INVESTIGATING NDVI BASED VEGETATION DYNAMICS AND ITS RELATION TO ENVIRONMENTAL VARIABLES IN PARAMBIKULAM FOREST, KERALA

Project Report submitted as a requirement for the partial fulfilment of the Degree of

Master of Science in Environmental Science

By

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DECLARATION

I hereby declare that the dissertation work entitled "INVESTIGATING NDVI BASED VEGETATION DYNAMICS AND ITS RELATION TO ENVIRONMENTAL VARIABLES IN PARAMBIKULAM FOREST, KERALA" is a bonafide research work carried out at the Kerala Forest Research Institute , Peechi, Kerala, during the period of February to April 2020 by me under the guidance of Dr. K.A Sreejith, Scientist, Department of Forest Ecology, KSCSTE-Kerala Forest Research Institute, Peechi and internal guide Dr. Anjana, Department of Environmental Science, Sacred Heart College, Thevara, Ernakulam submitted to Sacred Heart College, Thevara, Ernakulam in partial fulfilment of the requirements for the award of Master of Science in Environmental Science during the academic year 2018-2020. No part of this has previously formed the basis for the award of any degree/diploma/associate ship/fellowship or other similar titles of this or any other university/institution.

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CERTIFICATE

This is to certify that the dissertation entitled **"INVESTIGATING NDVI BASED VEGETATION DYNAMICS AND ITS RELATION TO ENVIRONMENTAL VARIABLES IN PARAMBIKULAM FOREST, KERALA"** submitted to Sacred Heart College, Thevara, Ernakulam for the degree of Master of Science in Environmental Science, by **Ms. Gladys Le Joseph**, Master of Science in Environmental Science, IV Semester, Sacred Heart College, Thevera, Ernakulam, is the result of bonafide research work carried out by her under my guidance at the Department of Forest Ecology, KSCSTE – Kerala Forest Research Institute, Peechi, Thrissur, Kerala. Further, I certify that this or part thereof has not been the base for the award of any other diploma or degree either in any institution or university and I take this opportunity to wish her good luck.

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This is to certify that the dissertation titled "INVESTIGATING NDVI BASED VEGETATION DYNAMICS AND ITS RELATION TO ENVIRONMENTAL VARIABLES IN PARAMBIKULAM FOREST,KERALA" is an authentic record of the work carried out by Ms. Gladys Le Joseph of M.Sc Environmental Science, Centre for Environmental Science, Sacred Heart College (Autonomous), Thevara, Kochi, Kerala, India, under the guidance of Dr. K.A Sreejith, Senior Scientist / Scientist E1, KFRI, in partial fulfillment of the requirements for the Master of Science in Environmental Science.

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ABSTRACT

The aim of this work was to study about the correlation between climatic variables mainly Temperature maximum, Temperature Minimum and Precipitation to Normalised Difference Vegetation Index (NDVI), to study the correlation between NDVI and Land Surface Temperature (LST) and change detection study at Parambikulam forest region was conducted. To obtain correlation between Climatic variables and NDVI, satellite images from LANDSAT 8 sensors were seasonally processed for the period2016. Visual interpretation techniques and empirical intervention were applied to design forest NDVI maps. Climatic Variables were obtained from CHELSA climatic site for the time period 2016. It was found that maximum and minimum Temperature doesn’t have any kind of correlation with Climatic variables whereas Precipitation shows correlation with NDVI during all the seasons. And to study the correlation between NDVI and LST Landsat 8 images from USGS for the year 2018 was used. And it was found that NDVI and LST show negative correlation during the rainy season and summer and show positive correlation during the winter season. Change detection study shows decreased vegetation in 2018 when compared to 2008.

Keywords: Normalized Difference Vegetation Index (NDVI), CHELSA (Climatologies at high resolution for the earth's land surface areas), Land Surface Temperature (LST)

CHAPTER 1

INTRODUCTION

Climatic variables have a significant role in the vegetation index of a region however not much studies are conducted on it. Temperature maximum, temperature minimum and precipitation are some of the important climatic variables. This study aims to study the relationship between vegetation index (NDVI) used in assessing the health of the vegetation and climatic variables. Field inventory may be possible for small areas. But for large areas field inventory may not be practically possible. Hence, for studying the relationship between climatic variables and NDVI, technologies like remote sensing and GIS are used.

1.1 REMOTE SENSING

Remote Sensing is the science and art of acquiring information about material objects, area, or phenomenon, without coming into physical contact with the objects, or phenomenon under investigation. Remote Sensing means sensing of earth's surface from space by making use of the properties of electromagnetic waves emitted, reflected, or diffracted by the sensed objects for the purpose of improving natural resource management and the protection of the environment. Remote sensing is an intensely growing field of science which has found applications in various fields. Remote sensing can be defined as the science and art of obtaining information about an object, area or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon under investigation (Lillesand et.al., 2004).

The advancements in remote sensing begin in the early 1960s by the development of image processing methodologies. The satellite imagery obtained contains the spectral and spatial information about earth's surface features at finite radiometric resolution. The basic principle behind remote sensing is the unique interaction of electromagnetic waves with targets. The electromagnetic light is reflected from the target at a particular wavelength. The target has different reflectance at each of the different wavelengths. This reflected energy is measured by the sensors at different bands and saved as digital numbers in imagery. The DN numbers are saved in each pixel of the imagery. The processing of the DN numbers classifies the images into different land cover and land use types. The advantage of remote sensing is that it can provide time series data for a large period of time (Richards, 1999).

1.2 LANDSAT 8

Landsat eight is an American Earth remark satellite, released on February eleven, 2013. It is the 8th satellite in the Landsat program. The LANDSAT 8 satellite has two essential sensors: the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). OLI will gather images using nine spectral bands in unique wavelengths of scene, near-infrared, and shortwave light to study a 185 kilometre (115 miles) wide swath of the Earth in 15-30 meter resolution TIRS to collect image facts for two thermal infrared spectral bands with a spatial decision of a hundred and twenty m across a 185 km swath from the nominal 705 km Landsat altitude (Board et al., 2014).

Data Characteristics:

- GeoTIFF data format
- Cubic Convolution (CC) resembling
- North Up (MAP) orientation
- Universal Transverse Mercator (UTM) map projection (Polar Stereographic for Antarctica)
- World Geodetic System (WGS) 84 datum
- 12-meter circular error, 90% confidence global accuracy for OLI
- 41-meter circular error, 90% confidence global accuracy for TIRS
- 16-bit pixel values

Fig 1.1: Landsat

Bands	Wavelength	Resolution
Band 1 – Coastal aerosol	0.43 - 0.45	30
Band 2 – Blue	0.45 - 0.51	30
Band 3 – Green	0.53 - 0.59	30
Band 4 – Red	0.64 - 0.67	30
Band 5 – Near Infrared	0.85 - 0.88	30
Band 6 – SWIR 1	1.57 - 1.65	30
Band 7 – SWIR 2	2.11 - 2.29	30
Band 8 – Panchromatic	0.50 - 0.68	15
Band 9 – Cirrus	1.36 - 1.38	30

Band10–Thermal Infrared (TIRS) 1	10.60 - 11.19	100 * (30)
Band11–Thermal Infrared (TIRS) 2	11.50 - 12.51	100 * (30)

Table 1: Landsat 8 Bands

1.3 Sentinel-2

The Sentinel-2A is the European Space Agency (ESA) operated satellite. It is an Earth observation mission from the EU Copernicus Programme that systematically acquires optical imagery at high spatial resolution (10 m to 60 m) over land and coastal waters. The mission consists of two twin satellites (Sentinel-2A and Sentinel-2B). The Sentinel Multispectral Instrument (MSI) acquires 13 spectral bands ranging from Visible and Near-Infrared (VNIR) to Shortwave Infrared (SWIR) wavelengths along a 290-km orbital swath. The details about the 13 spectral bands of the Sentinel MSI are enlisted in Table.1. The satellite‘s MSI data is complementary to data acquired by the Landsat 8 Operational Land Imager (OLI) and Landsat 7 Enhanced Thematic Mapper Plus (ETM+). Operated in a sun-synchronous orbit this satellite has a 10-day repeat cycle. A collaborative effort between ESA and the U.S. Geological Survey (USGS) provides another data portal for Sentinel-2 data products from which the images used in this study are acquired (ESA 2018).

The design of the Multispectral Instrument (MSI) on-board SENTINEL-2 has been driven by the requirement for large swath high geometrical and spectral performance of the measurements.

1.4 CHELSA

Weather in simple terms is the state of the atmosphere of a particular place over a specific period of time (usually one to a couple of days). Data which provides patterns and trends on weather conditions are considered weather data. Weather data comprises any facts and figures about the state of the atmosphere. Social and technological institutions are now considering and merging weather data (as the main external data) with internal data such as sales and operational data to optimize risk management. Weather conditions do not only affect planning but also have operational impacts on businesses. The business value of weather data can only be measured on a grand scale as economists have used weather forecasts to predict supply and demand patterns, improve marketing, streamline operations and even create economic models. Due to this invaluable nature of weather data, scientists and geographers are working continuously to improve the art of accurate weather forecasting. They make use of methodologies which involve data mining, processing and analysis so as to produce empirical evidence with accuracy (https://datarade.ai/data-categories/weather-data).

High-resolution information on climatic conditions is essential to many applications in environmental and ecological sciences. CHELSA (Climatologist at high resolution for the earth's land surface areas) present data of down scaled model output temperature and precipitation estimates of the ERA-Interim climatic reanalysis to a high resolution of 30 arc sec. The temperature algorithm is based on statistical downscaling of atmospheric temperatures. The precipitation algorithm incorporates aerographic predictors including wind fields, valley exposition, and boundary layer height, with a subsequent bias correction. The resulting data consist of a monthly temperature and precipitation climatology for the years 1979–2013 and 1901-2016. They compare the data derived from the CHELSA algorithm with other standard gridded products and station data from the Global Historical Climate Network. They compare the performance of the new climatologist in species distribution modelling and show that they can increase the accuracy of species range predictions. They further show that CHELSA climatological data has a similar accuracy as other products for temperature, but that its predictions of precipitation patterns are better (Karger. et al.,2017).

1.5 NDVI

A Vegetation Index (VI) is a spectral transformation of two or more bands designed to enhance the contribution of vegetation properties and allow reliable spatial and temporal inter-comparisons of terrestrial photosynthetic activity and canopy structural variations (Jensen, 2009).

There are many Vegetation Indices (VIs) which are functionally equivalent. Many of them make use of the inverse relationship between red and near-infrared reflectance associated with healthy green vegetation. Since the 1960s scientists are using satellite remote sensing to monitor fluctuation in vegetation at the Earth's surface. Vegetation index attributes include leaf area index (LAI), percent green cover, chlorophyll content, green biomass and absorbed photosynthetically active radiation (APAR) (https://www.sciencedirect.com/topics/earth-and-planetary-sciences/vegetation-index)).

Vegetation covers a considerable portion of the earth, and has an effect on weather and climate. It influences both albedo of the earth and the amount of water vapour and carbon dioxide in the air. With vegetation covering about 20% of our planet, it's no surprise that plants affect climate. It is surprising how much plants affect weather. Plants process and release water vapour and absorb and emit energy used to drive weather. Plants also produce their own micro-weather by controlling the humidity and temperature immediately surrounding their leaves through transpiration. Most plants and forest soils have a very low albedo, and absorb a large amount of energy. Vegetation includes all plants from evergreen forests to grassy meadows and cropland. Vegetation affects weather and climate mostly through evapo- transpiration and albedo (https://climate.ncsu.edu/edu/Vegetation).

The vegetation indices like NDVI and Surface Reflectance (SR) derived from canopy reflectance in the red and near-infrared wavebands are useful indicators of canopy structure, potential photosynthetic activity, chlorophyll content, across a wide range of vegetation types. The Normalized Difference Vegetation Index (NDVI) is the most popular vegetation index. NDVI is calculated on a per-pixel basis as the normalized difference between the red and near infrared bands from an image (La et al., 2013). While NDVI seems sensitive to differences in Canopy Cover (CC) in sparse canopies, it loses sensitivity in moderate and dense canopies (John et al., 1995).

Normalized Difference Vegetation Index (NDVI) quantifies plant life with the aid of measuring the difference among near-infrared (which plants strongly reflects) and purple light (which flowers absorbs).NDVI offers an illustration of the photosynthetic hobby of the plants and is calculated because the distinction between the near-infrared and seen reflectance divided by the sum of the two (Curran 1983, Sellers 1985). Strong and properly-nourished vegetation will absorb maximum of the visible wavelengths that it gets and could mirror returned a big share of the close to-infra-red mild, whereas poor circumstance plants or skinny regions will replicate greater seen wavelength mild and less close to-infra-crimson light. NDVI always ranges from -1 to +1(Chander et al. 2009.).

