Hochschule Rhein-Waal
Rhine-Waal University of Applied Sciences
Faculty of Communication and Environment

Degree Program Information Engineering and Computer Science, M. Sc.
Prof. Dr. Rolf Becker

Drought analysis using Normalized Difference Vegetation Index (NDVI), soil temperature, and precipitation in Xanten for the year 2018 and comparison with 2016 and 2017

Term Paper

WS 2019/2020

Module “Geoinformatics”

By

Bhuwan Acharya (Matriculation Number: 26129),
Bikash Paudel (Matriculation Number: 26192)

Abstract

Germany suffered from a severe drought in 2018. According to the German Drought Monitor 1 operated by the “Helmholtz-Centre for Environmental Research” (UFZ) the soil moisture in the upmost 180 cm of soil has still not recovered. Particularly in Eastern Germany as well as Bavaria the drought index yet reveals exceptional droughts until 2020 January. Drought has lot of impact on the vegetation in many regions. Here in this project, study has been conducted for the certain region of Xanten which lies in the Wesel district of North Rhine Westphalia. Eight small areas including residential land surface to lake, forest and cultivable land are included in this study. For the study, NDVI data was extracted from the Sentinel-2 imagery satellite. Temperature and Precipitation were taken from the German whether center DWD. Tools like QGIS, excel, Python were used for the extraction, process and analyze the data. Firstly, how the NDVI shows the effect on the vegetation were discussed. The relation between NDVI, temperature and precipitation on the year 2018 were studied using the various graphs and maps. Also, the correlation between them were calculated for the better understanding. For detail study, pixel-wise comparison was performed and correlations between them were also calculated. Finally, NDVI of 2018 was compared with that of 2016 and 2017 and analyzed what changes are there and weather there any effect of drought or not. From the analysis, it was found that there is a very weak relation between NDVI and temperature. It was also found that NDVI is slightly negatively correlate with the cumulative precipitation. Also, the major finding of the study was with the increase of temperature, NDVI was found to have less value which means vegetation decreases with increase of temperature over a three years period. It was also found that the vegetation has been maximum of the year 2017 and it was decreased on 2018 due to decrease. Such change can be due to the decrease in cumulative precipitation and increase in temperature from 2017 to 2018. Increasing temperature and decreasing cumulative precipitation are the consequences of drought so it can be concluded from the study that there was drought in Xanten region and there was a small impact on the Xanten region due to drought as it can be seen from the graph and map of 2018 where there is less vegetation then previous years.

Acronyms

AHVRR	- Advanced Very High-Resolution Radiometer
NDVI	- Normalized Difference Vegetation Index
NIR	- Near-Infrared
VIS	- Visible light
VCI	- Vegetation Condition Index
SPEI	- Standardized Precipitation Evapotranspiration Index
CRS	- Coordinate Reference System
EPSG	- European Petroleum Search Group
WGS	- World Geodetic System
CSV	- Comma-Separated Values
QGIS	- Quantum Geographic Information System
DWD	- Deutscher Wetterdienst
TIFF	- Tagged Image File Format
Mm	- Millimeter
IDW	- Inverse Distance Weighting
TIN	- Triangulated irregular network

List of Figure

Table of Contents

1. Introduction

Over the last century, extreme climatic events have increased worldwide in frequency and severity (John et al., 2013). Drought is possibly the most complex and problematic natural hazard because it exhibits high volatility over time and space and typically spreads over large geographical areas (Senay, et al., 2015).

In general, drought defines as “an extended period – a season, a year, or several years – of deficient rainfall or dry period relative to the statistical multi-year average for a region (Graham, 2000)”. It is characterized typically by type, frequency, duration, magnitude, severity, and geographic extent. However, it is tough to determine a universal definition due to the temporal and spatial variation of drought. There are four main types of droughts defined in the literature (Senay, et al., 2015):

- **Meteorological drought**, which for an extended time, is characterized by lower precipitation than the long-term average precipitation, i.e., it is dependent on the degree of dryness and length of that dry period.
- **Agricultural drought** occurs when the available water for plants and crops falls below the required limit, failing to meet the water needs of those particular crops and thus limiting the growth of vegetation; it usually occurs after meteorological drought and before the hydrological drought.
- **Hydrological drought** is associated with the lack of surface and groundwater availability (streamflow, soil moisture, and groundwater).
- **Socio-economic drought**, measured by social and economic indicators, is entirely focused on the impact of meteorological, agricultural and hydrological drought on the supply and demand of industrial goods; it occurs when a climate-related water supply deficit results in demand that exceeds supply.

Drought is the most significant abiotic factor that limits growth, has an adverse effect on growth and crop production. Stress leading to non-normal physiological processes influencing one or a combination of biological and environmental factors; Stress may develop damage that has occurred as a result of abnormal metabolism and may decrease growth leading to plant death (Fathi & Barari, 2016).). In particular, the severe drought that affected large areas of Europe in 2018 resulted in widespread losses in agriculture and forestry. This drought produced an overall loss of around US$ 3.9bn (€3.3bn), making it the year's costliest event in Europe (Löw, Petra, 2019). Consequently, assessment and monitoring of droughts are crucial for early warning systems and management to mitigate the severe effects of drought.

Efforts were made to develop and implement various quantitative indicators of the frequency and intensity of droughts—nevertheless, traditional approaches, particularly over large areas, mostly outcomes poor results while predicting and tracking. The use of satellite remote sensing in the monitoring of drought has gained more attention since it can be used to measure the meteorological or biophysical characteristics of the surfaces of Earth (Rhee, I m, & Carbone 2010). “Remote sensing phenology research uses information gathered by satellite sensors which measure wavelengths of light that green plants absorb and reflect. Throughout plant leaves, certain pigments strongly absorb visible (red) light wavelengths. The leaves strongly reflect near-infrared light wavelengths that are invisible to human eyes. Such reflectance properties often change as a plant canopy changes from early growth in the spring to late-season maturity and senescence.”[9].

Even though Hazaymeh and Hassan (2016) have shown that specific indices can be interpolated or re-analyzed, such as SPEI (Standardized Precipitation Evapotranspiration Index, Vicente-Serrano, et al., 2010), and used to assess meteorological drought. However, they have a low spatial resolution problem. Also, these indices show deficiencies in the monitoring of drought in near-real-time and in helping farmers and governments, particularly those in large regions and areas with sparse stations, to consider making crucial decisions (Unganai and Kogan, 1998, Rhee et al., 2010, Liang et al., 2012, Son et al., 2012, Sánchez et al., 2018).

In contrast, Kogan (1995) developed an index of vegetation condition (VCI), which detects drought based on scaled NDVI. The Normalized Difference Vegetation Index (NDVI) is one of the most commonly used and implemented indices calculated from multispectral information as the normalized ratio between the red and near-infrared bands. In contrast with other indexes that NDVI is sensitive to the effects of soil brightness, soil color, atmosphere, cloud and cloud shadow, and leaf canopy shadow (Baofeng, 2017). The Normalized Difference Vegetation Index (NDVI) (Tucker, 1979), computed from AHVRR satellite radiance data, is the most frequently used vegetation index and is represented mathematically by the following formula:

$$NDVI = (NIR - VIS) \div (NIR + VIS)$$

NIR refers to near-infrared and VIS to visible light, which is based on the fact that chlorophyll absorbs visible light whereas the mesophyll leaf structure scatters NIR (Pettorelli, 2013).

NDVI values range between + 1.0 and -1.0, where negative values correspond to an absence of vegetation. The barren rock, sand, or snow areas usually show very low NDVI values (e.g., 0.1 or less). Sparse vegetation such as shrubs and grasslands, or senescent crops may result in moderate NDVI values (about 0.2 to 0.5). High NDVI values (approximately 0.6 to 0.9) refer to dense vegetation such as that found in temperate and tropical forests or crops at the stage of their peak growth [9].

Although the NDVI data sets are quality controlled products, pitfalls remain to be avoided when using them (Pettorelli, 2013).

- **Mixed pixels**, which are as the pixel that encompasses water and land.
- **Misregistration** errors are the timing errors resulting from the onboard satellite clock.
- **Comparing NDVI values between pixels,** NDVI variations within a pixel may affect by many factors: plant architectural arrangement, interactions with canopy cover, height, the composition of species, vegetation vigor, leaf properties, and vegetation stress.
- **Quality of the information with respect to spatial location**

Nonetheless, NDVI alone may not be able to effectively diagnose vegetation drought (Heim, 2002), because many factors, such as land cover changes and infestation of pests, may contribute to an anomaly similar to that caused by drought. Drought indicators and indices are various concepts widely used to characterize the severity, spatial extent, and duration of the drought. While an indicator consists of parameters (precipitation, temperature, runoff, groundwater levels, reservoir levels, soil moisture levels, snowpack, and drought indices), an indicator often refers to a combination of indicators resulting in a quantified numerical value of the severity or magnitude of a drought (Wardlow, Anderson, & Verdin, 2012). Incorporating vegetation indices with drought indices and data such as soil temperature and precipitation can be a very effective method, as it provides useful and more detailed information on drought monitoring ((Karnieli, et al., 2010), (Nichol & Abbas, 2015)).

"Thus, the purpose of this paper is to scrutinize whether observational information in vegetation indices derived from satellite imagery over the summer period between 2016 and 2018 interrelated with soil temperature and perception of the specific time period in the Xanten regions with specific eight different regions of interest for the analysis of drought."

2. Material and Methods

2.1. Study Area

Xanten, a town located in the district of Wesel, is in the state of North Rhine-Westphalia. It has a total area of 72.39 km2(27.95 mi). According to Landesbetrieb Information und Technik NRW, the statistical offices of the German states collecting official statistics in Germany, Xanten has a population of 21,690 and a population density of 300/km2 by the end of 2018[12]. The town of Wesel borders Xanten to the east and the city of Uedem and Kalkar to the west. The Lower Rhine and the city of the Rees to the north and Alpen and Sonsbeck to the south. It is famous for its world's largest archaeological open-air museums. Museums were built at the site of the Roman settlements Colonia Ulpia Traiana. Geographically Xanten lies 24m above sea level. It experiences a warm and temperate climate.

Annual temperature in the Xanten varies very rarely from 20°F(-6.67°C) to the maximum of 86°F(30°C) but typically it ranges from 32°F(0°C) to 75°F(23.89°C). In summer, it is partly cloudy, and the winters are very cold, windy, and mostly cloudy. The summer season lasts around 3.2 months, i.e., from June 1 to September 9. The average daily high temperature is above 68°F(20°C). Winter season lasts for 3.7 months, i.e., from November 17 to March 8. The average daily high temperature is below 48°F(8.889°C) in winter. Xanten also experiences precipitation of about 777mm (30.6 inches) per year. The wetter season lasts around 8.1 months i.e., from May 19 to January 24, with more than 30% chances of the day being a wet day [13]. On average, July is the wettest month, and February is the driest month.

2.2.Dataset Description

2.2.1.NDVI

The NDVI dataset was acquired from the multispectral imagery of the Sentinel 2 satellite, which is a land monitoring constellation of two satellites. Its main objectives are Land observation including, vegetation, soil and water cover, inland waterways, and coastal areas. Also provides disaster relief support and Climate change monitoring are also the objective of this satellite (Pettorelli, Nathalie,2013). It provides global coverage of the Earth's land surface every ten days with one satellite and five days with two satellites, which makes the data great use in on-going studies. These satellites are equipped with the state-of-the-art MSI (Multispectral Imager) instrument, which offers very high-resolution optical imagery. Swath Width and Resolution provided by this satellite is 290km-10m,20m, and 60m spatial resolution. It has various level for data processing: -

- Level 1 - A - Radiometric corrections
- Level 1 - B - Geometric corrections
- Level 2 - A - Cloud screening
- Level 2 - B - Atmospheric corrections
- Level 2 - C - Geophysical variables retrieval algorithms
- Level 3 - Simulation of cloud corrections

2.2.2.Temperature and Precipitation

The temperature and precipitation data have been acquired from the German Weather Service Deutscher Wetterdienst (DWD). DWD measures the surface measurements operating the number of different measuring networks. The DWD’s and Bundeswehr Geoinformation Service’s main station network are the most important for the monitoring and forecasting of weather. They are comprised of around 200 meteorological stations for originating the synoptic report. Every half an hour, DWD stations transmit their synop reports. Besides the main measuring stations, DWD also operates a network of secondary measuring stations. Secondary measuring stations have more restricted programs, and there are approximately 300 Automatic Meteorological Data Acquisition systems (AMDA III) and Modular Data Acquisition system (MODES III) stations. Around 480 stations (AMDA III/N and MODES III/N stations) run for a unique network for measuring precipitation. Whenever the radar measurement receives the echo above a station, the precipitation reports from the stations are provided hourly rather than the regular daily reports. Since the current weather reports and the climate data from the day before to earlier days are freely available at the free DWD Open Data Server, so it is more suitable for our study. We can find all the meteorological and climatological spatial data and services. They are straightforward to access and all data are well processed. They have a different resolution, like 10 minutes, per day, per month to annual data. Temperature data are in °C (degree celsius), and Precipitation data are available in mm (Millimeter).

