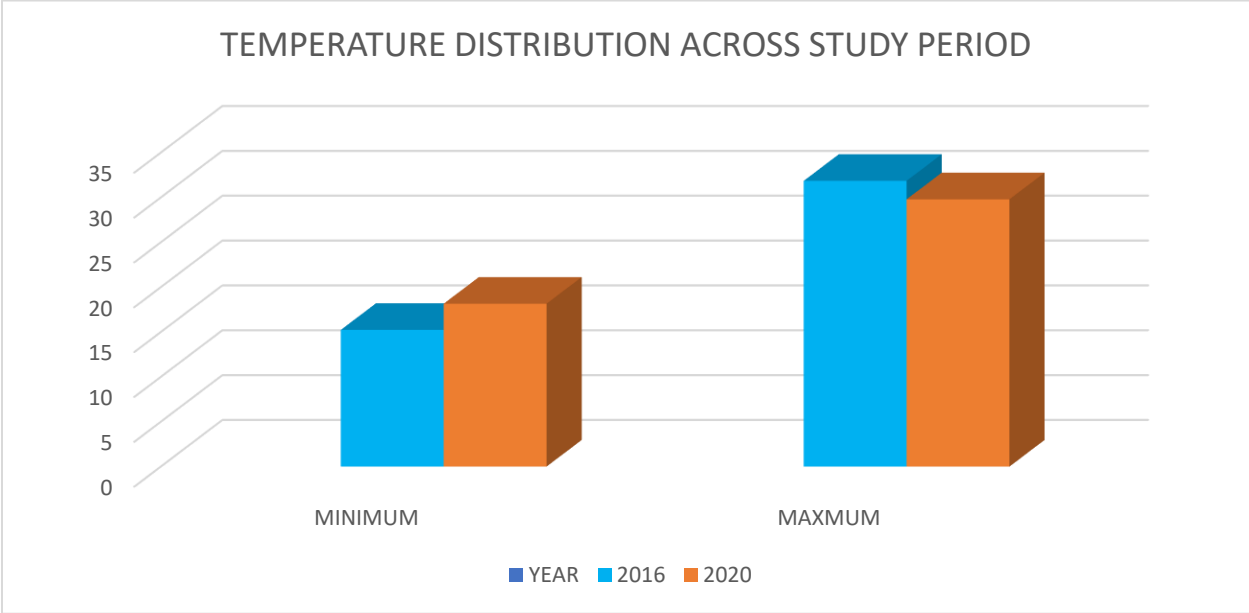


Figure 13:TemperatureS distribution

The results in figure 14 below shows huge difference in amount of precipitation received between the study period. From the 2016 period it shows minimum rainfall of 53.0798 and a maximum of 60-6124 unlike in the 2020 study period which has highest of these

values, with minimum values being 91.5231 and maximum of 103.1902. This is portraying positive correlation with tea spectral signature, Normalized difference vegetation index and soil adjusted vegetation index. This may have also contributed largely to the change in tea healthy status across the study period. Figure 5a below shows thematic maps for the study periods.