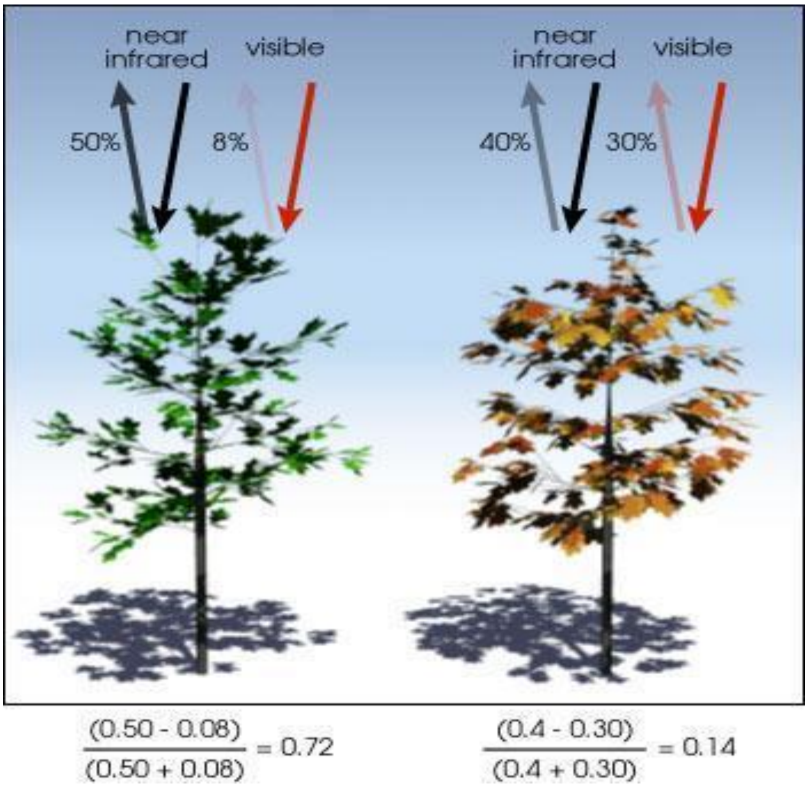


Fig 1.2: Light absorption

1.6 Land Surface Temperature

The Land Surface Temperature (LST) is the skin temperature of the land surface, as measured in the direction of the remote sensor. It is a mixture of vegetation and bare soil temperatures. It is because both respond rapidly to changes in incoming solar radiation due to cloud cover and aerosol load modifications. But the vegetation is closely related to LST. It is because the vegetation dense areas lower the surface temperature by evapo-transpiration. Landsat 8 is the most favourable satellite for the calculation of LST which is having two thermal bands (Lambin et al., 1996). LST could be measured on snow and ice, the grass on a lawn, the roof of a building, or the leaves in the canopy of a forest. So, it is simply the surface temperature. The important parameter of Land surface temperature is Greenhouse gases. So, The value of LST depends upon increasing atmospheric greenhouse gases. Accurate values of LST are also of special interest in a wide range of areas related to land surface processes, including meteorology, hydrology, agro meteorology, climatology and environmental studies.

Land Surface Emissivity (EM), a crucial parameter for LST. Land surface emissivity (LSE) is an important surface parameter and can be derived from the emitted radiance measured from space (Kalma et al., 2008).

1.7 CORRELATION COEFFICIENT

The correlation coefficient is a statistical measure of the power of the relationship among the relative moves of two variables. The values range between -1.0 and 1.0. A calculated value greater than 1.0 or much less than -1.Zero method that there was a blunder within the correlation measurement. A correlation of -1 indicates an ideal bad correlation, while a correlation of one indicates a super high quality correlation. A correlation of zero indicates no linear courting between the motions of the two variables. There are numerous kinds of correlation coefficients; however the one that is most common is the Pearson correlation (r). This measures the strength and direction of the linear courting between variables. It cannot capture nonlinear relationships between variables and can't differentiate between dependent and impartial variables. The power of the connection varies in diplomas based at the value of the correlation coefficient (Benesty et al., 2009).

1.8 OBJECTIVES

The main objectives of the study are as follows,

1. To identify correlation between NDVI and climatic variables.
2. To identify correlation between NDVI and Land Surface Temperature.
3. Vegetation change detection analysis of NDVI images from 2008 to 2018.

CHAPTER 2

LITERATURE REVIEW

The vegetation indices like NDVI and Surface Reflectance (SR) derived from canopy reflectance in the red and near-infrared wavebands are useful indicators of canopy structure, potential photosynthetic activity, chlorophyll content, across a wide range of vegetation types. The Normalized Difference Vegetation Index (NDVI) is the most popular vegetation index. NDVI is calculated on a per-pixel basis as the normalized difference between the red and near infrared bands from an image (La et al., 2013). While NDVI seems sensitive to differences in Canopy Cover (CC) in sparse canopies, it loses sensitivity in moderate and dense canopies (John et al., 1995).

The temporal variability of tendencies that included aspects of number one productiveness over the year become decreased than those associated with seasonality. This indicates that from year to year, grassland and shrubland ecosystems could range more in the timing of production and senescence than in the general amount of carbon fixed. The quintessential NDVI showed less temporal variability than annual precipitation. The coefficient variation of each precipitation and the NDVI has been definitely associated. The slope of the relationship became notably lower than 1, indicating that the variability of atmosphere function is a decreased proportion of the range of annual precipitation in areas with a high relative variability of this climatic variable than in areas of low variability. The variability of most of the NDVI developments analysed confirmed a poor and, in trendy, non-linear dating with annual precipitation. The same form of relationship has been reported elsewhere for annual precipitation and its coefficient of variant. Mean annual precipitation has been reported as the main control of above-ground Net primary production in grassland and shrubland ecosystems. Our effects recommend that this climatic variable is likewise related to the inter annual variability of carbon profits, inclusive of the primary production and its seasonality (Paruelo 1998).

The satellite records-primarily based Normalized Difference Vegetation Index (NDVI) is frequently used as an indicator of plants interest, as it exhibits a close to-linear relationship with the fraction of photo synthetically active radiation absorbed via the plants cover (FPAR) and Net Primary Productivity (NPP) discovered prolonged increase in seasons and improved biosphere CO_2 absorption inside the northern mid- and excessive latitudinal areas from satellite sensor based NDVI and atmospheric CO_2 concentrations. The worldwide mapping of NDVI traits between 1982 and 1990 revealed a preferred boom inside the NDVI within the northern mid- and excessive range areas and equatorial regions, and a lower in the semiarid regions of the Southern Hemisphere (Ichii 2002). Schultz and Halpert (1995) reported that the time version of NDVI is not fairly correlated with weather variation. Care should be taken when considering this record, however, as examine may have been awed due to the use of a beside the point records set (i.e. Uncorrected satellite sensor records), anomalous satellite sensor derived land floor temperatures and alternatively sparse determined precipitation.

Temporal correlations among NDVI, temperature and precipitation had been computed to have a look at the spatial variability of the relationships between those parameters as well as to analyze the ability for the combined use of NDVI and temperature for global bio-climate tracking. The month-to-month records have been correlated at each cell of a 10 range via 1°longitude worldwide continental grid using both the ambiguity and general (with annual cycle) time series. The onset of precipitation appears to typically act because the stimulus for plant life in regions where the amplitude of the annual temperature cycle is small. In regions where in the onset of the moist season is sudden, vegetation has a tendency to lag in the back of precipitation. Vegetation in cold regions is proven to be restricted with the aid of temperature, and by way of each precipitation and temperature in temperate areas. In pretty heat regions temperature commonly plays little function in modulating the seasonal cycle of plants due to the fact temperature exceeds the minimum essential for vegetative growth. Conversely, some extraordinarily wet regions acquire rainfall quantities in excess of a minimum precipitation threshold above which flowers are unresponsive (Schultz 1993).

The Sentinel-2A is the European Space Agency (ESA) operated satellite. It is an Earth observation mission from the EU Copernicus Programme that systematically acquires optical imagery at high spatial resolution (10 m to 60 m) over land and coastal waters. The mission consists of two twin satellites (Sentinel-2A and Sentinel-2B). The Sentinel Multispectral Instrument (MSI) acquires 13 spectral bands ranging from Visible and Near-Infrared (VNIR) to Shortwave Infrared (SWIR) wavelengths along a 290-km orbital swath. The details about the 13 spectral bands of the Sentinel MSI are enlisted in Table.1. The satellite‘s MSI data is complementary to data acquired by the Landsat 8 Operational Land Imager (OLI) and Landsat 7 Enhanced Thematic Mapper Plus (ETM+). Operated in a sun-synchronous orbit this satellite has a 10-day repeat cycle. A collaborative effort between ESA and the U.S.

Geological Survey (USGS) provides another data portal for Sentinel-2 data products from which the images used in this study are acquired (ESA 2018). The design of the Multispectral Instrument (MSI) on-board SENTINEL-2 has been driven by the requirement for large swath high geometrical and spectral performance of the measurements. NDVI gives an indication of the photosynthetic activity of the vegetation and is calculated as the difference between the near-infrared and visible reflectance divided by the sum of the two (Curran 1983, Sellers 1985). Strong and well-nourished vegetation will absorb most of the visible wavelengths that it receives and will reflect back a large proportion of the near-infra-red light, whereas poor condition vegetation or thin areas will reflect more visible wavelength light and less near-infra-red light (ESA Sentinel Online).

In this study, the updated Global Inventory Modelling and Mapping Studies (GIMMS) Normalized Difference Vegetation Index (NDVI) dataset for growing season (April to October), that may better replicate the flowers power, changed into used to research the inter annual versions in NDVI and its dating with climatic factors, if you want to preliminarily apprehend the weather impact on flora and provide theoretical foundation for the reaction of environment to climate alternate. Multivariate linear regression models, together with the Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR), have been followed to analyze the correlation between NDVI and climatic elements (temperature and precipitation) together. Average developing-season NDVI was considerably elevated at a charge of zero.0015/year from 1982 to 2013, larger than numerous regions in China. On the complete, its courting with temperature is high-quality and also more potent than precipitation, which indicates that temperature may be a limiting factor for the flowers boom within the Karst region. Moreover, the correlation coefficients between grassland NDVI and climatic elements are the biggest. Under the background of NDVI increasing fashion from 1982 to 2013, the period of 2009–2012 became selected to analyze the influencing factors of a sharp decline in NDVI. It can be observed that the decreased temperature and sun radiation, as a result of the increase in cloud cowl and precipitation, can also play important roles within the plant life cover trade. All in all, the systematic studies on the interannual versions of growing-season NDVI and its relationship with climate found out the heterogeneity and variability in the complicated climate alternate within the Karst ecosystem for the examined vicinity. It is the Karst characteristics that avert acquiring more consultant conclusions and inclinations in this region. Hence, more attention needs to be paid to promoting Karst research within the future (Piao et al.,2011).

Leaf phenology describes the seasonal cycle of leaf functioning and is essential for expertise the interactions among the biosphere, the weather and the ecosystem. In this, take a look at the spatial patterns in phenological versions in eight contrasting forest kinds in an Indian region the use of coarse resolution NOAA AVHRR satellite records. The onset, offset and developing season length for exceptional woodland sorts has been anticipated the use of normalized difference vegetation index (NDVI). Further, the relationship between NDVI and climatic parameters has been assessed to decide which climatic variable (temperature or precipitation) exceptional explain version in NDVI. In addition, we additionally assessed how speedy and over what time periods does NDVI reply to unique precipitation events. Our consequences advised strong spatial variability in NDVI metrics for unique forest kinds. Among the 8 woodland kinds, tropical dry deciduous forests confirmed lowest values for summed NDVI (SNDVI), averaged NDVI (ANDVI) and included NDVI (I-NDVI), at the same time as the tropical wet evergreen forests of Arunachal Pradesh had highest values. Within the different evergreen wooded area types, SNDVI, ANDVI and INDVI where maximum for tropical moist evergreen forests, followed by way of tropical evergreen forests, tropical semi-evergreen forests and were least for tropical dry evergreen forests. Differences in the amplitude of NDVI have been pretty awesome for evergreen forests as compared to deciduous ones and mixed deciduous forests. Although, all the evergreen forests studied had a similar growing season period of 270 days, the onset and offset dates have been quite one of a kind. Response of vegetative greenness to climatic variability regarded to differ with flowers characteristics and woodland sorts. Linear correlations between simple month-to-month NDVI and temperature were located to yield terrible relationships in comparison to precipitation, which showed an enormous positive reaction to flora greenness. The correlations advanced a lot for distinct forest sorts whilst the log of cumulative rainfall became correlated towards month-to-month NDVI. Of the eight forest kinds, the NDVI for 6 forest types was definitely correlated with the logarithm of cumulative rainfall that became summed for three–four months. Overall, this examination identifies precipitation as a major manager for flora greenness in tropical forests, extra so than temperature (Prasad et al., 2007).