2.3.Methodology

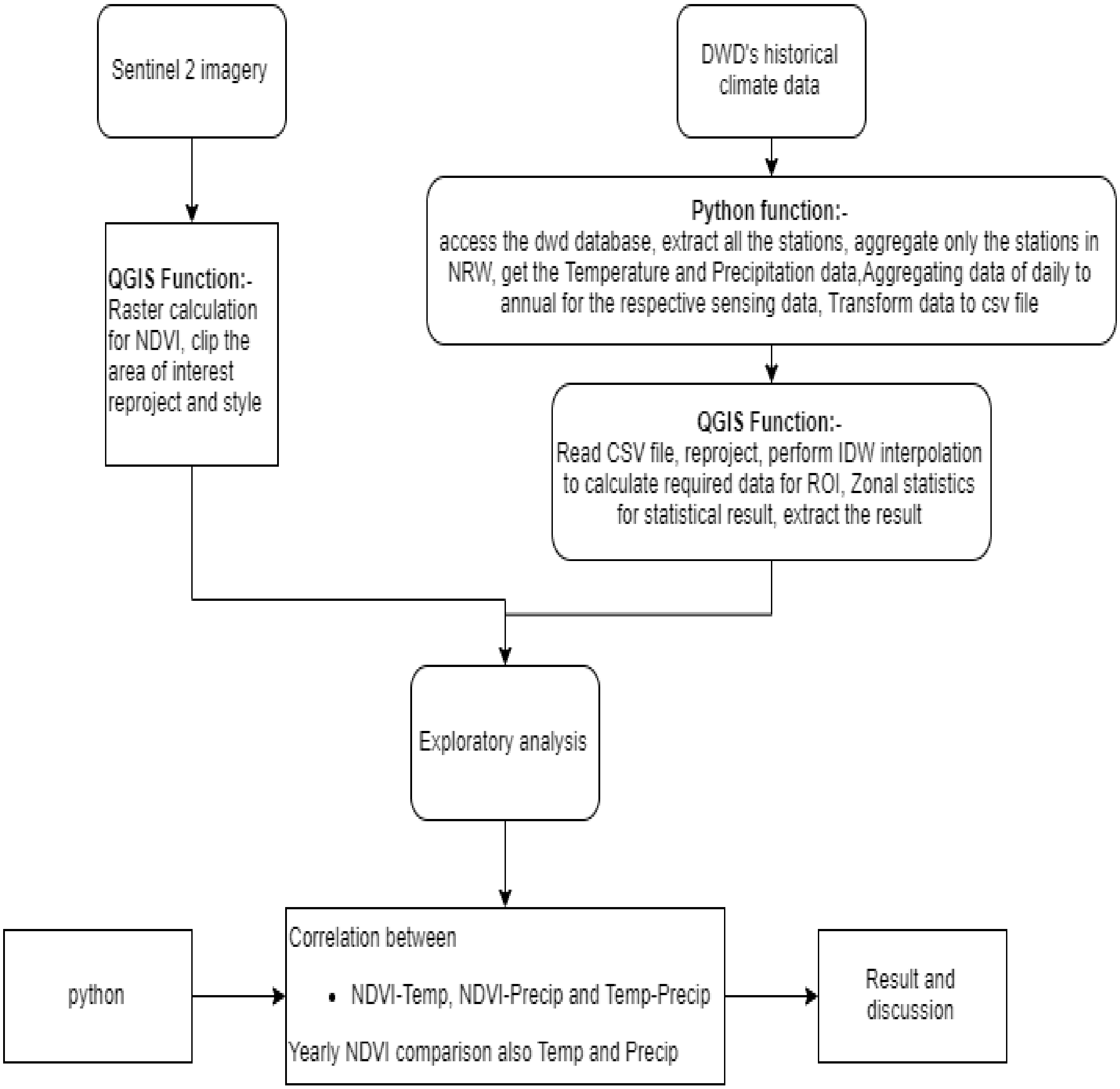

Figure 1:Schematic representation of the methodology used

Figure 1 shows the general view of how the data has been collected, processed, and analyzed. Every step will be explained in detail in the following sections.

2.3.1.Data Preprocessing

2.3.1.1. NDVI

The data for the NDVI calculation was extracted from the German weather station (DWD) directly from Copernicus open access data. The data for the given sensing date were searched and downloaded. It was also able to preview the image before downloading it. Three sensing dates were to be selected for the three years analysis i.e., one date for one year. For this study, the sensing dates of 2016-05-08, 2017-05-26, and 2018-05-08 were selected. Imagery data were then downloaded corresponding to the sensing dates. Since the Imagery is multispectral, NDVI is to be calculated from the available images of different bands. The multispectral images of sentinel 2 contain 13 spectral bands (443-2190 nm). The bands are as follow:

Table 1: Sentinel-2 Bands, Central Wavelength (µm) and resolution(m)

("Sentinel-2A (10m) Satellite Sensor." Satellite Imaging Corporation, www.satimagingcorp.com/satellite-sensors/other-satellite-sensors/sentinel-2a/.)

Sentinel-2 Bands	Central Wavelength (µm)	Resolution (m)
Band 1 - Coastal aerosol	0.443	60
Band 2 - Blue	0.490	10
Band 3 - Green	0.560	10
Band 4 - Red	0.665	10
Band 5 - Vegetation Red Edge	0.705	20
Band 6 - Vegetation Red Edge	0.740	20
Band 7 - Vegetation Red Edge	0.783	20
Band 8 - NIR	0.842	10
Band 8A - Vegetation Red Edge	0.865	20
Band 9 - Water vapour	0.945	60
Band 10 - SWIR - Cirrus	1.375	60
Band 11 - SWIR	1.610	20
Band 12 - SWIR	2.190	20

As already mentioned in the introductory part of the study, NDVI is calculated by the formula: -

$$NDVI = (NIR - VIS) \div (NIR + VIS)$$

Here, Band 8 is responsible for NIR. For the VIS, Red band is taken under consideration as described in the introductory part. Therefore, for calculating the NDVI in QGIS, the '.tif' responsible for NIR and VIS are added to the layer of QGIS as a Raster file i.e., Band 4 image and Band 8 image. Using the function of QGIS, Raster Calculation, NDVI is calculated using the formula for NDVI. The new layer is formed, which gives the NDVI. Since there are eight regions of study, so NDVI for a particular area was required, using another function of QGIS, clip raster by a mask layer, NDVI for the study reason was calculated. The Coordinate Reference System of the calculated NDVI is in EPSG:32631 - WGS 84 / UTM zone 31N projection. It is further projected to EPSG 4326 and saved using the proper name. Similarly, NDVI for all the sensing dates were calculated. Also, using the function Zonal Statistics of QGIS (used to extract the statistics of the raster images) was used to get the Average NDVI value for the particular study area i.e., Average NDVI for area 1 was calculated and similarly other study areas also. The statistics are added to the attribute table of the shapefile of ROI (Region of Interest), which is further exported as CSV for future analysis. Finally, the required NDVI images and NDVI values for the study were ready for analysis.

2.3.1.2. Temperature

Temperature data was downloaded using Python. Python programs were written for accessing the server and extracting the dataset. After the successful login to the server, historical data was required as the study was to be done for 2016,2017, and 2018. Also, as described already in section 2.2.2, there are different number of stations for precipitation and temperature i.e., there are some stations which only gives the precipitation data and some only temperature data. Therefore, the station's data were first extracted. Using those station names, stations that provide temperature data were filtered out. From those all the stations, Only the stations in the NRW (North Rhine Westphalia) state were filtered as the study area was in NRW. To become a more precise single station in the study region could be taken into consideration, but unfortunately, there was no station in the study region. Instead of taking closely located stations for the study, interpolation was performed to get more precise temperature value for the study region. Also, for interpolation, all the stations were listed out. For the study, NDVI was calculated for some of the particular sensing dates, and temperature data were also required for those dates. Since the dataset consists of the time series data, some aggregation functions were used in the Python for getting the annual mean temperature.

The annual temperature could also be extracted, but it was aggregated from the daily data because annual data would be considered from January 1st to December 31st. So, for the more precise study, temperature till the sensing data was aggregated from the daily data of a year before to the sensing date i.e., 2015-05-08 to 2016-05-09. Why is this important? It is essential because the value of NDVI differs from the seasons i.e., there is a different NDVI for summer season and winter season where there is also the change in the temperature with the season. After the aggregation, the mean temperature for the sensing date was calculated using the Python. Finally, the output, that is, the mean temperature of the various stations, were saved in the CSV format so that the QGIS can read it. The python code written for all this process are attached in the annex section of this report.

CSV file was loaded in the QGIS as a delimited layer since the data was spatial data set, so geolocation was also included in the dataset. The uploaded file is projected to the same CRS (Coordinate Reference System) as that of the NDVI layer. i.e., EPSG 4326. As already discussed above, interpolation has to be done, since there are two widely used interpolation techniques in QGIS; one of them is used for interpolation. TIN (Triangulated irregular network) Interpolation and IDW (Inverse Distance Weighting) interpolation are the two techniques. For this particular study, the IDW interpolation technique was used for calculating temperature in the study area. While performing the interpolation, standard values were used, and all the stations, providing temperature data located in the NRW state, were considered. The output of the interpolation was also projected in the same CRS system as for others. The resolution of the interpolation raster image was also set to 10m by 10m to correlate the NDVI and temperature more precisely. After interpolation, a similar approach done for calculating NDVI was performed, i.e., raster image was clip by using masked layer, and Zonal statistics were used to calculate the mean temperature and result were saved in the CSV file for all years.

2.3.1.3. Precipitation

As discussed in the above 2.3.1.2 section of temperature data, all the process was done in a similar fashion. The difference is that there were more stations for the precipitation than that of the temperature. so, stations were carefully extracted from the DWD database and processed similar to the temperature data for further analysis.

2.3.2. Visualization

The NDVI, temperature, and precipitation data were saved in the form of a CSV file. Using Python, all those CSV files were analyzed. The different Scatter plots, Pair plots, Regression lines were created the correlation between them were calculated. For creating such a graph, seaborn is used along with the matplotlib for the better graphs and ease of plotting the graphs. Seaborn is developed over the matlibplot library. It has been used in this project because it has fine default theme and graphs and graphs can be plotted with a very few lines of codes. Correlations between NDVI and temperature, NDVI and precipitation and temperature and precipitation were calculated. Also, for the comparison of NDVI of 2018 with 2016 and 2017, graphs were plotted showing the yearly change in NDVI concerning the particular study area. Also, a change in temperature and precipitation were also plotted. All those graphs were analyzed, and the result will be explained in the following section.

3. Results

The study area for this project are as follows: -

Figure 2: Aerial image of Xanten region on left and highlighted area of study with the 'id' in the right

From figure 2, the difference between the study areas can be seen. For the study, NDVI is calculated in different regions with different vegetation. Eight regions of interest are selected for the study. The sector with the id value '1' is the forest area. Areas with id values '3','23','17'and '27' are the cultivable land. Area 14 is the grassy land, and region 38 is the lake. As shown in figure 2, region 34 is the residential area. The detailed image of the study area are as follows: -

Figure 3: Aerial image of the regions of interest, top-left to bottom are arranged w.r.t id values 1,3,14,17,23,27,34 and 38 respectively.

NDVI has been calculated for all the regions of interest. The NDVI for sensing data 2018-05-08 has been calculated using the QGIS, as explained in the data preparation section.