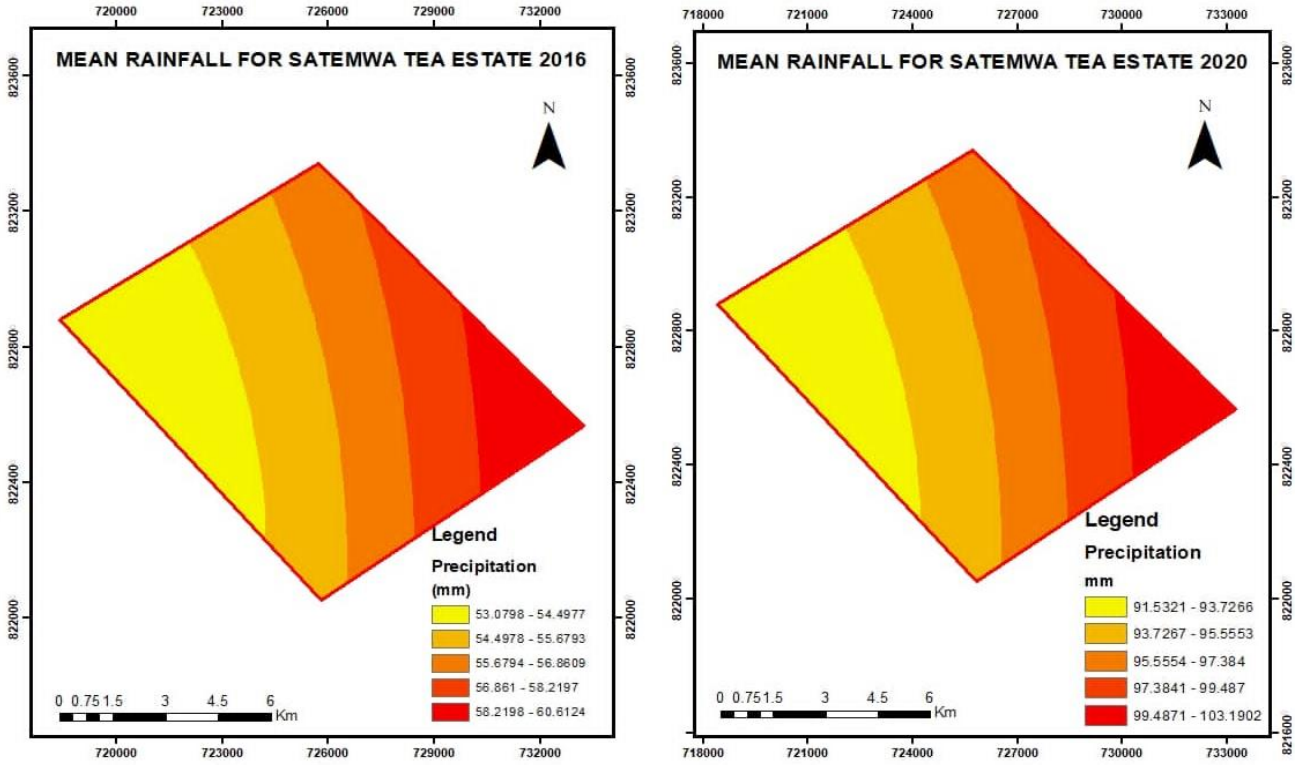


Figure 14:distribution of precipitation

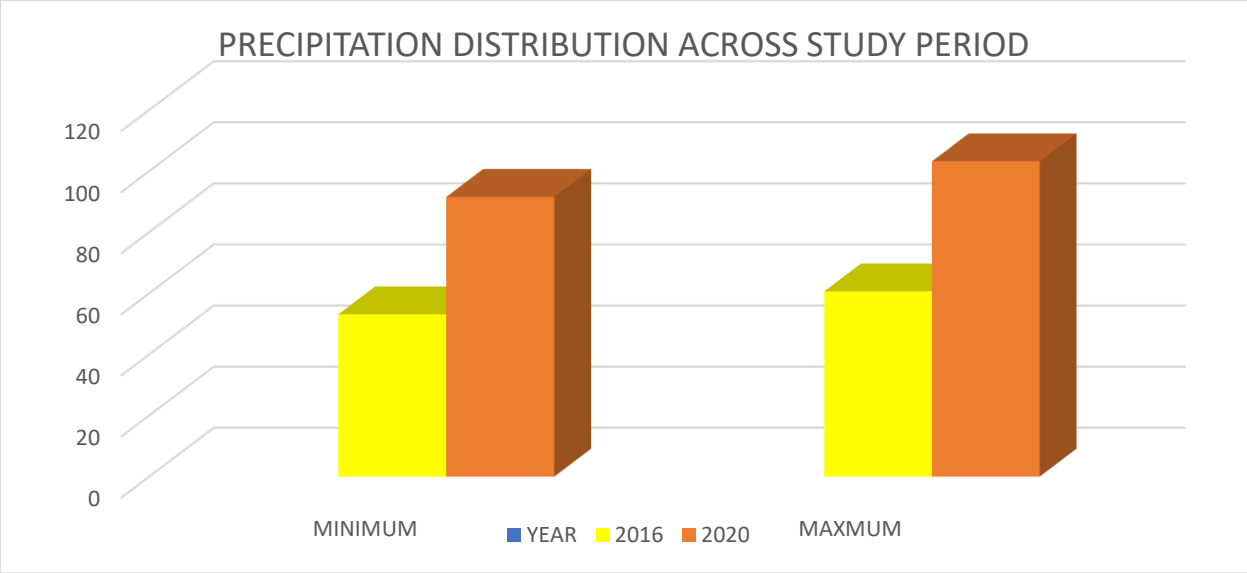


Figure15: graphical representation of precipitation distribution.

The result figure 11 below shows distribution of soil type of the study area. The study area is made up of largely clay soils, sandy clay loam and lastly sandy clay. The soil distribution shows same soil types and nutrients between the study periods. This means the soil properties and soil types has not significantly affected differences observed in terms of healthy status of tea plants.