2.1 FOREST COVER

Quantification of world forest trade has been missing despite the identified significance of forest ecosystem services. In this, have a look at, Earth commentary satellite for pc facts had been used to map worldwide wooded area loss (2.3 million square kilometres) and advantage (zero.8 million square kilometres) from 2000 to 2012 at a spatial resolution of 30 meters. The tropics had been the best climate domain to show off a fashion, with wooded area loss increasing with the aid of 2101 rectangular kilometres according to yr. Brazil's well-documented discount in deforestation was offset by using increasing woodland loss in Indonesia, Malaysia, Paraguay, Bolivia, Zambia, Angola, and somewhere else. Intensive forestry practiced inside subtropical forests resulted in the maximum charges of woodland alternating globally. Boreal forest loss due in large part to fireplace and forestry turned into 2nd to that inside the tropics in absolute and proportional terms. These effects depict a globally consistent and locally relevant record of woodland change (Hansen 2013).

Deforestation and fragmentation are essential worries in managing and holding tropical forests and have global significance. In the Indian context, within the ultimate one century, the forests have passed through big changes because of several regulations undertaken by way of government in addition to elevated population strain. The gift look has added spatiotemporal modifications in wooded area cover and variation in forest kind in the nation of Odisha (Orissa), India, over the last seventy five years. There is a decline in annual rate of deforestation at some stage in 1995 to 2010 which turned into an estimated 0.15 %. Forest type-wise quantitative loss of forest cowl well known shows big scale deforestation of dry deciduous forests. The landscape evaluation suggests that the wide variety of wooded area patches (in step with 1,000) are 2.463 in 1935, 10.390 in 1975, eleven.899 in 1985, 12.193 in 1995 and 15.102 in 2010, which indicates high anthropogenic stress at the forests. The mean patch size (sq.km) of wooded areas decreased from 33.2 in 1935 to 5.5 in 1975 and reached three.2 by 2010. The examiner verified that tracking of long term woodland modifications, quantitative lack of wooded area kinds and landscape metrics provides important inputs for management of woodland assets (Reddy 2013).

Digital approaches to optimize the facts content material of multi-temporal Landsat TM information sets for wooded area cover exchange detection are described. Imagery from 3 different years (1984, 1986, and 1990) has been calibrated to exo-atmospheric reflectance to minimize sensor calibration offsets and standardize information acquisition elements. Geometric rectification becomes observed by way of atmospheric normalization and correction routines. The normalization consisted of a statistical regression through the years primarily based on spatially nicely-defined and spectrally solid landscape functions spanning the complete reflectance range. Linear correlation coefficients for all bi-temporal band pairs ranged from 0.9884 to 0.9998. The correction mechanism used a dark object subtraction technique incorporating posted values of water reflectance. The affiliation among virtual data and forest cowl turned into maximized and interpretability stronger by using changing band-precise reflectance values into plant life indexes. Bi-temporal plants index pairs for each time c programming language (, four, and 6 years) had been subjected to two exchange detection algorithms, standardized differencing and selective major issue evaluation. Optimal characteristic choice was based totally on statistical divergence measures. Although limited to spectrally-radio metrically described exchange classes, consequences show that the relationship among reflective TM statistics and woodland canopy change is explicit enough to be of operational use in a woodland cover alternate stratification phase prior to an extra certain assessment (Asner 2001).

2.2 Land Surface Temperature

The Land Surface Temperature (LST) is the skin temperature of the land surface, as measured in the direction of the remote sensor. It is a mixture of vegetation and bare soil temperatures. The objective of the research of Karnieli et al., (2010) estimated the LST using Landsat 8 image. Using Erdas software he classifies his study area Penang Island, Malaysia. He uses maximum likelihood classification methods to classify the features. Then he compares and detects the changes in features in that place because of the change in LST. He drives the area which is consisting of vegetation to have lower LST than the urbanized areas. He concluded his results that Penang Island is the area categorized under moderate temperature because of the presence of tropical forest.

The objective of the research of Ramachandra et.al (2012) estimating the changes in LST over the years of 1989, 2000, 2005, 2006. Having these satellite images (Landsat 8) he estimated LST for those four years separately for the region Shimla, Himachal Pradesh. The Land use analysis shows that there has been a 55% increase in urban and open areas from 1989 to 2000 and 39% increase from 2000 to 2005, and 18.92% increase during 2005-06. That land use changes have also influenced the local climate. The minimum (min) and maximum (max) temperature were found to be − 2 º C and 31 º C. His study clearly shows that the rate of increase in urbanization leads to change in the land surface temperature.

The main objective of the project is carried out by Orhan and Yakara (2016) at Konya, Turkey to estimate the change in temperature over the years of 1984-2014 and 20112014. They have used Landsat 5 Image for the calculation of LST for the year 1984-2014 and

Landsat 8 image for the year of 2011-2014. In that project, the correlation analysis was performed using hourly data of meteorological stations for the LST map of 2011 and 2014 derived Landsat 5 and Landsat-8 satellite data. Konya and around are observed a temperature increase of 4-5 oC.2014 has been the year that most of the temperature. Generally, open areas, that are the northern and southern parts of the work area, are warmer. In particular, the reason for the temperature rise in the southern zone of the region, the transition point of the Mediterranean climate, the host province of Konya, and therefore, due to the effect of heat island is seen. When analyzed NDVI, 2014 compared to 1984 in terms of density of plants include more agricultural areas and Greenfields in the region. The increase in the LST and agricultural areas caused an excessive amount of water needs. It can be said the value of surface temperature (increased summer drought effect) is a continuous increase. As a source of water for agricultural activities is only used as an underground water source, also associated with the level seen in falling groundwater levels. It seems that the most important problem is the uncontrolled use of groundwater resources in the region. As a result; when the value of 10 groundwater observation wells was investigated in Konya province, it was observed that values decreased in general. It can be said to be affected by the decrease in groundwater level by climatic effects and the use of water activities. This study examined the relationship between the thermal infrared band of the Landsat-5 for 2011 and Landsat-8 for 2014 and hourly data of meteorological stations. The regression results showed that measured temperatures and LST were in good agreement with R2 values over 0.90.

The main objective of the research carried out by Alipour et.al (2012) is LST estimation from the thermal band of Landsat sensors at Alastair city. They have used the Qin algorithm based on NDVI coefficient Emissivity and the result ranges between 26 to 46 ° C shows more vegetation. The results Qin algorithm based on the Emissivity coefficient from classification method ranges between 31 to 51 degrees and the surface shows a red area (areas with high temperatures that faces the sun) and it has less vegetation. In both algorithms when they use classification for calculating emissivity, the distance between the maximum and minimum temperatures and surface areas increased with a temperature between 40 and 50 degrees was more. One of the differences between the two methods is their sensitivity to the change in atmospheric parameters. Qin algorithm sensitivity to parameters such as atmospheric water vapour is more than Jimenez algorithm. It showed that if any detailed information about atmospheric water vapour is available, the performance of the two algorithms will be improved. Emissivity coefficient has a significant impact on the results. By changing the size of the emissivity of 0.1, the results of 2 to 3 degrees would change. Two methods to retrieve the land surface temperature (LST) from thermal infrared data supplied by band 6 of the Enhanced Thematic Mapper plus (ETM+) sensor onboard the Landsat 7 satellite are compared. The land surface emissivity (LSE) values needed in order to apply these methods have been estimated from an NDVI based method and classification method. The results show that the Qin algorithm using NDVI Emissivity factor has obtained better results than other states in the study area. Sensitivity analysis performed on the algorithm showed that the sensitivity of results to small changes emissivity coefficient is very high level and highly values the land surface temperature will affect. Results are influenced by various errors, each of them carefully putting the final impact. For the best results, they have suggested the Calibration parameters of the two algorithms using ground-based measurements accurately.

In 2013 Orhan et.al researched the effect of vegetation indices on LST at Salt Lake Basin Area, Turkey. The main purpose of this paper is to investigate multi-temporal land surface temperature changes by using satellite remote sensing data. The study included a real-time field work performed during the overpass of Landsat-5 satellite on 21/08/2011 over Salt Lake, Turkey. Normalized vegetation index (NDVI), vegetation condition index (VCI) and temperature-vegetation index (TVX) were used for evaluating drought impact over the region between 1984 and 2011. The remotely sensed and treated satellite images and resulting thematic indices maps showed that dramatic land surface temperature changes occurred (about 2ºC) in the Salt Lake Basin area during the 28 year period (1984–2011). Analysis of air temperature data also showed increases at a rate of 1.5–2ºC during the same period. Intensification of irrigated agriculture particularly in the southern basin was also detected. The use of water supplies, especially groundwater, should be controlled considering particularly summer drought impacts on the basin. This study examined the relationship between the thermal infrared band of the Landsat-5 TM and real-time ground data collected using an infrared thermometer. The regression results showed that measured surface temperatures and converted Landsat-5 TIR data were in good agreement with R2 values about 0.90 in the selected study area. According to the results of their investigation, a large amount of land has been affected in the basin by especially agricultural facilities due to increasing drought effects and uncontrolled use of groundwater in the Salt Lake Basin Area (Turkey). The outcome of this study shows that dramatic land surface temperature changes occurred (about 2°C) in the Salt Lake Basin Area during the 28-year period (1984–2011) along with the increase in agricultural fields. The analysis of climatic data shows that the changes detected in air temperature data in the basin also support these findings. It is evident that air temperatures went up in the basin at a rate of about 1.5–2°C during the same period. They conveyed their result that the air temperature changes and land-use changes together can be responsible for LST changes seen in the basin.

The global forest ecosystems are in a country of permanent flux at a diffusion of spatial and temporal scales. Monitoring strategies primarily based on multispectral satellites-acquired records have tested ability as a way to discover, become aware of, and map modifications in wooded areas. This paper, which reviews the strategies and the effects of virtual change detection on the whole in temperate woodland ecosystems, has essential additives. First, the distinctive perspectives from which the variety in the change occasion has been approached are summarized, and the correct preference of virtual imagery acquisition dates and c program language period for change detection are discussed. In the second part, pre-processing routines to establish an extra direct linkage among digital far off sensing data and biophysical phenomena, and the actual change detection techniques themselves are reviewed and severely assessed. A case taken in temperate forests (north-central U.S.A.) then serves as an illustration of the way the exceptional alternate detection stages discussed on this paper may be integrated into an efficient and successful tracking approach. Lastly, new trends in virtual change detection which includes the use of radar imagery and understanding-based professional structures are highlighted (Coppin et al.,1996).

CHAPTER 3

MATERIALS AND METHOD

3.1 STUDY AREA

The area for the study was selected as Parambikulam forest region.

Parambikulam Tiger Reserve, which includes the Parambikulam Wildlife Sanctuary, is 391 square kilometres in Palakkad district of Kerala, South India. Parambikulam wildlife sanctuary is in the Sungam range of hills between the Animalai Hills and Nelliyampathy Hills. Parambikulam Wildlife Sanctuary was declared as a part of the Parambikulam Tiger Reserve on 19 February 2010. The tiger reserve has a span of 643.66 km2. The Western Ghats, Animalia Sub-Cluster, together with all of Parambikulam Wildlife Sanctuary, the UNESCO World Heritage Committee for choice as a World Heritage Site. The sanctuary is the home of 4 distinct tribes of indigenous peoples consisting of the Kadar, Malasar, Muduvar and Mala Malasar settled in six colonies. Parambikulam Tiger Reserve implements the Participatory Forest Management Scheme (PFMS). People from tribal colonies within the reserve are engaged as guides for treks and safaris, and are furnished employment via numerous eco-tourism responsibilities (Sreehari et al., 2016).

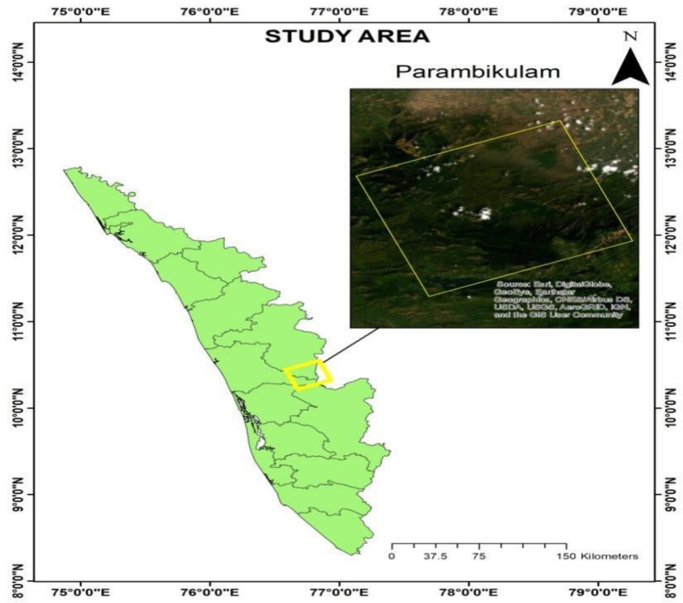


Fig 3.1: Study area (Parambikulam)

3.2 monthly variations in NDVI value for different forest types in Parambikulam.