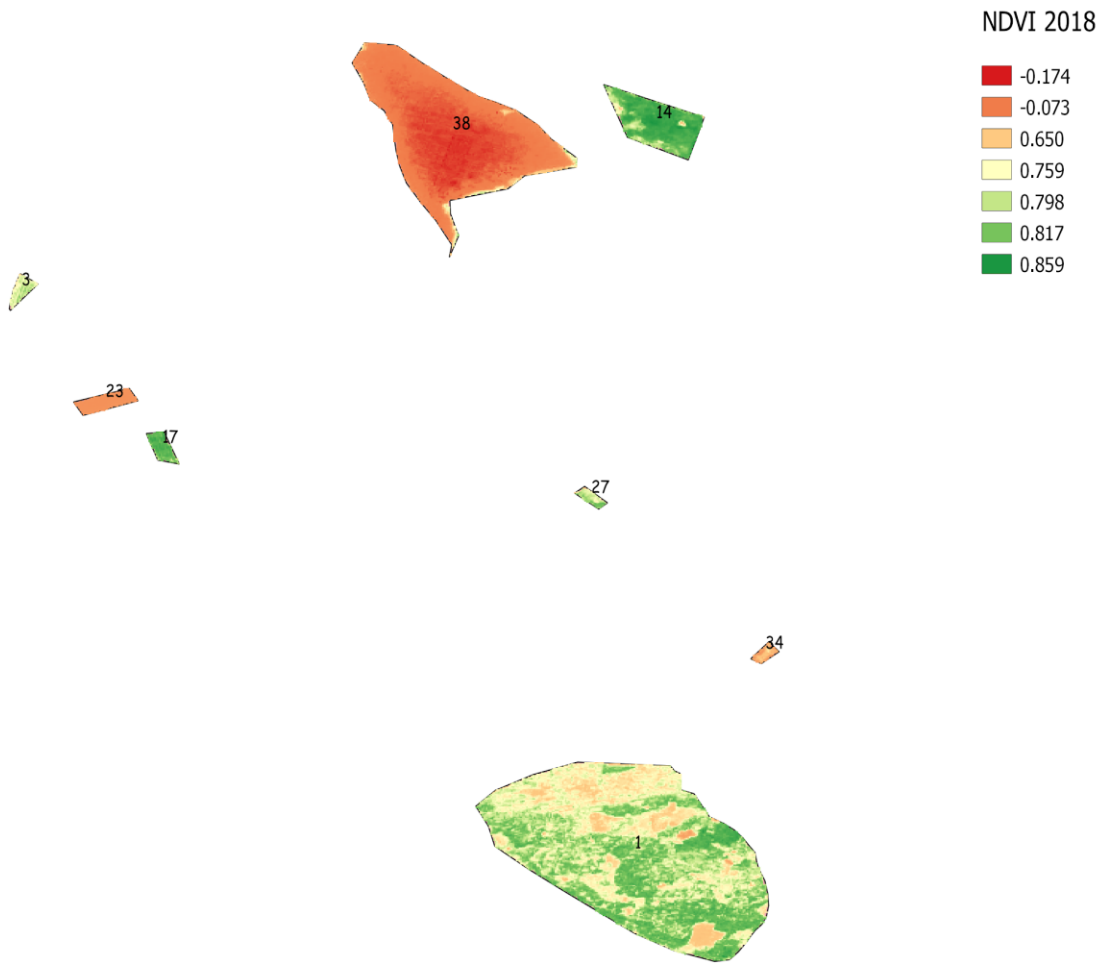

Figure 4: NDVI on the day 2018-05-08 on the Regions of interests. Classified on the basis of maximum and minimum value of NDVI

As discussed earlier in the introductory part of this report, Maximum NDVI can be obtained in the place where there is more vegetation. Soil and water reflect the light more, which means more visible light is reflected, thus resulting in low NDVI value. From figure 4, it can be seen that study area 1 has mixed NDVI values. The area where there is green labelling are the area with high vegetation. Looking at the study area from figure 3, it is clear that area 1 is the area of forest. Why is there different NDVI can be the question; it is because there are some bare lands, small area with water like pond. It is not only that but it might be due to the different vegetation i.e., some trees are old and some are very young and green which created the difference in NDVI value. Area 14, 17 seems to have more NDVI values nearly 1 which means there are more vegetation than other study field. Those area have large amount of the green vegetation than any other region. It seems like there more healthy plants resulting higher NDVI value. Whereas at area 38, it has very little NDVI value than that of the other study regions. From figure 3 we can see that area 38 is the lake so calculated NDVI was expected around -1 to -2 and it is exactly what can be seen on map. Despite of area 23 being the cultivable land it has been labeled with very low NDVI; it is because there were no crops during the sensing period and the NDVI value was due to the bare soil at that time. Area 3 has the value between 0.75 to 0.79 which shows that there is a vegetation but they are either old or less healthy than that of the vegetation in region 14 and 17. Area 34 shows mixed NDVI value because it is the residential area with a garden around them. Outer part of region 34 have the value around 0.07 because they the houses and in the inner areas there are some kind of vegetation for the value around 0.7.

Observing the area 1 for the further detail analysis as follow:

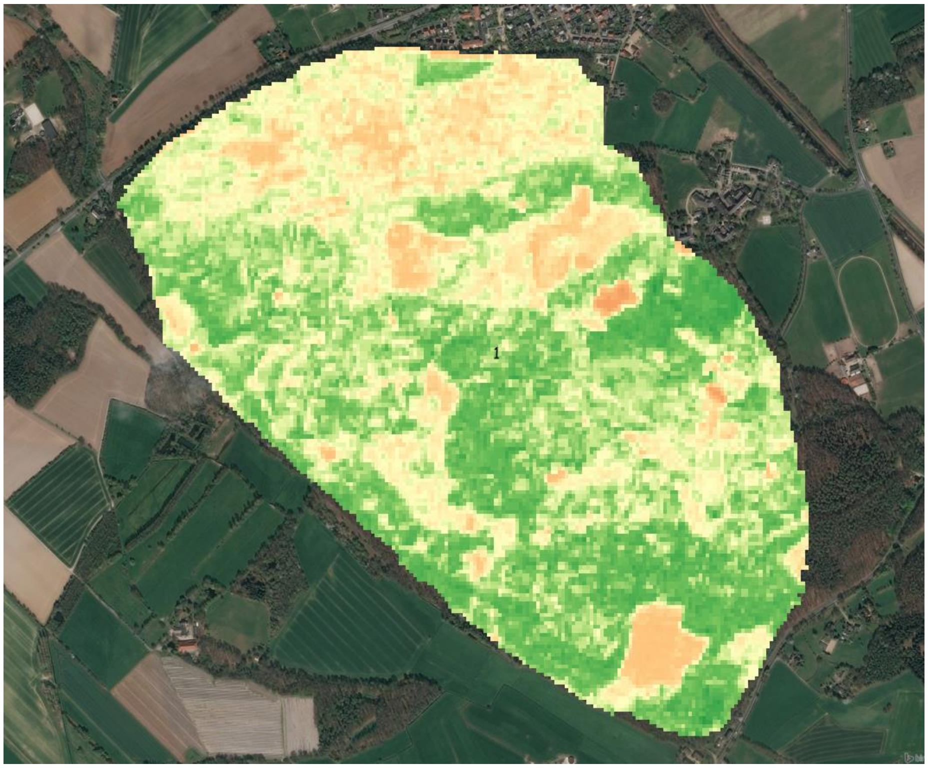

Figure 5: Zoomed image of the study area 1

Observing more on area 1, as shown in figure 5, Although being a forest, some regions have the NDVI value very low; this is because some parts have the water in the area, and some contain bare soil. That is not only the case, but healthier trees also absorb more amount of the light more for the photosynthesis process than that of the unhealthier and growing old trees. Since the NDVI is the value of light reflected, such uneven amounts of light reflection from the different trees and plants show the difference in vegetation resulting in different NDVI values. It can also be considered that healthier plants reflect the light less than that of the unhealthy trees. Despite of having more forest areas and less land and water there are a lot of region labeled with yellow and orange, it is because the images are classified by the minimum, and maximum NDVI observed in the particular study region i.e., maximum NDVI observed in the study region is 0.859, and minimum NDVI recorded is -0.175. Even though it has an NDVI in a positive value, it has been labeled yellow because of the classification values, i.e., a slight change in NDVI value also shows a color difference in labeling. The area which is greener has more healthy vegetation than that of the area with yellow and orange labeling. Here the yellow labeling does not mean it is soil or the water, but they are the unhealthy or old plants in those regions. If the NDVI in the study region is classified in the standard NDVI i.e., -1 to +1, then different images can be obtained, as shown in figure 6 as follow:

Figure 6: study areas classified by the standard NDVI value between -1 to +1

Figure 6 shows that areas with water and the bare land are having the very less NDVI i.e., negative NDVI value and areas with vegetation are having the more NDVI. As discussed above, there is almost no vegetation in the region 38 and 23, so in figure 6, it can be seen that those reasons are labeled yellow. It can also be seen in the figure 6 that area 1(forest area) is almost completely labeled with green as it has more vegetation. From this analysis, it can be stated that NDVI can be used to show the effect in vegetation as healthier vegetation are more likely to have NDVI near region +1 and less healthy vegetation have less than +1 NDVI value (nearly 0.6-0.7) and soils and water having almost no vegetation resulting the NDVI in the negative value. Also, NDVI showing the difference when there is just a slight change in the vegetation that supports the statement that NDVI can show the effect on vegetation.

The relationship between NDVI with temperature was also analyzed, and the results found are explained with the figure as follows: -

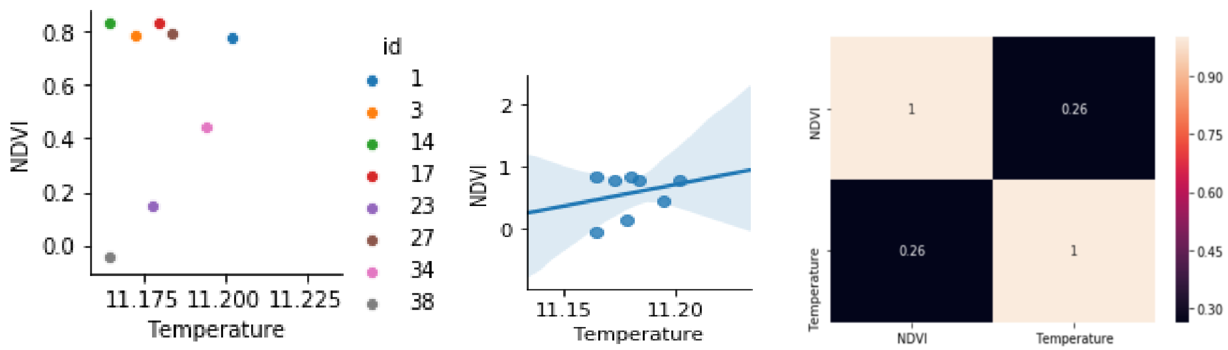

Figure 7: Scatter plot, regression line and the correlation between the NDVI and Temperature in the year 2018

In figure 7, a Scatter plot shows the difference in NDVI in the different areas of study. NDVI varies from 0 to 0.859 i.e., study regions 14, and 17 has the maximum vegetation of almost 0.9 as already discussed above, and study region 38 has the lowest vegetation nearly zero as it is an area of the lake. There is not much variance in temperature. It is found that temperature varies from 11.175 °C to 11.2°C. Since the temperature does not vary within the small areas but while performing interpolation, the resolution was maintained by 10x10m so that comparison can be made between NDVI and temperature. The regression line has been plotted between NDVI and temperature, and it can be seen that NDVI has been increasing with the gradual increase in the temperature. It can also be seen on the heatmap, which is showing the correlation between NDVI and temperature, and they are also positively correlated with the correlation value of 0.26. In general case NDVI or vegetation decreases with the increase of temperature but here completely opposite relation has been found. This might be due to the less variation in temperature in the study region. The temperature is almost the same just the difference in point might have concluded in the different relationship. Since it is not enough to say that temperature is negatively correlated with NDVI just looking at the mean value of both the temperature and NDVI for the given particular regions of study. For the further study, pixel-wise comparison of region 1, 14 and 38 has been made to find out the relation between NDVI and temperature.