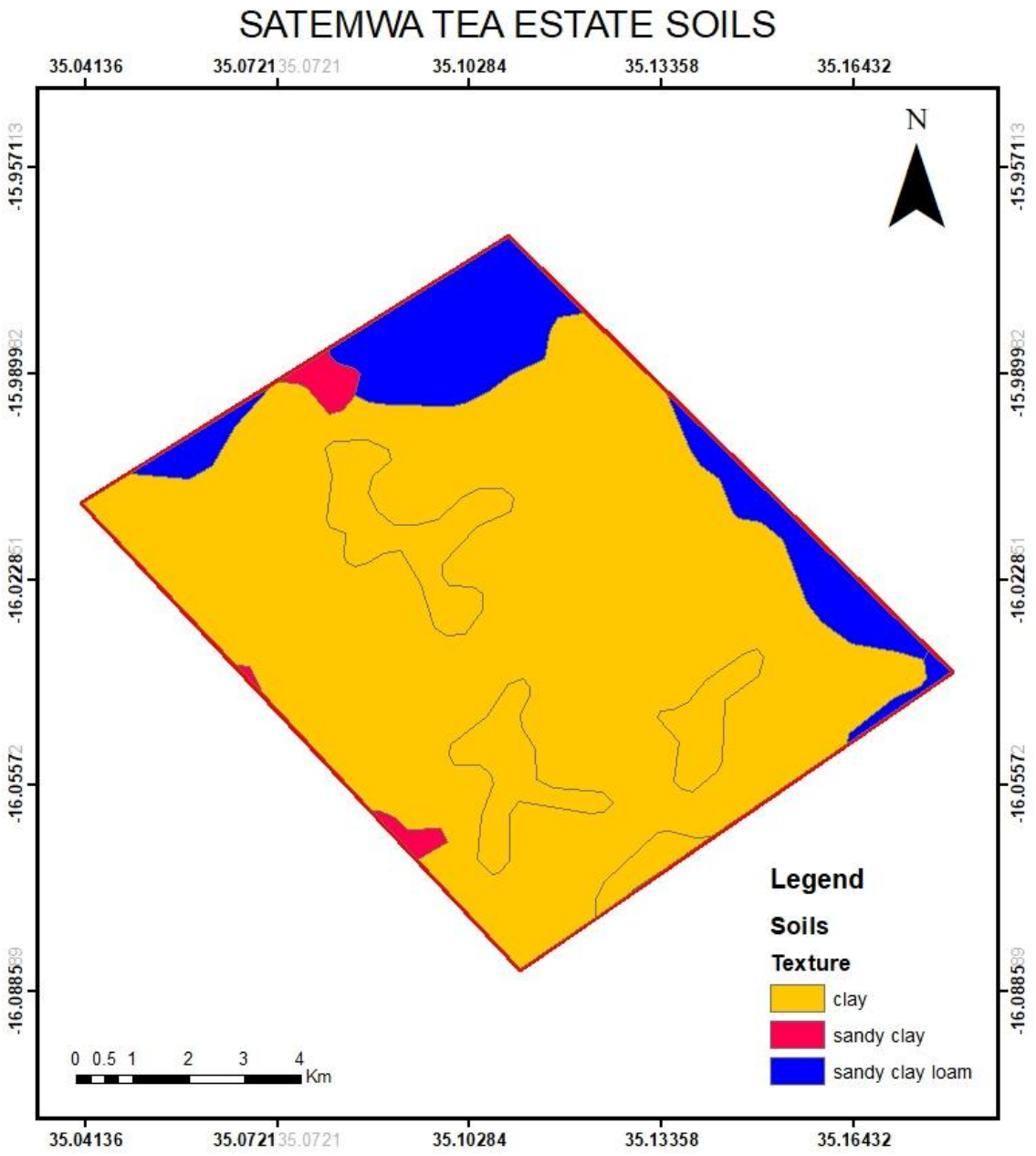


Figure 15:distribution of soil properties

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

This research aimed at comparing tea healthy status of satemwa tea field using spectral reflectance. Earth observation data downloaded on united states geological survey inform of Landsat 7 was used to come up with spectral reflectance's of tea and other land features, NDVI, and SAVI. NDVI and SAVI were used to consolidate results of spectral reflectance and they have all shown a positive relationship with respect to reflectance's generated. Annual precipitation, Temperature and soil maps were also prepared and compared to determine how significantly they contributed to variations in tea healthy status across the study period. Land surface temperature results has shown decrease across the study period. Results of annual precipitation has shown increase across the study period. The results of the research would prompt farm managers to go into tea fields to see what has contributed to decrease in healthy status in the case that the biophysical factors under assessment showed little variation. For the purpose of this study only Land surface temperature, soil and precipitation were assessed but the methodologies can be simulated to assess other factors such as humidity and moisture.

The following are the recommendations based on the study findings:

1. Study period should be increased to at least 10 years for more accurate results if there is no limited time frame for the project
