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NDVI, temperature and precipitation changes and their relationships with drought during 2016–2018 in Xanten, Germany

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Abstract

The time lag between anomalies in precipitation and vegetation activity plays a critical role in early drought detection as agricultural droughts are caused by precipitation shortages. Understanding precipitation-vegetation interaction has great importance to implementing adaptation and mitigation measures for terrestrial ecosystems. Spectral vegetation index time series data, such as the normalized difference vegetation index (NDVI), from moderate resolution, polar-orbiting satellite sensors have widely been used for analysis of vegetation seasonal dynamics from regional to global scales. The aim of this study is to analyze the drought in 2018 in comparison to the years 2016 and 2017 utilizing different data sources and tools. We will investigate whether there is a correlation between calculated spectral indices, temperature, and precipitation of specific areas in the region of Xanten. We will describe that the drought affects vegetation and the Normalized Difference Vegetation Index (NDVI) which shows the impacts on vegetation. We will also figure out that the dry season is related to the Cumulative Precipitation or CP (i.e. the precipitation sum) over the last year and there is a correlation between CP and NDVI. Lastly, we will represent that drought is related to the Average Temperature (AT) over the last year and will make a correlation between AT and NDVI as well as AT and CP. The results can provide technical basis and beneficial reference ecological management strategies in Germany for associated policymakers.

Keywords: Drought Detection, Vegetation, Anomalies, NDVI, CP, AT

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List of Abbreviations

NDVI	Normalized Difference Vegetation Index
CP	Cumulative Precipitations
AT	Average Temperature
ROI	Regions of Interest

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1 Introduction

Vegetation is the Earth’s natural linkage of soil, atmosphere and moisture. It displays obvious seasonal and annual changes (Cui and Shi, 2010; Zhang et al., 2011) and acts as a sensitive indicator of global climate changes (Schimel et al., 2001; Weiss et al., 2004). Vegetation responds to climate changes in both explicit and subtle ways. Studying these changes has become a global interdisciplinary effort for researchers who seek to understand what is happening and to find the most efficient means of doing so (Meng et al., 2011a, 2011b). The underlying report is set in the context of **Difference Vegetation Index (NDVI), Cumulative Precipitation (CP), and Average Temperature (AT**). In particular, it deals with drought and correlation between calculated spectral indices, temperature, and precipitation of specific areas in the region of Xanten. Our research intends to contribute to a better comprehension of the impacts (assuming any) of these climatologically observations in the vegetation lists derived from satellite imagery throughout the summer periods in the range of 2016, 2017 and 2018. We will also likewise inquire about the NDVI correlated with temperature and/or precipitation!

1.1 Motivation and Challenges

The major goal of this project is to investigate whether there is a correlation between calculated spectral indices, temperature, and precipitation of specific areas in the region of Xanten. We will aggregate the measurements for a one-year-period before and up to the sensing dates (2016, 2017, and 2018) and then we will use daily time series to derive average temperature and cumulative precipitation. Annual data would not work directly, because they are covering a period from January 1st to December 31st whereas the sensing dates of our images are sometime between May and June of each year. Therefore, we will have to aggregate the annual data ourselves from daily measurements. Hourly measurements would result in a large amount of data to be processed without providing additional information after aggregation. Apart from that, it is also a goal to elaborate on the utilized steps on how to carry out the implementation.

It is expected that the resulting scene classification process will resemble a rough prototype. Part of the project's scope is to review literature and related work. The approach, to achieve the just mentioned goals, relies on knowledge, which is drawn from the accomplished research. The tasks will be performed using the tools Python and QGIS to retrieve, manipulate and display the data needed for this investigation.

Furthermore, we will create a dataset for our research, such as multispectral imagery, from reliable sources. The model is then supposed to classify scenes of an excerpt of Xanten. Visualizing the results in QGIS is the last extent of the underlying work.