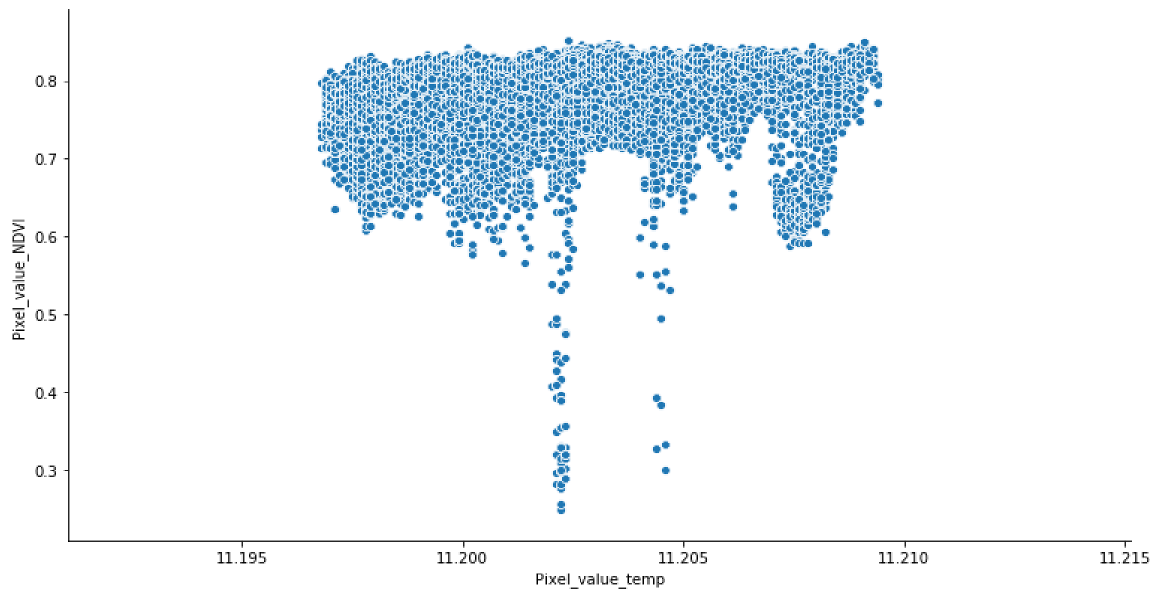

Figure 8: Pixel value of NDVI and Temperature of the study region 1 for 2018_05_08

Figure 8 is the scatter plot between NDVI and temperature for the region 1. Using the gdal2xyz function of QGIS, every pixel value of the study region 1 has been calculated and processed using excel for the visualization. All the data point are calculated from the pixel of 10mx10m resolution. Figure 8 shows that lot of value lies between 0.7 to 0.8 and on closer look, it can be seen that NDVI is increasing with the increase of temperature. For ease linear regression line and the correlation has been calculated as follow:

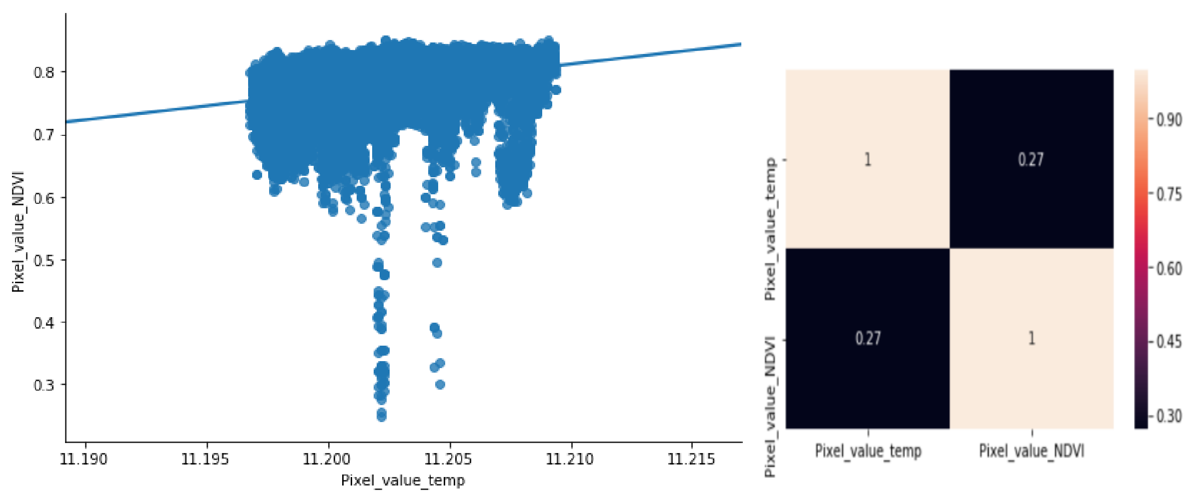

Figure 9: Linear regression line plotted for the pixel-wise relation between NDVI with Temperature for 2018_05_08 of Region 1 and also correlation between them is calculated

From figure 9, it can be seen that temperature and NDVI are positively correlated and the heatmap shows the correlation value between them. It can be found that the correlation found between the mean temperature and mean NDVI value of all the region is same as the pixel-wise correlation between them. Finally, it can be concluded that NDVI and temperature are positively correlated.

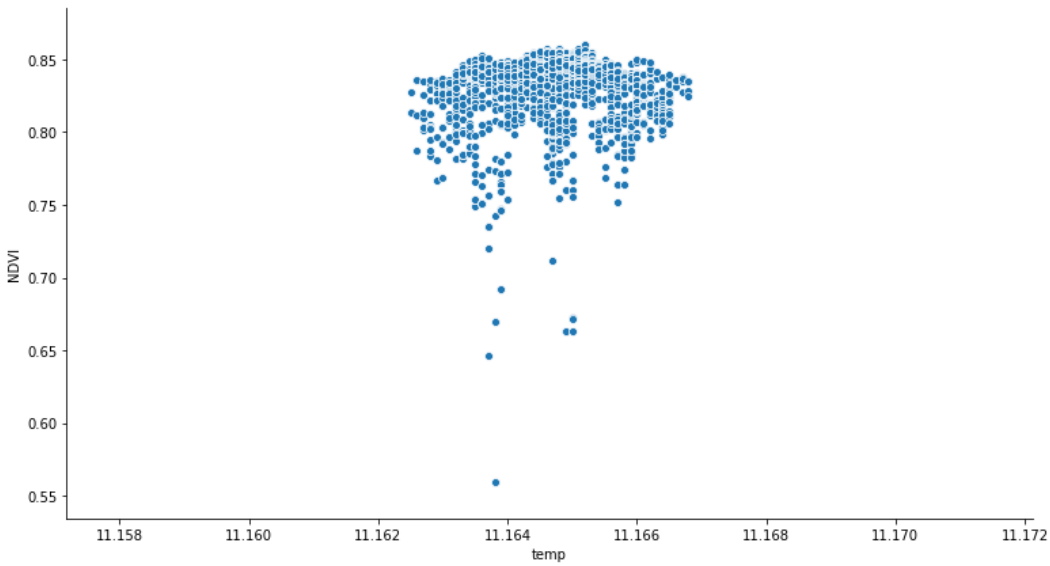

Figure 10:Pixel value of NDVI and Temperature of the study region 14 for 2018_05_08

Figure 10 shows the relation between NDVI and temperature. They are all the pixel value. It is found that there is a lot of vegetation in this area. Maximum of 0.85 NDVI value can be found in this region. To confirm the relation between temperature and NDVI to be positively correlated or not regression line has been drawn as follow:

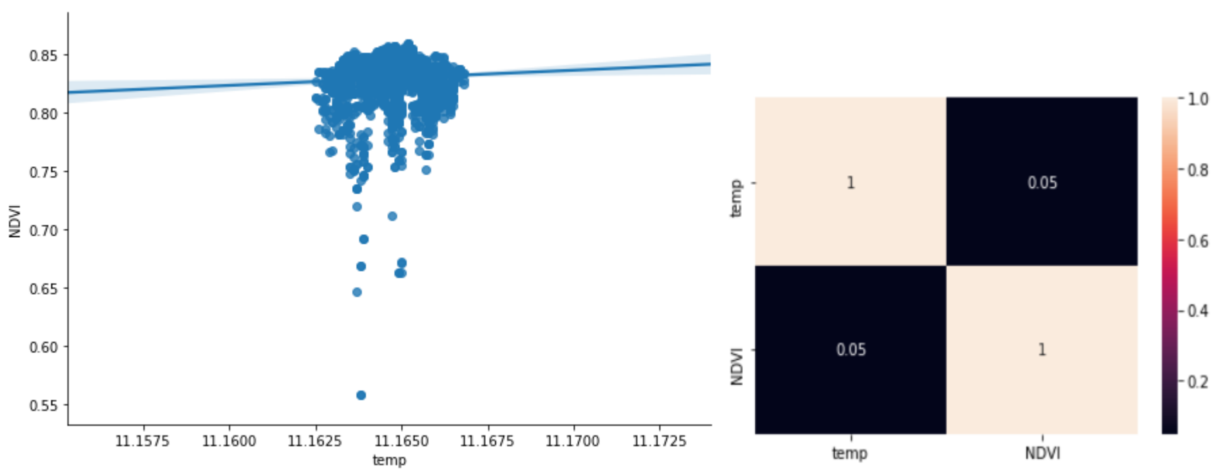

Figure 11:Linear regression line plotted for the pixel-wise relation between NDVI with Temperature for 2018_05_08 of Region 14 and also correlation between them is calculated

From figure 11, it can be found that the temperature is positively correlated with the NDVI. They seem to be weakly correlated but it can not be denied that when temperature increases the NDVI also increases.

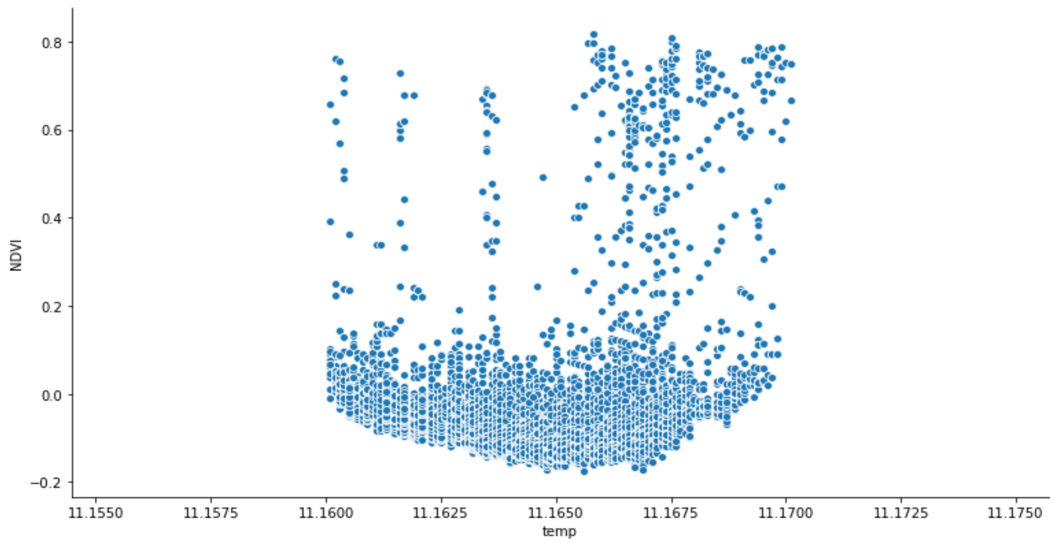

Figure 12: Pixel value of NDVI and Temperature of the study region 38 for 2018_05_08

From figure 12, it can be found that there is very less vegetation in the region 38. It is already known that region 38 is the lake so it is obvious that there will be less NDVI which can be seen in the figure 12. Despite of the region being lake there are some data showing the vegetation this is because the shapefile that has been used for the study does not exactly cover the area of lake. The shape file covers some of the land area around the lake which have some vegetation on them so, some values like 0.8, 0.7 are seen in the graph.