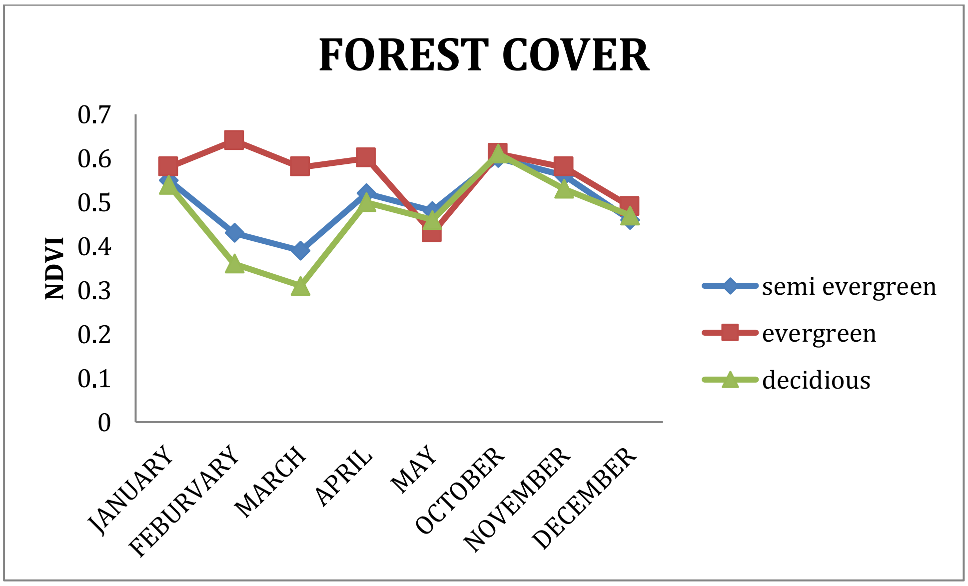


Fig 3.2: monthly variation in NDVI value for different forest types in Parambikulam.

From the graph (fig 3.2) it can be discerned that evergreen forests show a higher value of NDVI all throughout the year and this is because they stay all green throughout the year and hardly shed leaves unlike deciduous species , which shows a dip in NDVI from January- may this is the period during which leaf fall occurs. Deciduous tree species shed their leaves to conserve water and to ensure better survival during harsh dry weather conditions, they must re grow new foliage during the next suitable growing season; this uses resources which evergreens do not need to expend. NDVI values of semi evergreen forests fall between that of evergreen and deciduous species .Semi-evergreen is a botanical term which refers to plants that lose their foliage for a very short period, when old leaves fall off and new foliage growth is starting (Chivers 2013.).

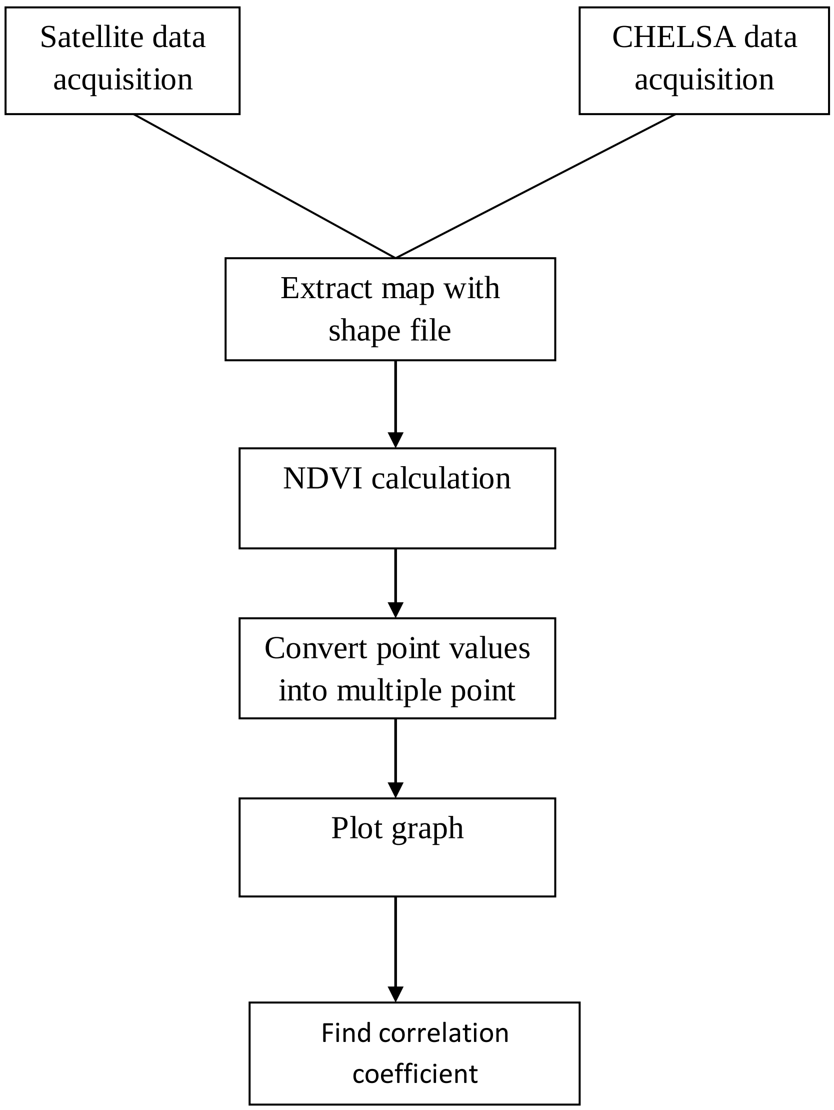
3.3 METHODOLOGY

Arc GIS 10.4

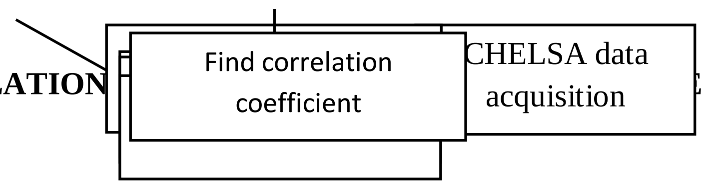
Arc GIS 10.4 is the software used for the study. Arc Map is the main component of Esri (Environmental Systems Research Institute) ArcGIS and is used mainly to view, edit, create, and analyze geospatial data. It allows the user to explore data within a data set, symbolize features accordingly, and create maps. Arc GIS desktop contains arc tool box, which is the collection of tools for different operations and functions (Johnston et al., 2001)

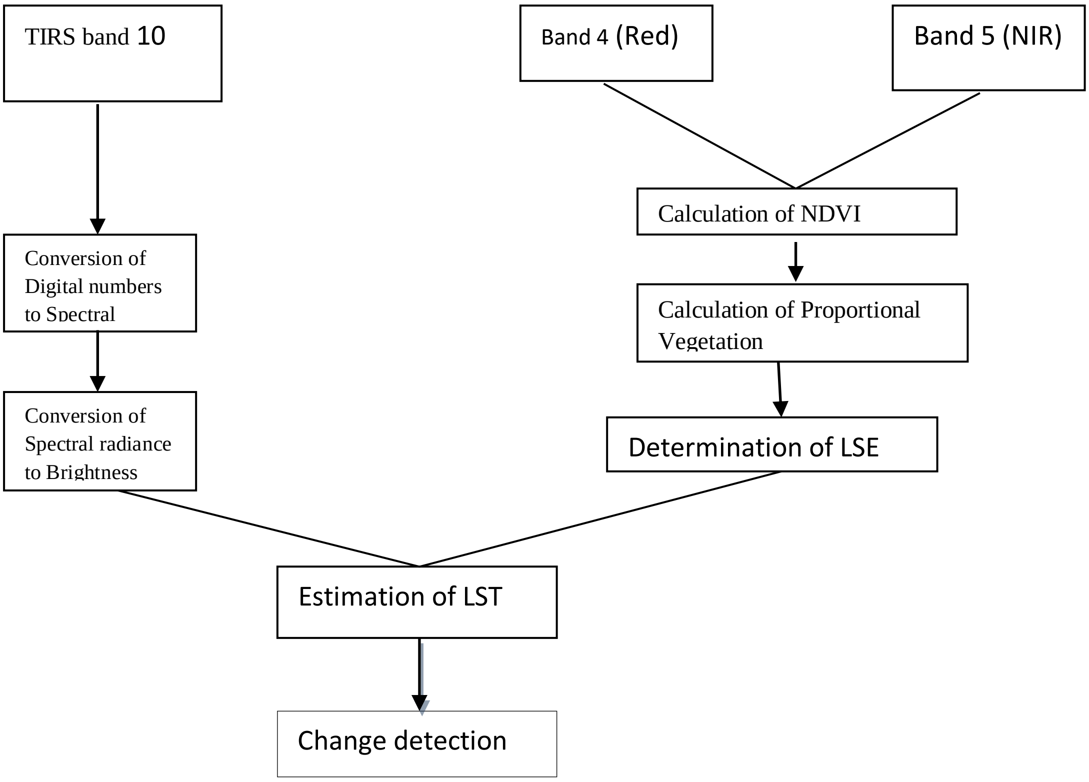
For this study I have collected data on the basis of seasonal changes. For this I have taken three different months in a year which has three different seasons such as, January, March and December respectively for winter, summer and monsoon.

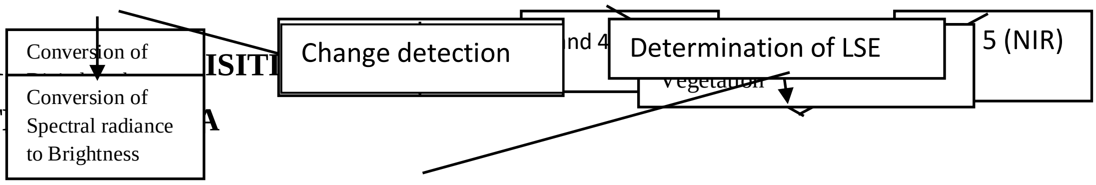
3.3.1 CORRELATION BETWEEN NDVI AND CLIMATIC VARIABLES



3.3.2 CORRELATION [illegible] TEMPERATURE







3.3.1 … ISITI…
SAT… A

The United States Geological Survey (USGS) is a science bureau within the United States Department of the Interior. The USGS provides science about the natural hazards that threaten lives and livelihoods; the water, energy, minerals, and other natural resources we rely on; the health of ecosystems and environment; and the impacts of climate and land-use change. The scientists develop new methods and tools to enable timely, relevant, and useful information about the Earth and its processes.

Landsat 8 image data of the years 2016 and 2018 were downloaded from USGS earth explorer.

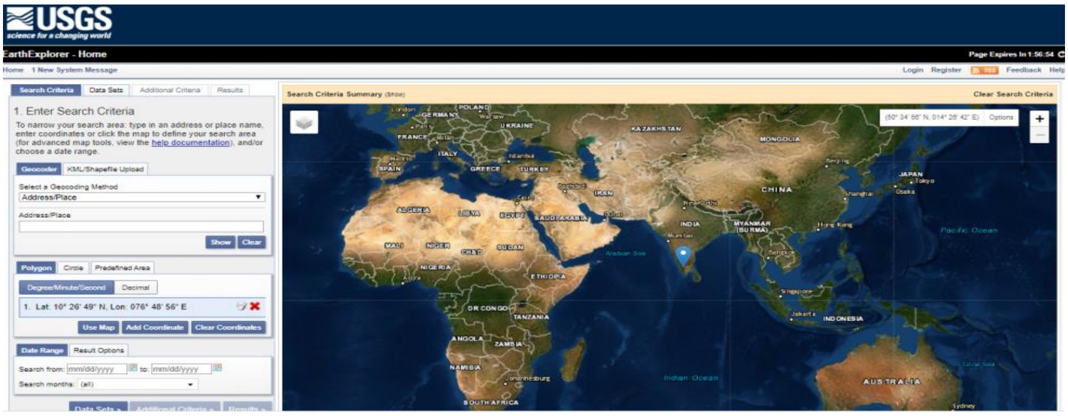


Fig 3.1: USGS home page

CLIMATE DATA

Climate data for the year 2016 were downloaded from CHELSA climatic site.

Fig 3.2: CHELSA home page

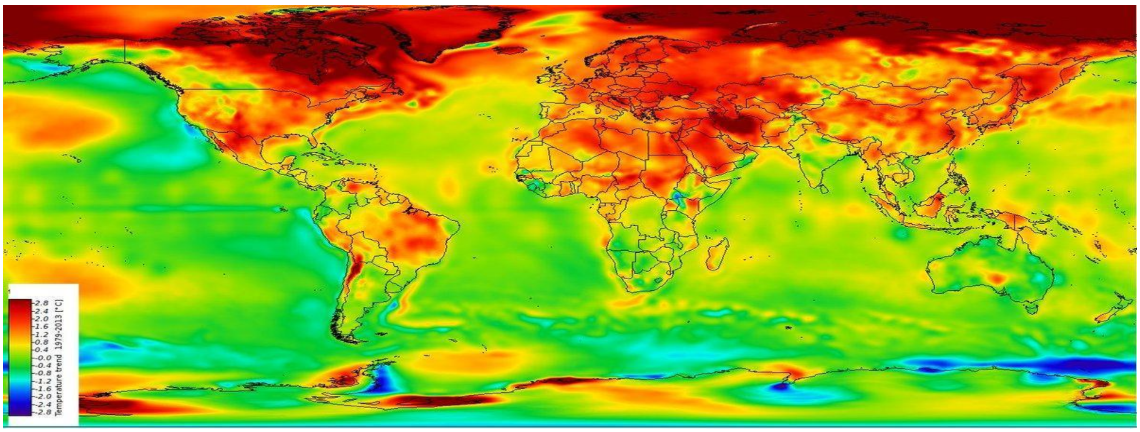


Fig 3.3: CHELSA downloaded image

3.3.2 DATA PROCESSING

Images downloaded from USGS and CHELSA contains a lot of unwanted regions and hence we have to remove the unwanted regions and extract it using Parambikulam shape file.