2. Use of data with high resolution such as Landsat 8 or Aster data if the data is available for the study period would be highly recommended
3. There is need to assess many other factors such as humidity and moisture to see how they have contributed to the results findings using the same methodology applied in this study.

REFERENCES

- P. Kingra, D. Majumder. Application of Remote Sensing and GIS in Agriculture and Natural Resource Management Under Changing Climatic Conditions. Agri. Research J., 53(3), 295 (2016)
- Z. J. Mamatkulov, E.Yu. Safarov, R.K. Oymatov, I.I. Abdurahmanov. Application of GIS and Remote Sensing in crop monitoring and yield forecasting in case of low yielded farmlands. J. Problems Architecture. Const., Samarkand, Spatial Volume, 130 (2019)
- C. AtzbergSer. Advances in remote sensing of agriculture: context description, existing operational monitoring systems and major information needs. J. Remote Sens, 5, 949 (2013)
- Chen, C. H. (2007). Image processing for remote sensing. In Image Processing for Remote Sensing. https://doi.org/10.1201/b11656-14
- Land surface temperature estimation. Arnfield 2003; Bastiaanssen et al. 1998; Hansen et al. 2010; Kalma et al. 2008; Kogan 2001; Su 2002; Voogt and Oke 2003; Weng 2009; Weng et al. 2004; Anderson et al. 2008; Brunsell and Gillies 2003; Karnieli et al. 2010; Kustas and Anderson 2009; Zhang et al. 2008). Arnfield 2003;

APPENDEX

i. NDVI=(NIR-RED)/(NIR+RED)
ii. SAVI=(1+L) (NIR-RED)/(NIR+RED+L)