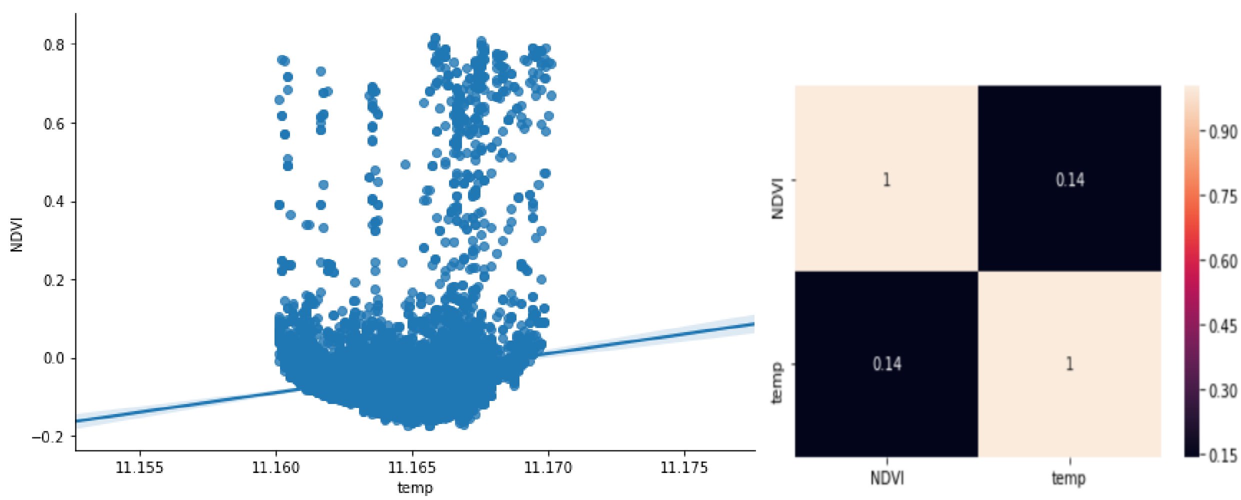

Figure 13: Linear regression line plotted for the pixel-wise relation between NDVI with Temperature for 2018_05_08 of Region 38 and also correlation between them is calculated

Figure 13 shows the correlation between NDVI and temperature in region 38. Positive correlation is again found for this region also. It shows that NDVI is positively correlated with the Temperature. It also shows that for other analysis, average value of temperature, precipitation and NDVI of a study reason can well represent the relation between them.

Relationship between NDVI with precipitation was also analyzed and the results found are explained with the figure as follow: -

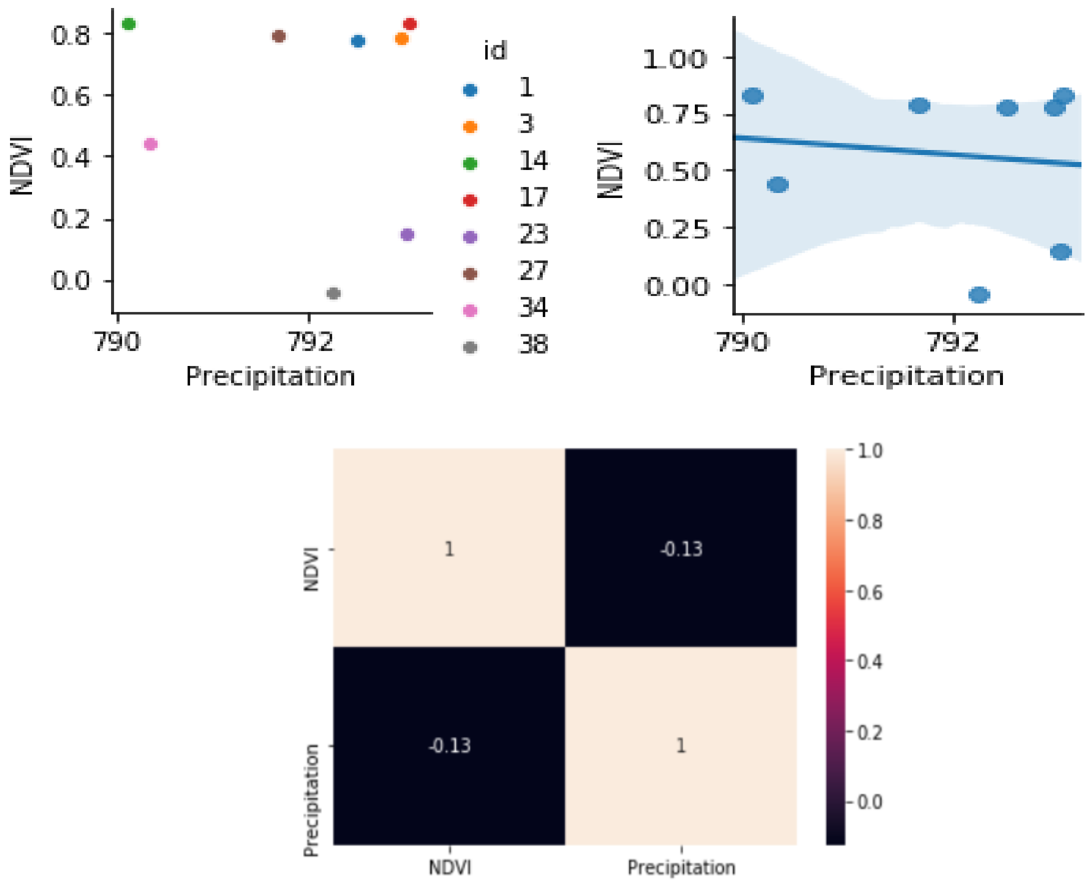

Figure 14: Scatter plot, regression line and the correlation between the NDVI and Temperature in the year 2018

From Figure 14, it can be seen that precipitation varies from 790 to 792 mm, this is very less variation in precipitation. NDVI has been plotted over the change in precipitation to find out how much they are correlated to each other. From the regression line, it is seen that with the increase of precipitation, there is a significant decrease in the NDVI value. Since there is just a slight increase in the precipitation and still the NDVI is decreasing. On plotting the heatmap and calculating the correlation, it can be seen that NDVI and precipitation have very weak correlation between them and are negatively correlated. This is a very weak correlation but it can still be concluded that there is a correlation between them.

Relationship between temperature with precipitation was also analyzed and the results found are explained with the figure as follow: -

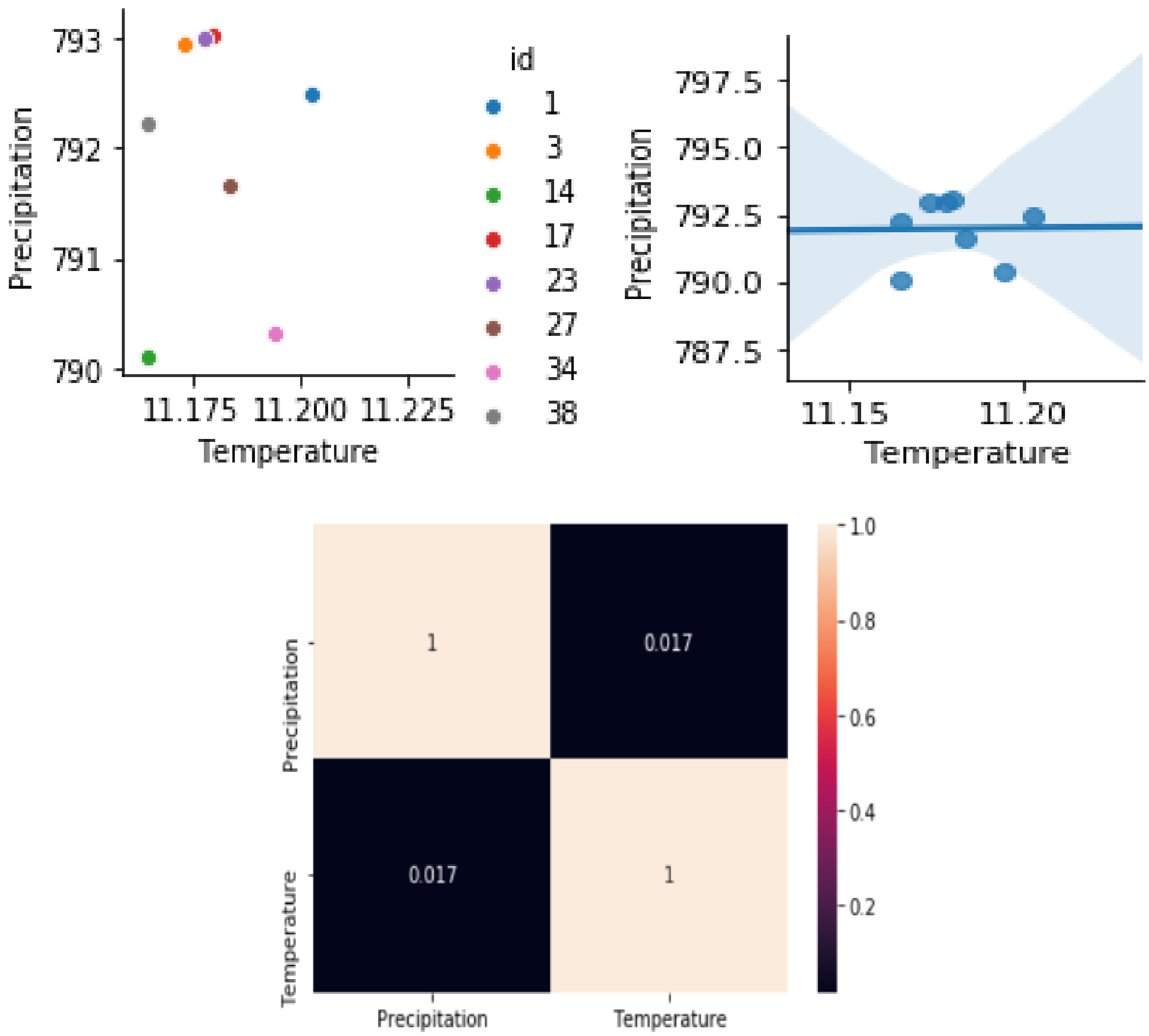

Figure 15: Scatter plot, regression line and the correlation between the Precipitation and Temperature in the year 2018

Figure 16 shows the relation between temperature and precipitation for 2018-05-08. It can be seen in the first figure that there is not much variation in temperature and precipitation so the relation between them seems to be very obvious. From the regression line and the correlation value it can be concluded that they are almost independent to each other. There exists a very weak correlation between them. Still it can be concluded that with the increase of temperature, precipitation is also increasing.

NDVI, Temperature, and Precipitation through the period of 3 years from 2016-05-08 to 2018-05-08 were also plotted in the graph.