3.3.3 NDVI CALCULATION

Normalized Difference Vegetation Index (NDVI), is used to measure the tree cover intensity of an area using the difference between the near infrared (NIR) band image and visible red band image. NDVI values range from -1 to 1. 1 being the maximum tree cover and 1 is the sparse tree cover). Bands 4 and 5 images of Landsat 8 satellite are visible red band image and NIR band image respectively.

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

NDVI value and climate information was extracted from the raster sources using random sample points.

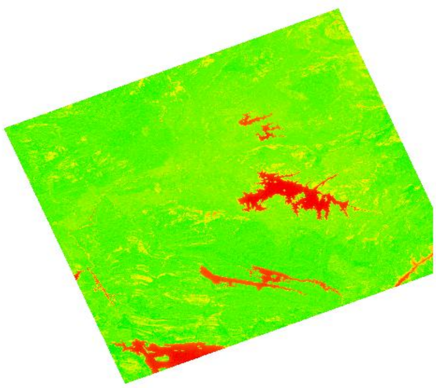


Fig 3.4: NDVI January

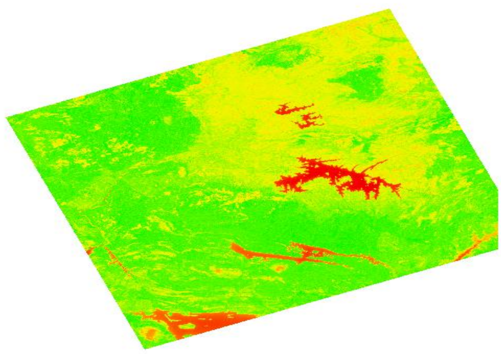


Fig 3.5: NDVI March

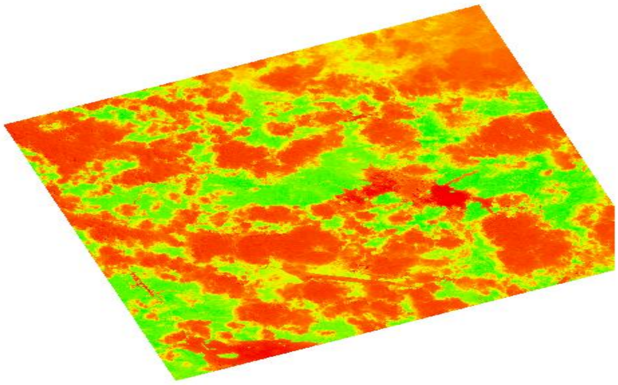


Fig 3.6: NDVI August

3.2.4 PLOT GRAPH

The obtained attribute table is converted to excel sheet and the results are averaged for point raster values. The averaged NDVI values are graphically represented for better identification. Then the correlation between NDVI and climatic variables were calculated.

LAND SURFACE TEMPERATURE

3.3.1 Top of Atmosphere (TOA) Radiance:

Using the radiance rescaling factor, Thermal Infra-Red Digital Numbers can be converted to TOA spectral radiance.

$L\lambda = ML * Qcal + AL$

Where:

$L\lambda$ = TOA spectral radiance (Watts/ (m2 * sr * µm))

ML = Radiance multiplicative Band (No.)

AL = Radiance Add Band (No.)

Qcal = Quantized and calibrated standard product pixel values (DN)

3.3.2 Top of Atmosphere (TOA) Brightness Temperature:

Spectral radiance data can be converted to the top of atmosphere brightness temperature using the thermal constant Values in Metadata file.

$BT = K2 / \ln (k1 / L\lambda + 1) - 272.15$

Where:

BT = Top of atmosphere brightness temperature (°C)

$L\lambda$ = TOA spectral radiance (Watts/ (m^2 * sr * μm))

K1 = K1 Constant Band (No.)

K2 = K2 Constant Band (No.)

3.3.3 Normalized Differential Vegetation Index (NDVI):

The Normalized Differential Vegetation Index (NDVI) is a standardized vegetation index which Calculated using Near Infra-red (Band 5) and Red (Band 4) bands.

$$NDVI = (NIR – RED) / (NIR + RED)$$

Where:

RED= DN values from the RED band

NIR= DN values from Near-Infrared band

3.3.4 Land Surface Emissivity (LSE):

Land surface emissivity (LSE) is the average emissivity of an element of the surface of the Earth calculated from NDVI values.

NDVI values between 0.2 and 0.4 correspond to areas with sparse vegetation; moderate vegetation tends to vary between 0.4 and 0.6; anything above 0.6 indicates the highest possible density of green leaves (Dense Vegetation).

PV = [(NDVI – NDVI min) / (NDVI max + NDVI min)] ^2

Where:

PV = Proportion of Vegetation

NDVI = DN values from NDVI Image

NDVI min = Minimum DN values from NDVI Image

NDVI max = Maximum DN values from NDVI Image

$$E = 0.004 * PV + 0.986$$

Where:

E = Land Surface Emissivity

PV = Proportion of Vegetation

3.3.5 Land Surface Temperature (LST):

The Land Surface Temperature (LST) is the radiative temperature which is calculated using the Top of atmosphere brightness Temperature, Wavelength of emitted radiance, and Land Surface Emissivity.

$$LST = (BT / 1) + W * (BT / 14380) * \ln (E)$$

Where:

BT = Top of atmosphere brightness temperature (°C)

W = Wavelength of emitted radiance

E = Land Surface Emissivity

Thus, the LST calculated for the images taken in 2018.

CHAPTER 4

RESULT AND DISCUSSION

Results for the studies, correlation between NDVI and Climatic variables, Correlation between NDVI and LST and Change detection are shown below,

4.1 CORRELATION BETWEEN NDVI AND CLIMATIC VARIABLES

4.1.1 TEMPERATURE MINIMUM

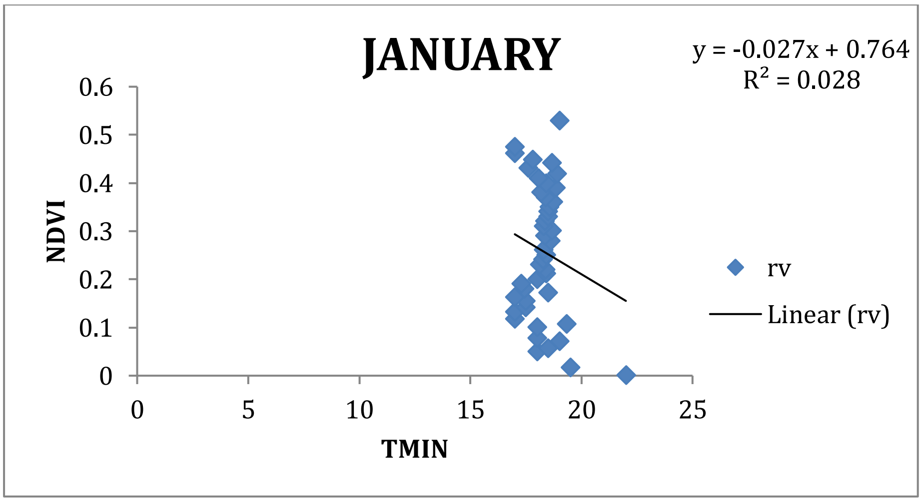


Fig 4.1: correlation between NDVI and TMIN (winter)

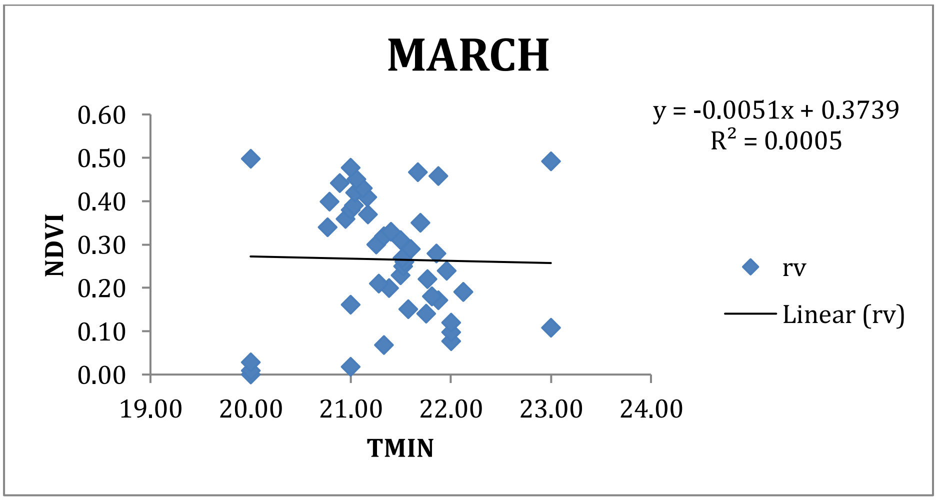


Fig 4.2: correlation between NDVI and TMIN (summer)

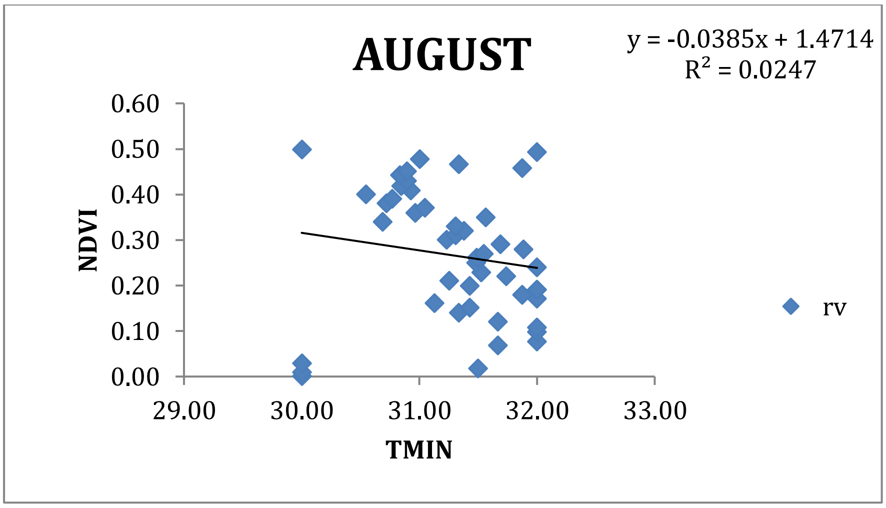


Fig 4.3: correlation between NDVI and TMIN (monsoon)

The graphs (4.1,4.2 and 4.3) shows the relation between NDVI and Minimum temperature during different seasons in a year. It is clear from the graph that Tmin doesn't have any significant correlation with NDVI. In these three seasons most correlation is seen during August and doesn't show any correlation during March.