1.2 Methodology

The normalized difference vegetation index (NDVI) was proposed by Rouse et al. (1974) based on differences in pigment absorption features in the red and near-infrared regions of the electromagnetic spectrum (Equation (1)). The values of NDVI range from −1.0 to 1.0, increasing positive NDVI values indicate increasing amounts of green vegetation. NDVI values near zero and decreasing negative values indicate no vegetated features such as barren surfaces (rock and soil) and water, snow, ice and clouds (Schnur et al., 2010). Since it has many advantages such as the simplicity of the algorithm, the capacity to broadly distinguish vegetated areas from other surface types, more sensitive to detect green vegetation than using a single band (Zhang et al., 2005), it can be used to monitor local or global vegetation changes, which can indicate environmental changes brought by natural factor such as climate changes (Qiu and Cao, 2011) and anthropogenic activities such as urban expansion process (Fung and Siu, 2000), to assess crop production (Wardlow and Egbert, 2008) and net primary productivity (NPP) of vegetation (Piao et al., 2006, 2008), and it was also mostly used to indicate climate changes by establishing relationship between climatic factors and NDVI (Nemani et al., 2003; Roerink et al., 2003) and so on:

NDVI = (NIR – RED)/ (NIR + RED) … … … (1)

Where RED and NIR stand for the spectral reflectance measurements acquired in the visible (red) and near infrared regions, respectively. Climatic factors, land use changes, the fertilization effect of CO_2 and so on could make different impacts on vegetation; among them, temperature and precipitation are the main indicators used to describe climate conditions, and they can affect vegetation growth in an obvious manner (Fang et al., 2004; Ji and Peters, 2004). **NDVI, temperature** and **precipitation** data have been used to study the effects of climate change on vegetation for a long time by many scholars.

There are a number of ways climate change may contribute to drought. Warmer temperatures can enhance evaporation from soil, making periods with low precipitation drier they would be in cooler conditions. Droughts can persist through a "positive feedback," where very dry soils and diminished plant cover can further suppress rainfall in an already dry area.

Drought is the world's costliest stochastic natural disaster, affecting more people than any other natural disaster and has been more frequent in recent years over increasingly larger areas. Drought is essentially a shortage of water caused by an imbalance in the supply of the demand for water, usually triggered by a severe and persistent deficit in precipitation. However, drought is a slow process of accumulation of such deficit, and the severity of drought at a given moment is related not only to the current precipitation but also to the cumulative effect of earlier deficit in precipitation.

2 Deployed Tools

We have mainly used two tools including QGIS and Python. For the purpose of gathering the sentinel image, we used Copernicus and Earth explorer.

2.1 QGIS

We can implement a huge number of geospatial data to edit, visualize and analyze with Quantum Geographic Information System (QGIS).

2.2 Python Environment

For carrying out the implementation of this project, a Python 3.6.5 Anaconda environment is created.

It contains some major packages (plus its dependencies):

• NumPy 1.15.4

• Pandas: 0.23.0

• Matplotlib: 2.2.2

• GDAL 2.2.3

NumPy6 is known for scientific computing using its N-dimensional array object. It is often a dependency on many other packages like Pandas. Pandas is a popular and well optimized library for data manipulation and analysis. In particular, it offers data structures and operations for manipulating numerical tables and time series. Matplotlib is a library which offers various types of plotting features. It includes NumPy as an extension as well. This offers an object-oriented API to integrate plots into applications using GUI toolkits such as Tkinter, wxPython, Qt or GTK+. GDAL9 is utilized for geospatial functionalities.

3 Result & Discussion

In this section, we will describe each indices and the relationship among the factors-

3.1 Vegetation and NDVI Analysis with Drought

This section of the report elaborates on the ideas to solve three major tasks of reaching this project's objectives. The first challenge is to collect the Sentinel image of Xanten and nearby regions and the creation of a manageable dataset from Copernicus and EarthExplorer. Its output is the input to the next task, which is about Normalized Difference Vegetation index (NDVI) calculation for the region of interest (i.e. scene images of Xanten) with the help of QGIS software. Then we need to find out mean Temperature and Cumulative Precipitation of that region from 2016 to 2018 specifically, May and June.