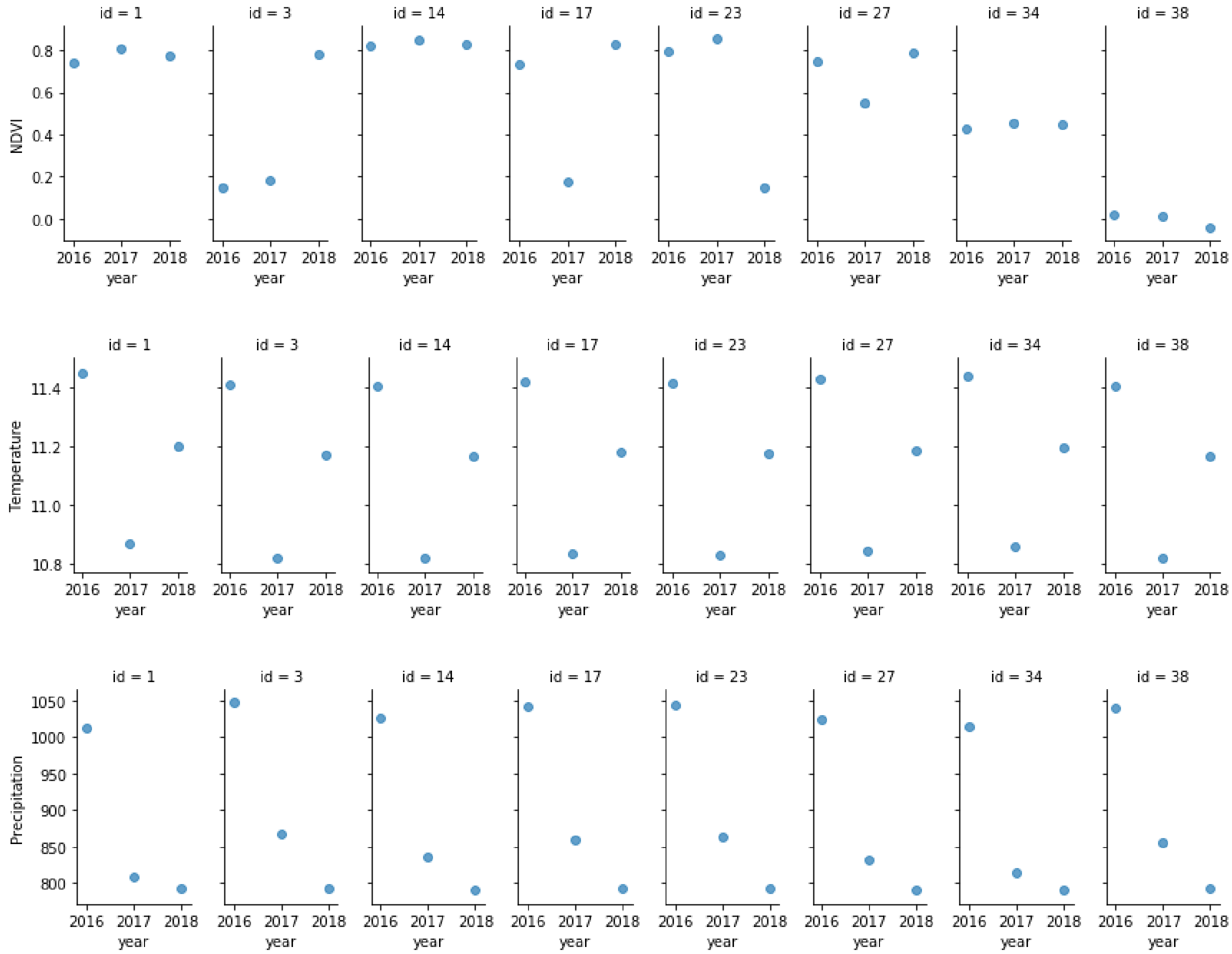

Figure 16: Scatter plot showing the change in NDVI, temperature, and precipitation in the three years in the different study areas

From figure 17, It can be seen how the NDVI has been changed from 2016 to 2018. In the study area 1, the NDVI increased from 2016 to 2017 by a tiny amount of 0.1 and again decreased with almost the same amount by 2018. This region consists of forest areas, so it has a high NDVI every year. There is also a small variation from 2016 to 2018 in NDVI; this might be because of the change in tree's condition i.e., some areas of the jungle have become denser than before, and some regions have old trees and started becoming less active resulting very less absorption of visible red light. Due to such small changes in the forest, there is a slight change in the NDVI value in the study region. When observed in region three, it is seen that the vegetation has increased drastically from 2016 to 2018.

The NDVI value in 2016 was very low at around 0.2, and it has increased to 0.8 within two years. This massive change in vegetation might be due to the area being the cultivable field. This particular area might be bare land on 2016 and may have done vegetation by 2018 at the time of recording the reflections by the satellite due to which NDVI has increased rapidly. Region 14 seems to follow the same trend as in region 1. It also contains vegetation all the three years so if temperature is considered then it can be concluded that when the temperature decreased then the vegetation has increased and opposite also exists i.e., increase in temperature shows reduction in vegetation. Observing NDVI in area 17, it can be seen the drastic decrease and step increase from 2016 to 2017 to 2018. Similar to region 3, it is also the cultivable land, so there is much change in the value of NDVI due to the plantation of some kind of crops. It is also the same with the area 23 and 27. On looking at the graph of region 34 and 38, the NDVI is almost constant (Value to NDVI is similar); this is because area 34 is the residential area, and area 38 is the lake. Since there is not much vegetation in the lake, so almost no change in NDVI in region 38. The small changes in area 34 are due to the trees and grass in the backyard or garden of the apartment. The change in NDVI can also be seen in figure 18, as shown below.

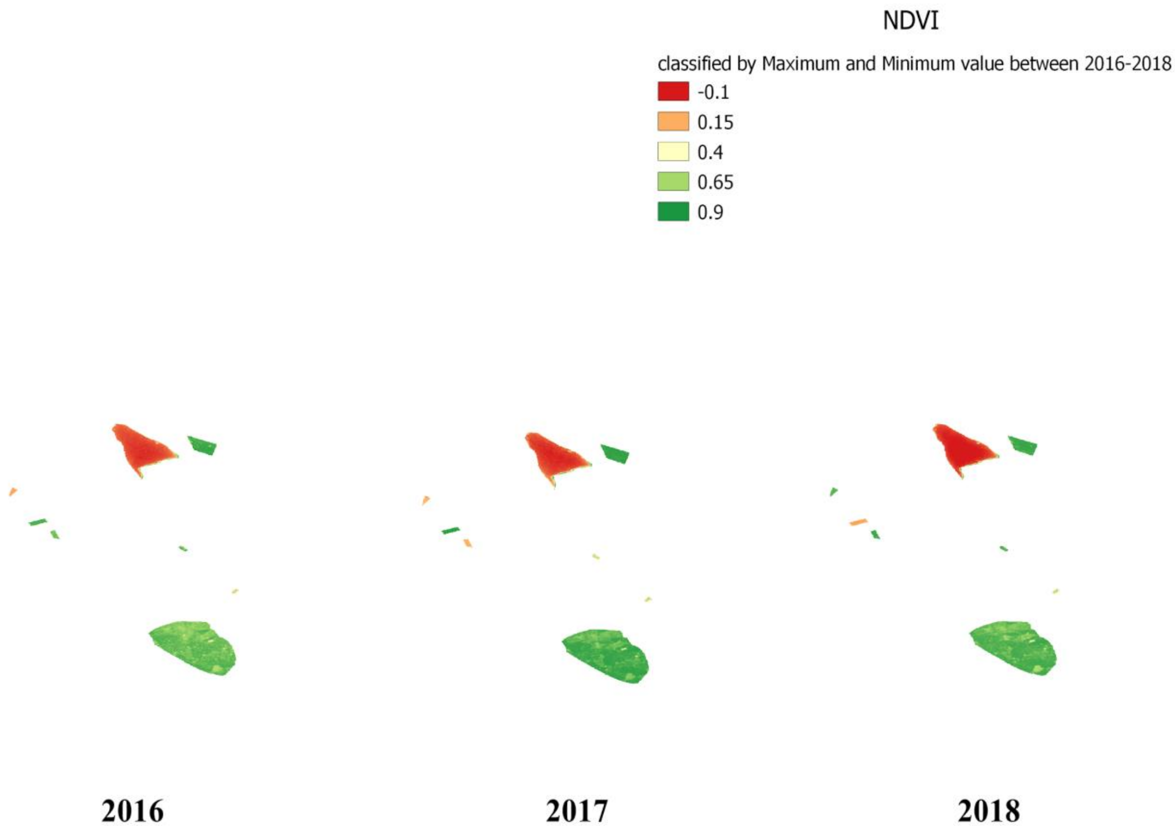

Figure 17: NDVI of the year 2016,2017 and 2018 in the study areas

From figure 18, it is found that the minimum NDVI in this three year is -0.1, and the maximum is 0.9. From figure 18, the change in the NDVI can be seen as mentioned in the above paragraph as well as it can be seen that how the NDVI has increased from 2016 to 2017 in region one and decrease in NDVI from 2017 to 2018. Change in region 3, 17, and 23 can also be seen clearly in figure 18. Further analysis will be explained in the following sections in this report.

The graph of temperature and precipitation are also plotted yearly. On observing the graph, it is found that the temperature has decreased from 2016 to 2017. From the data, there is not much change in annual temperature i.e., 0.6°C less in 2017 than that of 2016. Also, the temperature seems to have increased by 0.4°C from 2017 to 2018. A similar trend is seen in all areas of study. Whereas on observing the cumulative precipitation over three years in the region of interest, it is found that cumulative precipitation has a significant decrease. It is not a small change i.e., In 2016, the cumulative precipitation for the study areas was approx. 1050 mm, some areas might have little less, and some have little more, whereas, in 2017, the total cumulative precipitation decreased to approx. 850mm, and it even decreased in 2018 to 780mm. This similar change has been observed in all the study regions, as shown in figure 17. The change in temperature and precipitation can also be seen in figure 19 as follows.

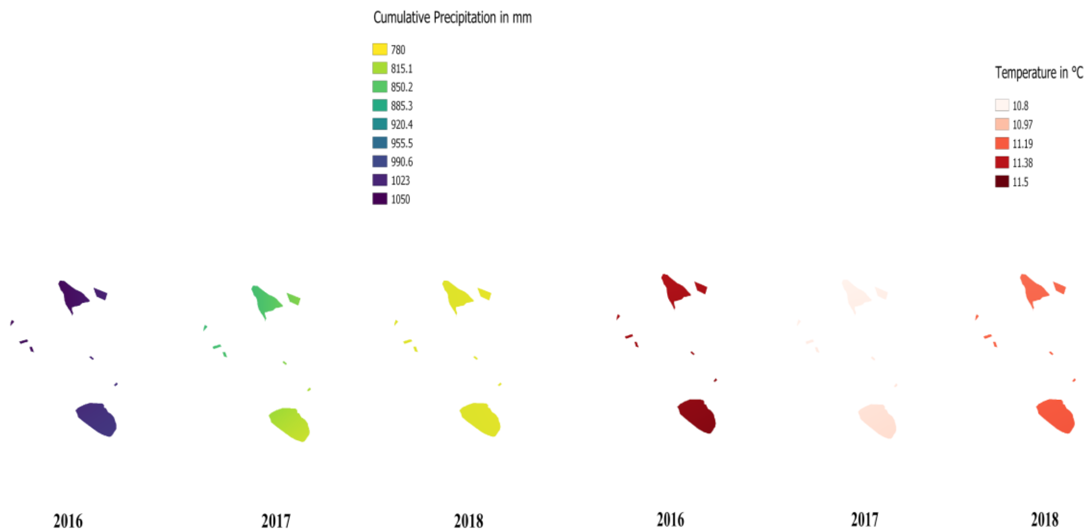

Figure 18: Change in precipitation (in the left) and temperature (in the right) of the year 2016,2017 and 2018 in the study areas

From figure 19, the vast precipitation difference can be seen very clearly, and if the data is observed, it varies from 780mm to 1050mm in a year. There is a noticeable change in precipitation, so this can be one of the significant regions responsible for the drought. In the temperature figure, it can be seen that the temperature varies from 10.8°C to 11.5°C. There was a maximum temperature of 11.5°C in 2016, but by 2018 the temperature was around 11.2°C. Temperature can be one of the factors for drought, but it does not seem to have more significance as there is very little change in the mean temperature. From figure 17, For some of the region it can be seen that with the decrease of temperature there is a increase in NDVI which means increase of vegetation so for further study some more analysis are performed as follow:

The relationship between the NDVI with temperature, NDVI with precipitation and temperature with precipitation for all the years 2016,2017, and 2018, various graphs were plotted as shown in the figure below.