4.1.2 TEMPERATURE MAXIMUM

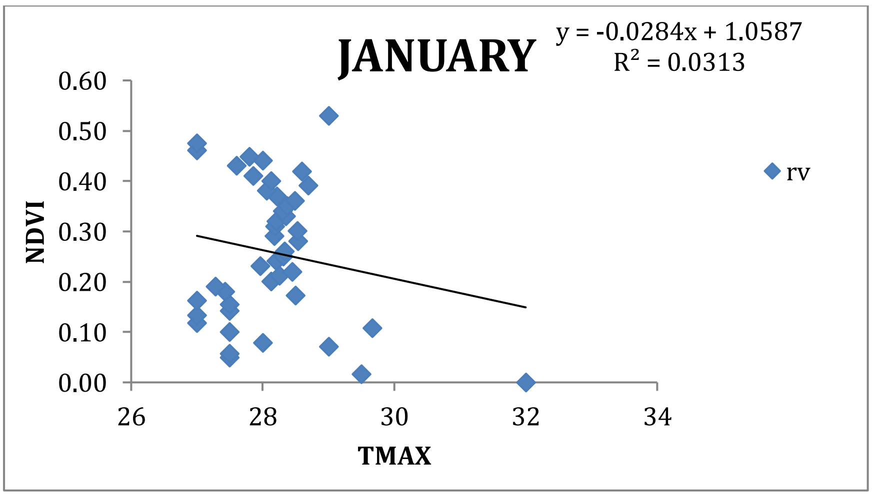


Fig 4.4: correlation between NDVI and TMAX (winter)

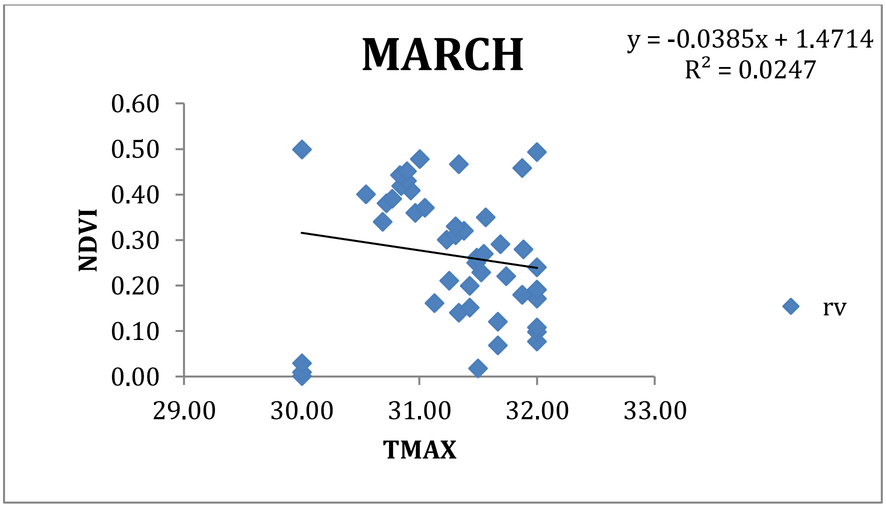


Fig 4.5: correlation between NDVI and TMAX (summer)

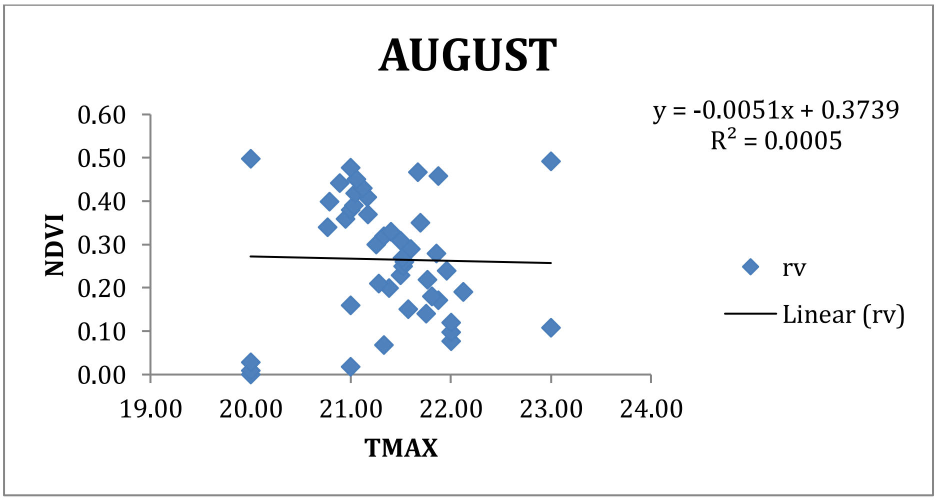


Fig 4.6: correlation between NDVI and TMAX (monsoon)

From the graphs (4.4, 4.5 and 4.6) shows the relation between NDVI and Maximum temperature during different seasons in a year. It is clear from the graph that Tmax doesn't have any significant correlation with NDVI. In these three seasons most correlation is seen during August and January and least correlation is seen during March.

4.1.3 PRECIPITATION

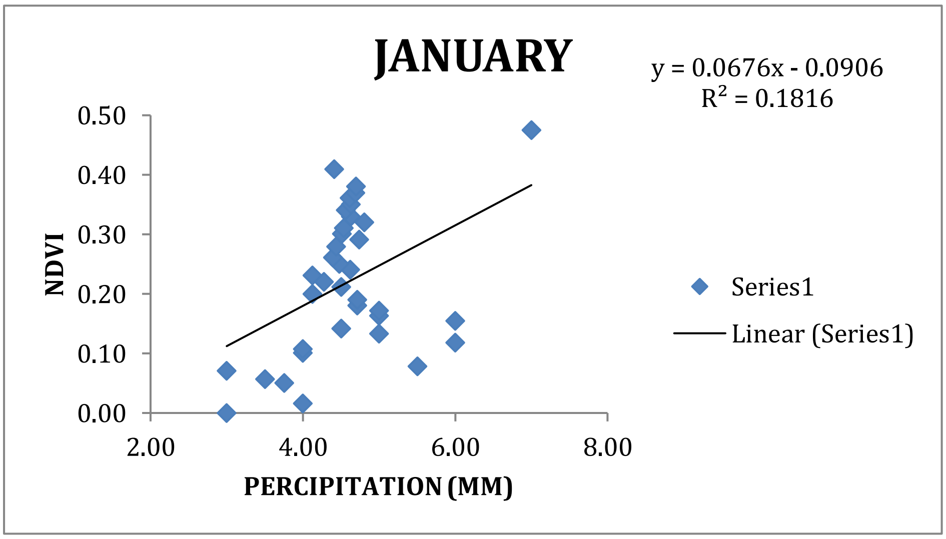


Fig 4.7: correlation between NDVI and Precipitation (winter)

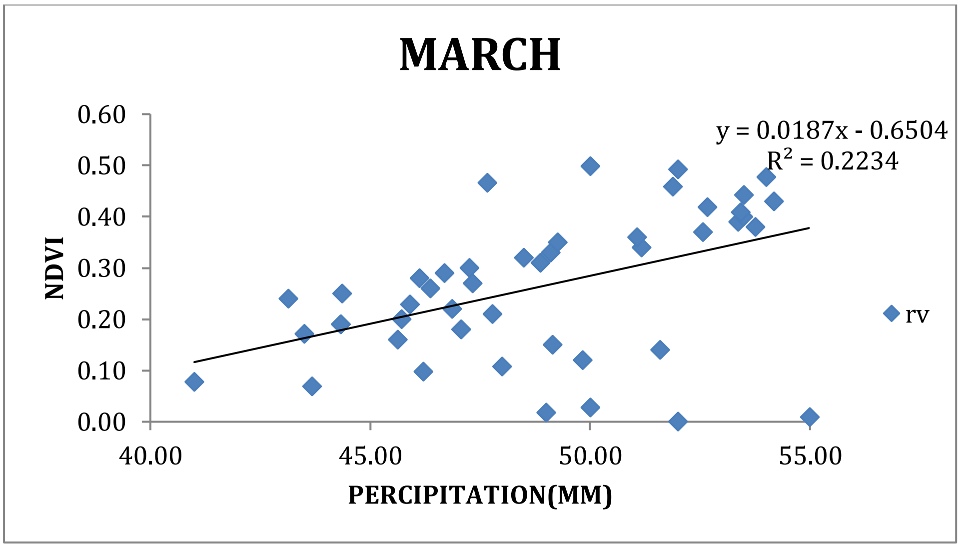


Fig 4.8: correlation between NDVI and Precipitation (summer)

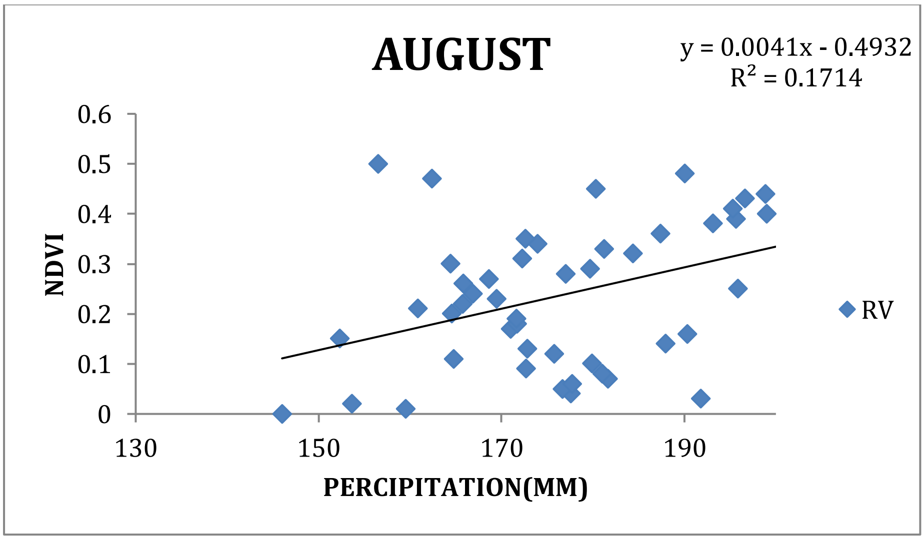


Fig 4.9: correlation between NDVI and Precipitation (monsoon)

From the graphs (4.7, 4.8 and 4.9) shows the relation between NDVI and Precipitation during different seasons in a year. It is clear from the graph that Precipitation has a significant correlation with NDVI. In these three seasons most correlation is seen during March and least during August.

Graphs (4.1, 4.2, 4.3, 4.4, 4.5, 4.6, 4.7, 4.8 and 4.9) show the correlation between the seasonally averaged NDVI and the climatic variables. Although the analysed period was short (one years), it clearly shows the geographical distribution of the NDVI–climate relationship. A negative correlation between the NDVI and temperature was observed during all the three seasons. And show a positive NDVI–precipitation correlation during all the three seasons. Usually NDVI shows a greater correlation with Precipitation but in our study it only shows 18%, 22% and 17% during winter, summer and rainy season this may be due to uncertainty in data downloaded from CHELSA and USGS (Ichii, K et al. (2002)). When the Regression method was applied in relationship between vegetation NDVI and precipitation, the results assumed a different response of vegetation to precipitation by various land cover categories. This agrees with the research conducted in the dry regions with regards to NDVI-rainfall relationships on different land cover types.

Graphs (4.1, 4.2, 4.3, 4.4, 4.5, 4.6, 4.7, 4.8 and 4.9) show the plot between measured NDVI and Precipitation. Based on analyses of correlation coefficient values, the spatial relations between NDVI and precipitation indicates positive correlation at every growing season of the year suggesting that there is positive correlation between NDVI and Precipitation (Usman et al., 2013). The precipitation decrease led to the NDVI decrease, as precipitation plays an essential role in vegetation activity in these regions (Park et al., 2010).

4.2 CORRELATION BETWEEN NDVI AND LST

Land Surface Temperature

LST was calculated for different seasons during 2018 and the results are shown here with its intermediate outputs.

4.2.1 Top of Atmosphere (TOA) Radiance:

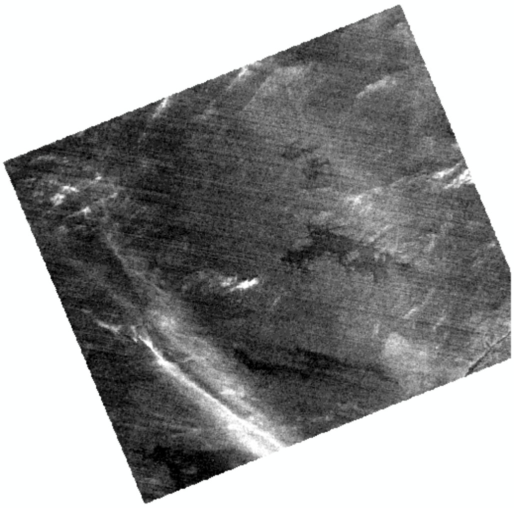


Fig 4.10: TOA January

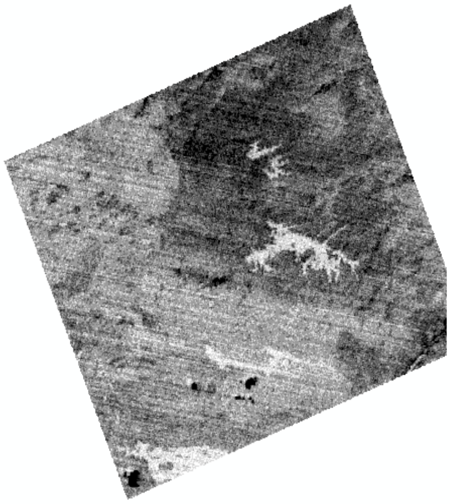


Fig 4.11: TOA March

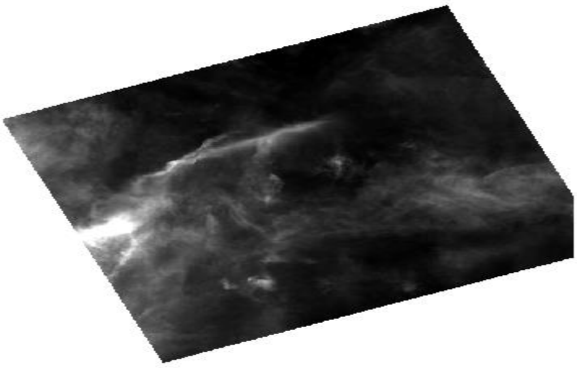


Fig 4.12: TOA August

To calculate brightness temperature from Landsat thermal bands, Landsat thermal band DN values were converted to spectral radiance. TOA radiance is every light which reflects off the planet as seen from space measured in radiance units. Atmospheric correction was performed to remove the influence of just that portion of light reflected off the atmosphere on the image and preserve the part reflected off the surface below. So, through this step I converted DN to top atmosphere spectral radiance.

4.2.2 Top of Atmosphere (TOA) Brightness Temperature:

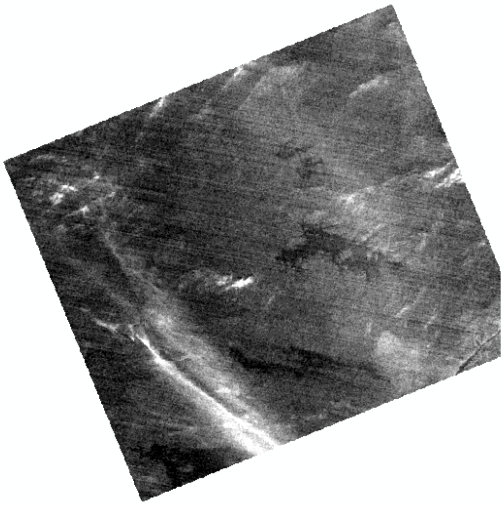


Fig 4.13: Brightness temp January

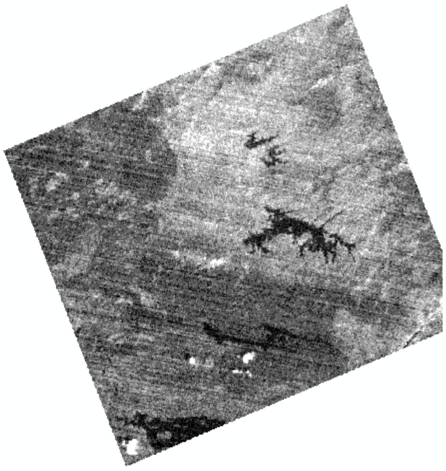


Fig 4.14: Brightness temp March

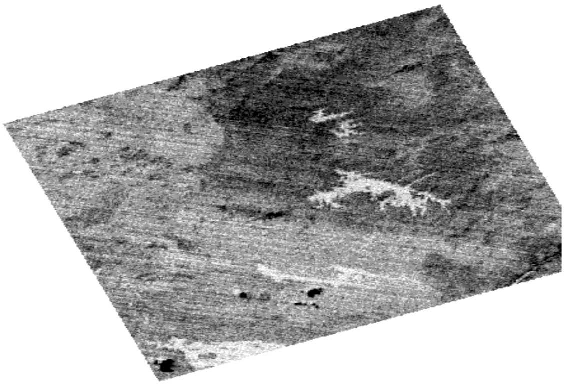


Fig 4.15: Brightness temp August

Brightness temperature or radiance temperature is the temperature a black body in thermal equilibrium with its surroundings would have to be to duplicate the observed intensity of a grey body object at a particular frequency. Through this step, the brightness temperature of these two images was calculated.

4.2.3 Normalized Differential Vegetation Index (NDVI):

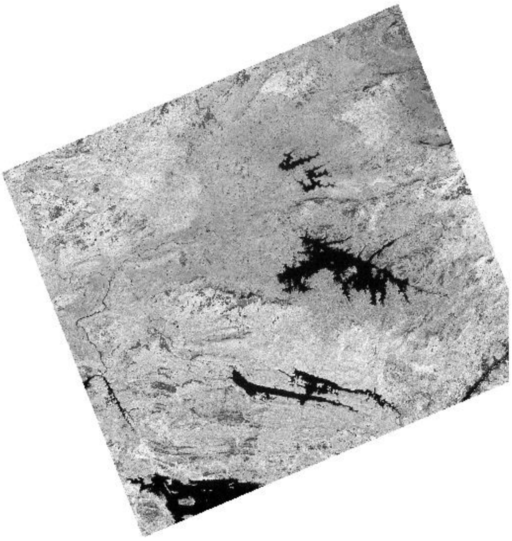


Fig 4.16: NDVI January

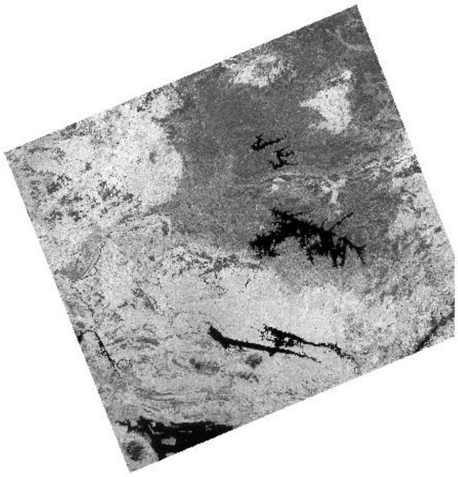


Fig 4.17: NDVI March

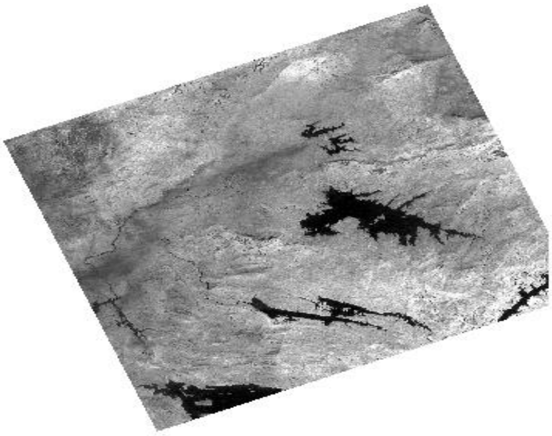


Fig 4.18: NDVI August

The normalized difference vegetation index is an important part while calculating LST. The result of LST depends upon the value of NDVI; usually, it ranges between -1 to 1. The area where we got maximum vegetation has +1 value. LST and NDVI are negatively correlated.

4.2.4 Land Surface Emissivity (LSE):

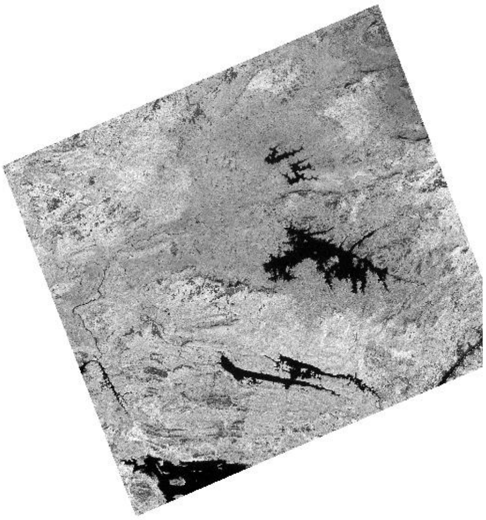


Fig 4.19: LSE January

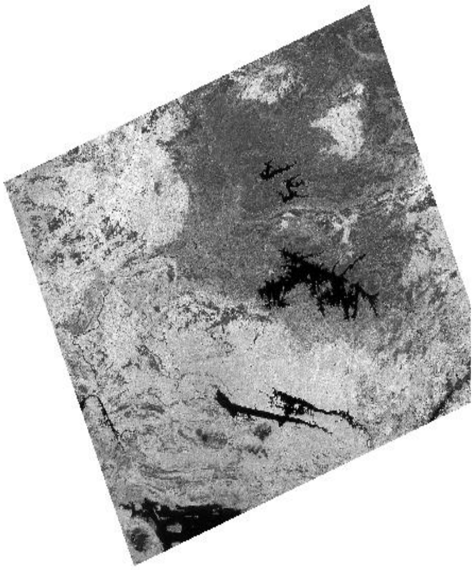


Fig 4.20: LSE March

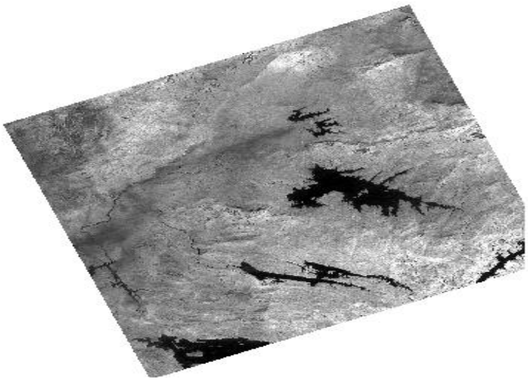


Fig 4.21: LSE August

4.2.5 Land Surface Temperature (LST):

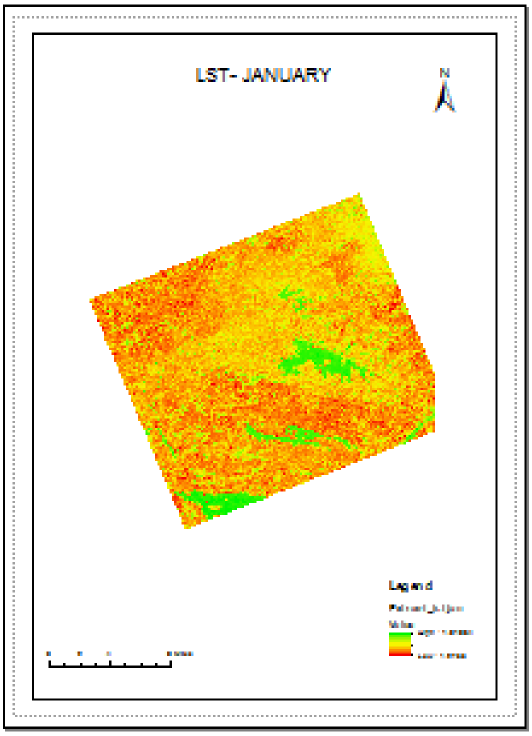


Fig 4.22: LST January

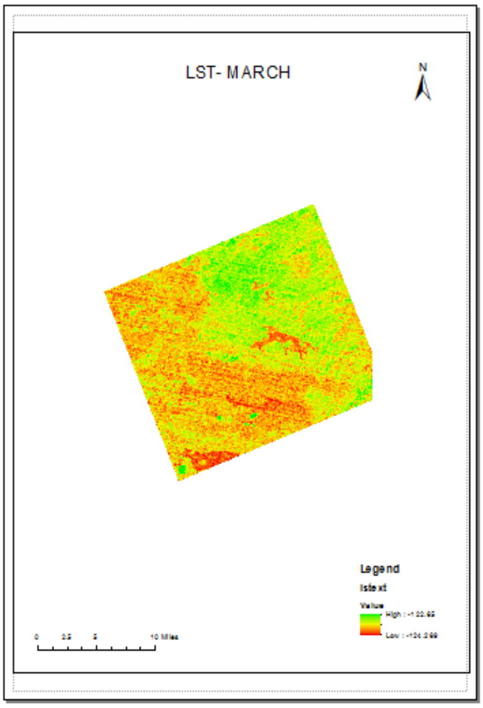


Fig 4.23: LST March

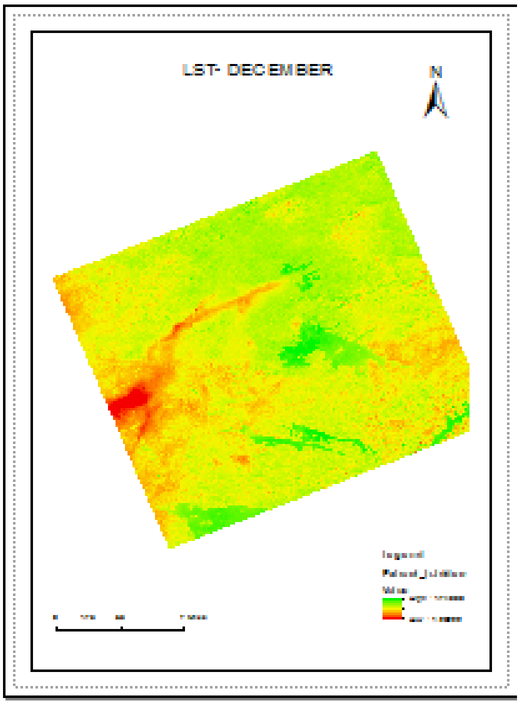


Fig 4.24: LST August

4.2.6 CORRELATION BETWEEN NDVI AND LST

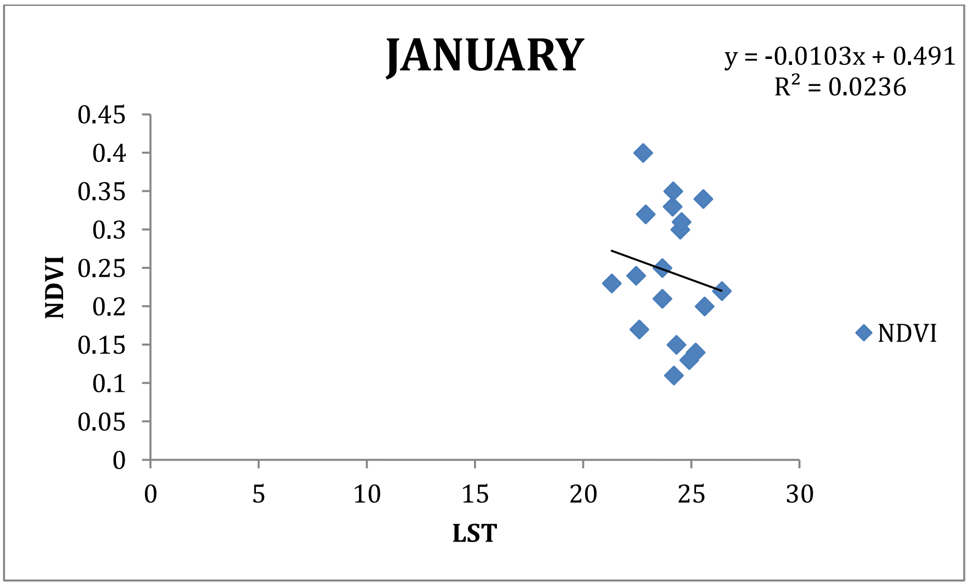


Fig 4.25: Correlation between NDVI and LST (January)