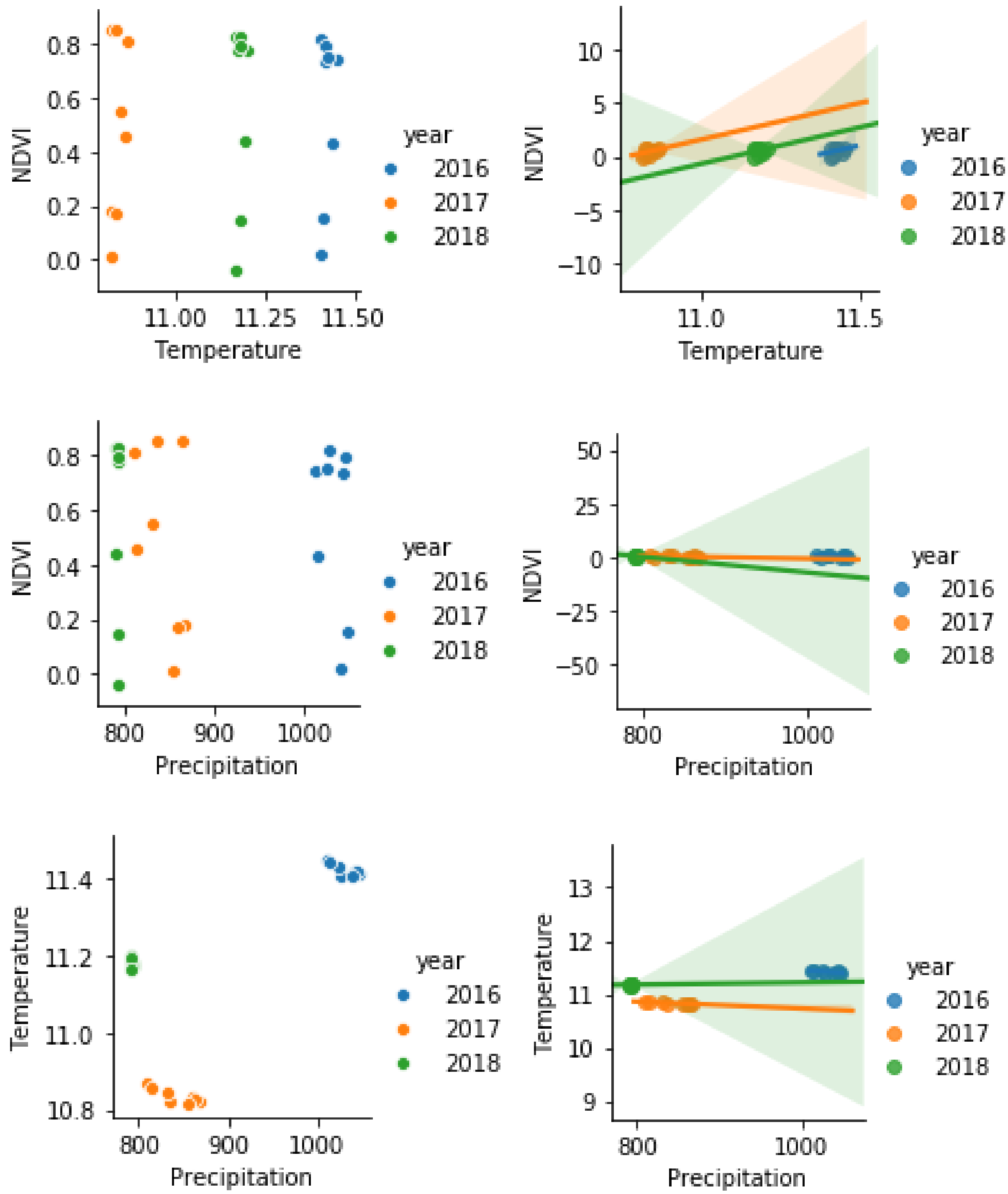

Figure 19: Relationship between NDVI and temperature, NDVI and precipitation and temperature and precipitation for 2016,2017 and 2018. Eight values each year represents the values in 8 study regions

Figure 20 clearly shows that not only in 2018 but the value of NDVI is positively correlated with temperature in the years 2016 and 2017. There are eight values every year, and those represent the value of NDVI of the eight specific study regions. It can be seen that the mean temperature increased 2017 but decreased again on 2018, and decrease of cumulative precipitation each year. Similar to that of the 2018 correlation between precipitation and NDVI, the year 2016 and 2017 also follows a similar relationship i.e., they are negatively correlated with a small value. The relationship between temperature and precipitation for all three years seems to have a constant relationship. There is almost no correlation between temperature and precipitation and they behave like completely independent of each other.

From figure 20, the relationship between temperature and NDVI plotted yearly, It can be seen that in 2016 the temperature was more than that of the 2018 and 2017, but observing on NDVI it can be seen that NDVI has more negative value than that of 2017 and 2018. It can also be seen on the graph with regression line that 2016 is having the minimum NDVI. Looking at the 2017 regression line it can be seen that it has the maximum NDVI in comparison to 2016 and 2018. From the regression line drawn in the graph, it can be concluded that when there is a lower temperature than there is more vegetation and when the temperature goes on increasing, then the vegetation goes on decreasing. Unlike the temperature, precipitation has also changed over the years, but there is not much variation seen on the NDVI even though the precipitation from 2016 to 2017 decreased in a large amount. It shows that the precipitation and NDVI has very weak relation between them. The relationship between temperature and precipitation is also fragile i.e., and the temperature does not seem to have more impacts on the precipitation and vice versa.

From the discussion above where the relationship between temperature and NDVI of 2018 has the positive correlation which shows that increase in temperature has increased the NDVI but while comparing it with the other year where there is different mean temperature every year shows that when there is a low mean temperature than there is higher amount of vegetation. Even though relation in 2018 has a different conclusion that NDVI has a positive correlation with temperature, it is found that they have the inverse relation while observing for several years i.e., NDVI decreases with an increase of temperature. The positive correlation might have occurred because of the small study region and minimal variation in the temperature in 2018. From the comparison done on an annual basis, it is clear that with the increase of temperature, NDVI is decreasing.

The comparison between the NDVI of 2018 with 2016 and 2017.

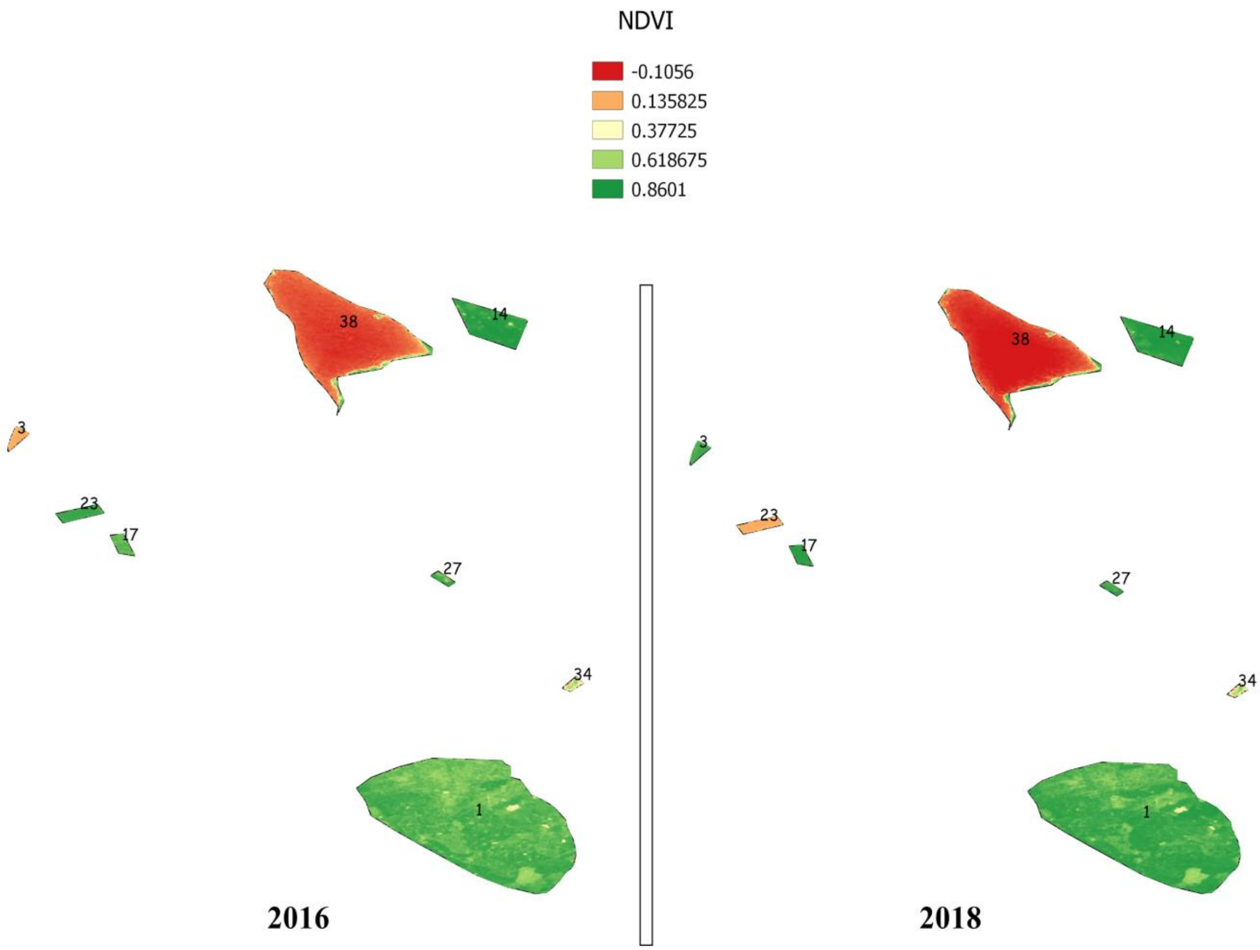

Figure 20: NDVI in 2016 vs NDVI in 2018

It is already discussed above how the NDVI has changed from 2016 to 2018. Observing figure 21, it is found that the bare land of area 3 was cultivated in 2018, and area 23 has been changed to bare land. Other areas have almost the similar NDVI. Looking at region 1, it is seen that the forest has become more dense and healthier than before. In the case of area 38(lake area), it can be found that the NDVI has even more decreased in 2018 than that of 2016. The regions 17 and 27 are also labeled with dark green which means there is increase in vegetation in that regions also. Region 34 seems to have a constant value as it is an residential area.

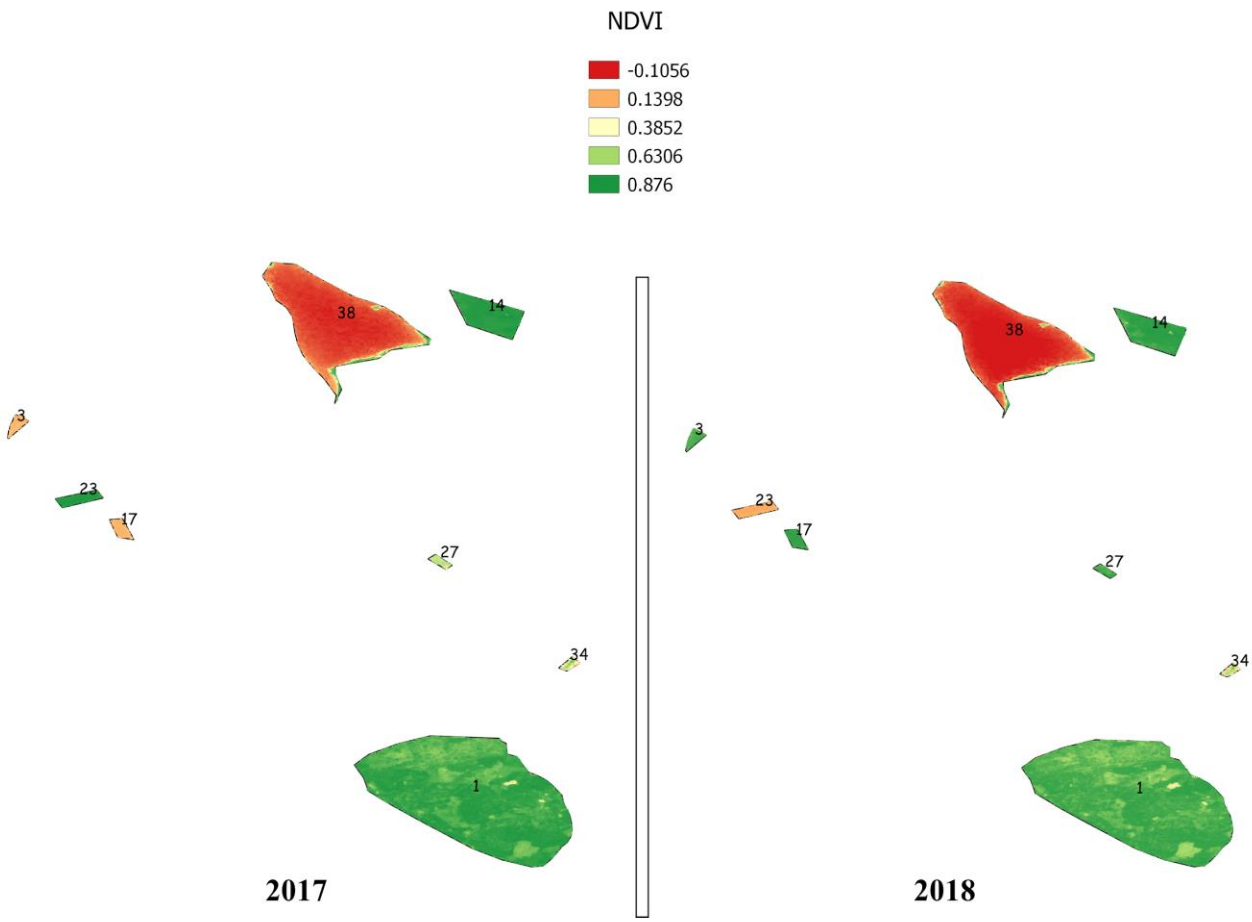

Figure 21: NDVI in 2017 vs NDVI in 2018

Figure 22 shows the comparison of NDVI between 2017 and 2018. As seen in the graph in the above section, the map also shows the same thing. Region 3 and 17 have a drastic change in vegetation, which can be seen very clearly in the graph. As discussed in the study areas of the report above, those regions are cultivable land, so the drastic change could have occurred due to the cultivation of some kind of crops in the field. The change is noticed in region 1 also which shows that the NDVI has changed by a small amount in the forest area. As seen in figure 3, most of the regions of area 1 are covered with forest, and some parts of the forest are growing dense, whereas some are turning browner or less green. Due to such changes in the tree, there is a significant change in the NDVI value. Region 27 seems to have increased in NDVI that may be due to grown crops i.e., area 27 is also a cultivable land so grown crops are denser and greener resulting higher vegetation index. Other regions have a similar NDVI value as that in 2017.