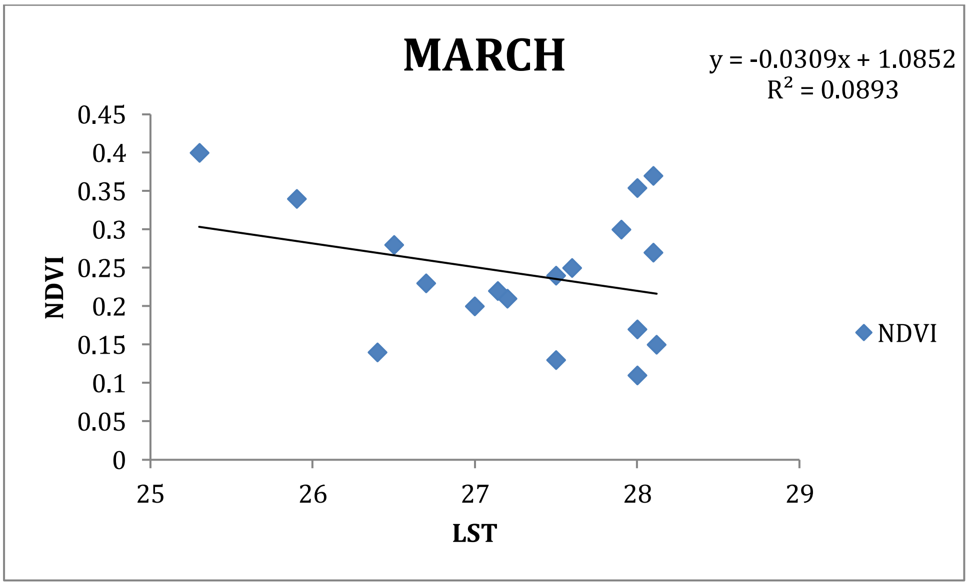


Fig 4.26: Correlation between NDVI and LST (March)

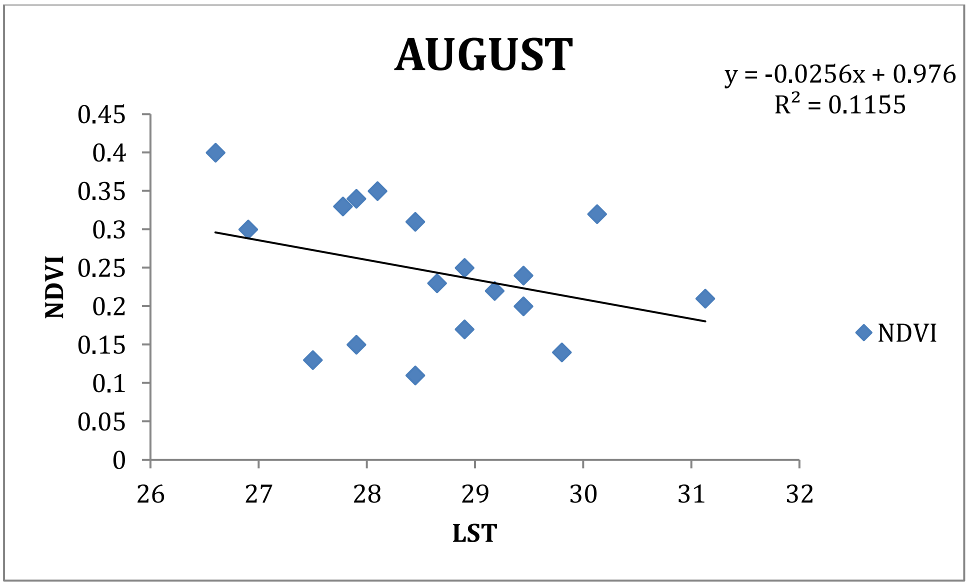


Fig 4.27: Correlation between NDVI and LST (August)

The graphs (4.25, 4.26 and 4.27) show the relation between NDVI and LST during different seasons in a year. It clearly shows that during monsoon and rainy season NDVI and LST are negatively correlated whereas during winter season it shows some positive correlation.

From the graphs (4.25, 4.26 and 4.27) by taking NDVI as Y-axis and LST as X-axis it defines that wherever the value of NDVI increases, the value of LST starts to fall. In contrast to the common perception that LST and NDVI are typically negatively correlated, we demonstrate that this relationship, in fact, varies with location, season, and vegetation type. Many attempts have been made to interpret this relationship in terms of various biophysical and geographical variables (e.g., land use and land cover, fractional vegetation cover, moisture conditions, topography). This study revealed a correlation between LST and NDVI. So, this study is one of the examples that prove LST and NDVI are negatively correlated (Sr uthi et al., 2015).

4.1 CHANGE DETECTION

	Area (sq.Km)	
Class	2008	2018
Spares vegetation	44.80296	46.59
Moderate vegetation	334.0741	355.58
Dense vegetation	447.8451	424.56

Table 3: Change Detection

Change detection study between 2008 and 20018 resulted in decrease in dense vegetation from 447.8451 to 424.56sq.Km whereas moderate vegetation region has shown a slight increase from 334.0741 to 355.58sq.Km and spares vegetation region has also shown an increase from 44.80296 to 46.59sq.Km. These increases in moderate vegetation and spares vegetation regions may be due to the decrease in dense vegetation regions.

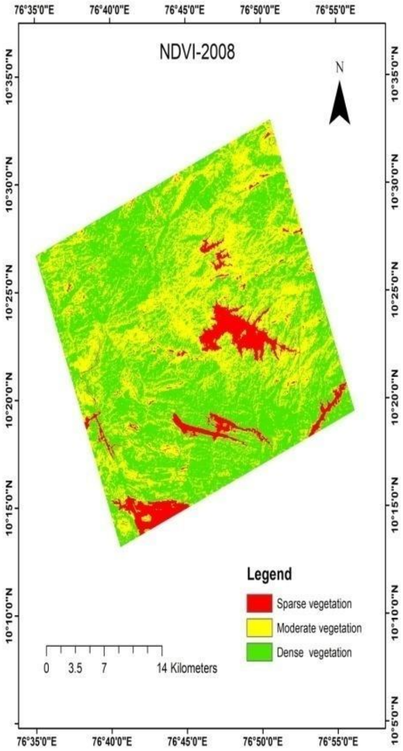


Fig 4.28: NDVI 2008

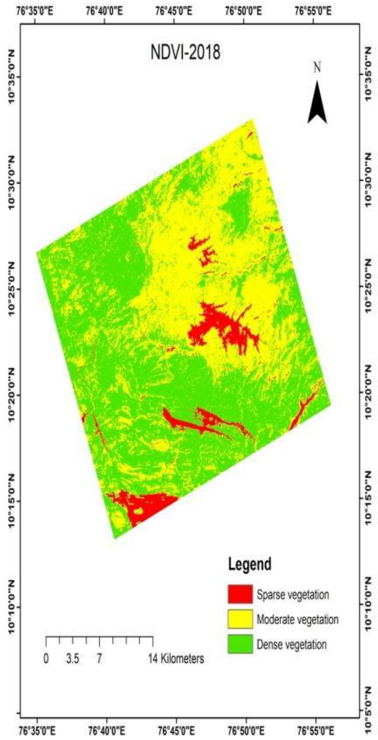


Fig 4.29: NDVI 2018

The results of the NDVI calculation range from -1 to 1. Negative values correspond to areas with water surfaces, manmade structures, rocks, clouds, snow; bare soil usually falls within 0.1- 0.2 range; and plants will always have positive values between 0.2 and 1. Healthy, dense vegetation canopy should be above 0.5, and sparse vegetation will most likely fall within 0.2 to 0.5. However, it's only a rule of thumb and the season, type of plant and regional peculiarities should be taken into consideration to know exactly what NDVI values mean.

(https://eos.com/blog/ndvi-faq-all-you-need-to-know-about-ndvi/)

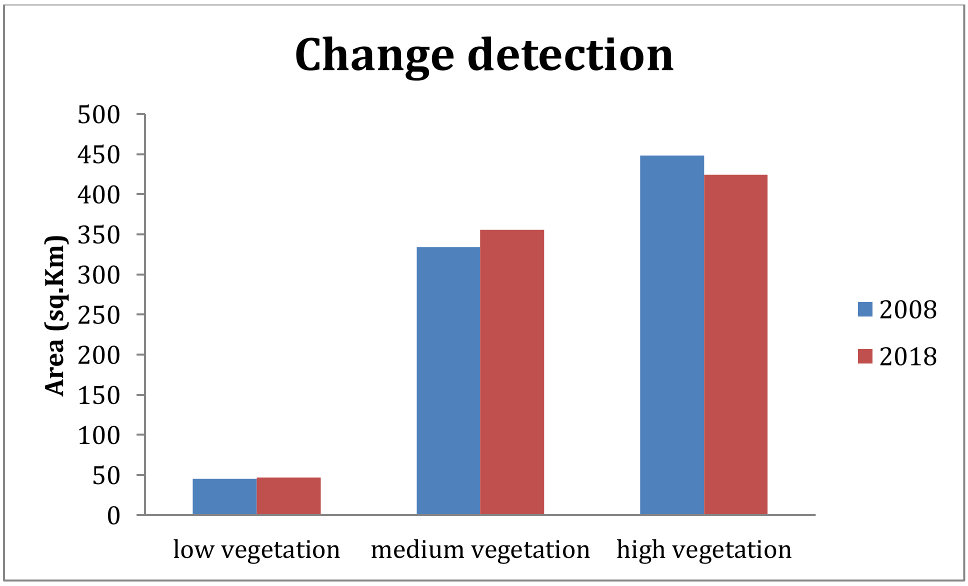


Fig 4.30: change detection

The graph (fig: 4.30) clearly shows a decrease of vegetation in the year 2018 when compared to 2008. Change detection shows a decrease in dense vegetation regions and a respective increase in moderate vegetation and spares vegetation regions. This increase in moderate vegetation and spares vegetation regions may be due to the decrease in dense vegetation regions. It may be due to change in climatic conditions (Chandrashekara et al., 1994).

CHAPTER 4

SUMMERY

Correlation study between NDVI and Climatic Variables for the year 2016, Correlation study between NDVI and LST for the year 2018 and Change detection study for the year 2008 and 2018 was conducted for Parambikulam forest region. Climatic variables were downloaded from CHELSA climatic site and maps for different seasons were downloaded from USGS earth explorer. The downloaded maps were extracted with study area with the help of ArcGIS 10.4 software. NDVI calculations were also done with the help of ArcGIS software. Then graphs were plotted with the help of Microsoft Excel and then correlation coefficient was calculated from the graph. The results showed that NDVI showed some significant correlation with NDVI and precipitation whereas no significant correlation between NDVI and temperature variables during all the three seasons. The presence of vegetation and water bodies reduces the LST level. Furthermore, the relationship between LST–NDVI was interpreted quantitatively by linear regression analysis at the pixel level. For whole Parambikulam region, LST shows a strong negative correlation with NDVI. In future, many additional research works may be included. LST may be retrieved using, several new statistical methods can be applied to estimate the correlation between LST and different. LU–LC indices (NDVI). A change detection study showed a decrease in high vegetation regions and an increase in low and medium vegetation regions in 2018 when compared to 2008.

CHAPTER 5

CONCLUSION

Correlations between the seasonal variations in the NDVI and climatic variables, Correlation between NDVI and LST and change detection were analysed. It was observed that in Parambikulam region precipitation has a significant effect on its vegetation. Vegetation growth in Parambikulam region was not limited primarily by temperature. A comparison of NDVI trends and the NDVI–climate relationship indicated that NDVI trends were controlled by precipitation in the Parambikulam forest region. The cause of NDVI increase in this region is still unknown. These results give us possible vegetation–climate relationships and future change in the terrestrial carbon cycle. However, we have to keep in mind that this study is not conclusive due to NDVI data quality and lack of long-term data. Correlation study between NDVI and LST showed a strong negative correlation. The presence of vegetation and water bodies reduces the LST level. For whole Parambikulam region, LST shows a strong negative correlation with NDVI. In future, many additional research works may be included. LST may be retrieved using, several new statistical methods can be applied to estimate the correlation between LST and different. LU–LC indices (NDVI).A change detection study showed a decrease in dense vegetation regions and an increase in spares and moderate vegetation regions in 2018 when compared to 2008.

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