4. Discussion

Analysis of the NDVI, temperature, and precipitation in the region of Xanten were performed in the above sections. As discussed in the result section, it is found that NDVI is one of the factors that show the effect on the vegetation. NDVI can show the minimal changes in vegetation to the drastic change. The NDVI value can also identify healthy vegetation and unhealthy vegetation. It is also found how the NDVI distinguish between soil, water and plants. From amount of vegetation to quality of vegetation, NDVI is able to distinguish between them so, it can be concluded that it can show every effect on the vegetation.

The relation between NDVI, temperature and precipitation were also analyzed. It is seen that NDVI has a positive correlation with temperature and negatively correlated with precipitation. Even though there is a small relationship between temperature and NDVI, the pattern of positive correlation can be seen for every year's data. It is also found that when there is low average temperature then there is maximum vegetation and when there is a high average temperature then the NDVI or vegetation will decrease i.e., Low vegetation can be seen. NDVI may look like increasing with the small increase in temperature but when there is significant change in temperature then the NDVI will decrease. Similarly, precipitation also follows a similar fashion i.e., every year, there is a negative correlation found between NDVI and precipitation. There exists a fragile relation on NDVI with precipitation, which has very low significance on the NDVI by precipitation. Although there is a positive correlation between the temperature and NDVI, they are significantly little correlation, and this might be because the areas of study are very close to each other, and considering very few regions for study might have led to this conclusion. Despite being a small area of study, a similar kind of pattern found every year supports that NDVI has a relation with the temperature and precipitation.

Comparison between 2016,2017, and 2018 was also done in the above sections. It was clear from the graph and mapped how the NDVI increased when there is a lower temperature. The mean temperature in 2017 was the lowest than that of 2016 and 2018, the correlation line drawn between the NDVI and temperature shows how the vegetation has increased. Looking only at the data point then it seems to have almost the same NDVI value, but the regression line clearly distinguishes the relationship between NDVI and temperature. Even though in the particular year there is no significance relation of NDVI and temperature, in a long run it is clear from the graph that how temperature plays a vital role in the vegetation. Temperature is a vital element for the study of vegetation. Whereas on observing the cumulative precipitation, it is seen that NDVI has a negative correlation between them, which means with the increases of cumulative precipitation is causing a decrease in NDVI. The only increase in precipitation does not necessarily need to increase the NDVI rather, it is decreasing. On creating the regression line between NDVI and precipitation, it is found that whatever the precipitation value was there, the NDVI value over the three-year period of time has a similar NDVI. It also proves that the general perception like more precipitation increases the vegetation is not the fact anymore. There are other factors like temperature which are playing vital roles for the vegetation. Also, making the comparison, it is found that vegetation in the study area has increased from 2016 but decreased than that of 2017 in 2018. In the case of drought, the decreasing pattern of precipitation and increase in the temperature shows that there is a drought in 2018, and although it is small, there is a little effect on the vegetation due to such conditions as it can be seen that NDVI has decreased by a small amount from 2017 to 2018.

Decreasing cumulative precipitation and increasing temperature are the consequences of the drought. If the data, graphs and maps are observed carefully then it can be seen that from 2016 to 2018, temperature has increased and precipitation has decreased resulting drought. Such condition has impact on the NDVI or vegetation i.e., vegetation is decreasing due to drought. It is found from the study that Xanten has also experienced some of the drought but does not have significant impact on the NDVI. Just a small change in NDVI can be seen in the graph and maps.

5. Conclusions and Outlook

The study provides the temporal insight of NDVI that shows the effect on vegetation. The importance of temperature and precipitation for the vegetation is well explained in this study. Comparison between the NDVI over different years with respect to temperature and precipitation shows the fact about the condition of vegetation at that time and the relation between them. From the study, it can be concluded that the temperature has more effect on the vegetation than that of the precipitation. It also shows the consequences of the current issue of climate change and global warming that increase in temperature harms the vegetation. It can also be concluded from this study that precipitation has not much impact on the vegetation than that of temperature because, in this study, there was much variation on the precipitation but has very less impact on the vegetation whereas the small change in temperature has a more significant impact on the vegetation. Although it is found that temperature and NDVI have a positive correlation in the year 2018 showing an increase in NDVI with an increase in temperature, it is proven false when comparing yearly i.e., with 2016 and 2017 data. It is also found that there is not much change in the NDVI over the three years. The main aim of the study was to find out the effect of drought on vegetation in 2018. It is found that there is a small increase in the temperature, and decreasing precipitation, which is a consequence of drought, and due to such changes, a small change can be noticed in the vegetation from 2017 to 2018. The slight decrease in NDVI value shows the decrease in vegetation, even though it is not much, but this change might be the consequences of drought, and the study supports this fact.

The study area could be larger area for the more accurate relationship between NDVI with temperature and precipitation, which is one of the critical outlooks for this study. Taking a small region limits the variation in temperature and precipitation so, the result form from the data of small area are not very clear and obvious. It can mislead the analysis so considering the bigger areas could be the future study. Also, for the study of the effect of vegetation, only considering temperature and precipitation are not enough, so more factors are to be considered for future analysis. The accuracy of the study comparison over the long term can be done rather than only for three years.

List of references

1. John, R., Chen, J., Ou-Yang, Z.-T., Xiao, J., Becker, R., Samanta, A., Sandram, G., Wenping, Y. and Batkhishig, O. (2013). Vegetation response to extreme climate events on the Mongolian Plateau from 2000 to 2010. Environmental Research Letters, 8.
2. Löw, Petra. "The Natural Disasters of 2018 in Figures: Munich Re." Munichre.com, 8 Jan. 2019, www.munichre.com/topics-online/en/climate-change-and-natural-disasters/natural-disasters/the-natural-disasters-of-2018-in-figures.html.
3. Karnieli, A., Agam, N., Pinker, R. T., Anderson, M., Imhoff, M. L., Gutman, G. G., Natalya ,P.and Goldberg, A. (2010). Use of NDVI and Land Surface Temperature for Drought Assessment: Merits and Limitations. JOURNAL OF CLIMATE, 23, 618-633.
4. Nichol, J. E., & Abbas, S. (2015). Integration of remote sensing datasets for local scale assessment and prediction of drought. Science of the Total Environment, 505, 503-507.
5. Graham, S. (2000, August). Drought : The Creeping Disaster. United States. Retrieved August 20, 2015, from http://earthobservatory.nasa.gov/Features/DroughtFacts/
6. Senay, G. B., Velpuri, N. M., Bohms, S., Budde, M., Young, C., Rowland, J., & Verdin, J. P. (2015). Drought Monitoring and Assessment: Remote Sensing and Modeling Approaches for the Famine Early Warning Systems Network. In Hydro-Meteorological Hazars, Risks and Disasters (pp. 233–262). Elsevier.
7. Fathi, Amin & Barari, Davood. (2016). Effect of Drought Stress and its Mechanism in Plants. International Journal of Life Sciences. 10. 1. 10.3126/ijls.v10i1.14509.
8. NDVI, the Foundation for Remote Sensing Phenology, www.usgs.gov/land-resources/eros/phenology/science/ndvi-foundation-remote-sensing-phenology?qt-science_center_objects=0#qt-science_center_objects.
9. Baofeng. "Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications." *Journal of Sensors*, Hindawi, 23 May 2017, www.hindawi.com/journals/js/2017/1353691/.
10. Tucker, C. J. (1979, May 1). Red and photographic infrared linear combinations for monitoring vegetation. (U. States, Ed.) Remote Sensing of Environment, 8(EARTH

RESOURCES AND REMOTE SENSING), 127-150. doi:10.1016/0034-4257(79)90013-0

11. "Bevölkerung der Gemeinden Nordrhein-Westfalens am 31. Dezember 2018" (in German). Landesbetrieb Information und Technik NRW. Retrieved 20 feb 2020.

12. "WeatherSpark.com." *Average Weather in Xanten, Germany, Year Round - Weather Spark*, weatherspark.com/y/54682/Average-Weather-in-Xanten-Germany-Year-Round.

13. "Sentinel-2 - ESA Operational EO Missions - Earth Online." *ESA*, earth.esa.int/web/guest/missions/esa-operational-eo-missions/sentinel-2.

14. Pettorelli, Nathalie. "NDVI and Environmental Monitoring." *The Normalized Difference Vegetation Index*, Oct. 2013, pp. 56–69., doi:10.1093/acprof:osobl/9780199693160.003.0005.

15. Wardlow, B. D., Anderson, M. C., & Verdin, J. P. (2012) Remote Sensing of Drought: Innovative Monitoring Approaches. United States of America: Taylor & Francis Group, LLC

16. K. Hazaymeh, Q.K. Hassan, Remote sensing of agricultural drought monitoring: a state of art review, Aims Environ. Sci., 3 (4) (2016), pp. 604-630

17. L.S. Unganai, F.N. Kogan, Drought monitoring and corn yield estimation in Southern Africa from AVHRR data Remote Sens. Environ., 63 (1998), pp. 219-232

18. J. Rhee, J. Im, G.J. Carbone, Monitoring agricultural drought for arid and humid regions using multi-sensor remote sensing data, Remote Sens. Environ., 114 (2010), pp. 2875-2887

19. S.L. Liang, X.W. Li, J.D. Wang, Advanced Remote Sensing: Terrestrial Information Extraction and Applications Academic Press (2012)

20. N.T. Son, C.F. Chen, C.R. Chen, L.Y. Chang, V.Q. Minh, Monitoring agricultural drought in the lower Mekong basin using MODIS NDVI and land surface temperature data, Int. J. Appl. Earth Observ. Geoform., 18 (1) (2012), pp. 417-427

21. N. Sánchez, Á. González-Zamora, J. Martínez-Fernández, M. Piles, M. Pablos, Integrated remote sensing approach to global agricultural drought monitoring, Agric. For. Meteorol., 259 (2018), pp. 141-153

22. F.N. Kogan, Application of vegetation index and brightness temperature for drought detection, Adv. Space Res., 15 (11) (1995), pp. 91-100

23. R.R.J. Heim, A review of twentieth-century drought indices used in the United States, Bull. Am. Meteorol. Soc., 83 (8) (2002), pp. 1149-1165

Statement of authorship

I, hereby declare that my contribution to the work presented herein is my own work completed without the use of any aids other than those listed. Any material from other sources or works done by others has been given due acknowledgment and listed in the reference section. Sentences or parts of sentences quoted literally are marked as quotations; identification of other references regarding the statement and scope of the work is quoted. The work presented herein has not been published or submitted elsewhere for assessment in the same or a similar form. I will retain a copy of this assignment until after the Board of Examiners has published the results, which I will make available on request.