3.1.1 Creation of Sentinel-2A Image

Utilizing information from related work like observation of the earth, there are some present available tools such as Copernicus and EarthExplorer. Sentinel-2 is an Earth observation satellite; dedicated to monitoring the land environment, as part of the European Global Monitoring for Environment and Security (GMES) program. In these tools we will look for the location (Xanten) the sentinel-2A image from the given dates 10/06/2016; 26/05/2017; 11/05/2018. We will also select the region more than our expected region of interest to collect the data; so that, if we do not get data for those regions, we can get nearby regions data. Moreover, we need to be concerned about the data for less cloud.

3.1.2 NDVI Calculation

Calculation of NDVI for giving pixels always results in a number that ranges from negative one (-1) to positive one (+1) however, no green leaves give a value near to zero. A zero signifies no vegetation and close to +1 (0.8 to 0.9) denotes the highest possible density of green leaves. The NDVI values calculated from pixel values of **NIR (Band-4) and Red (Band-8).** In our case, for sentinel2 NDVI is calculated by (Band8A-Band4)/(Band8A+Band4)

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

Table of Landsat Band

Band Number	Description	Wavelength	Resolution
Band 1	Coastal / Aerosol	0.433 to 0.453 µm	30 meter
Band 2	Visible blue	0.450 to 0.515 µm	30 meter
Band 3	Visible green	0.525 to 0.600 µm	30 meter
Band 4	Visible red	0.630 to 0.680 µm	30 meter
Band 5	Near-infrared	0.845 to 0.885 µm	30 meter
Band 6	Short wavelength infrared	1.56 to 1.66 µm	30 meter
Band 7	Short wavelength infrared	2.10 to 2.30 µm	60 meter
Band 8	Panchromatic	0.50 to 0.68 µm	15 meter
Band 9	Cirrus	1.36 to 1.39 µm	30 meter
Band 10	Long wavelength infrared	10.3 to 11.3 µm	100 meter
Band 11	Long wavelength infrared	11.5 to 12.5 µm	100 meter

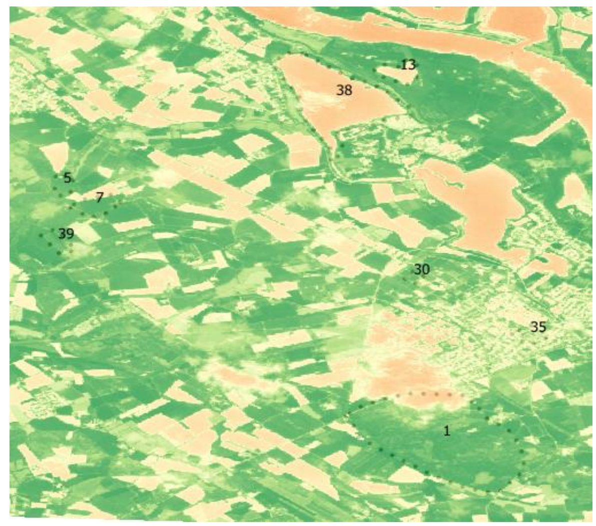
Table 1: Landsat Bands

NDVI will be computed for a time to understand the changes of land cover during the study period. The NDVI is the most used for measuring vegetation cover. It ranges from values -1 to +1. Very low values of NDVI (-0.1 and below) correspond to uncultivable areas of rock, sand, or urban. Zero denotes the water cover. Moderate values represent low density of vegetation (0.1 to 0.3), while high values specify vegetation (0.6 to 0.8)

To calculate the NDVI we needed to extract the sentinel-2 image of each year. Extraction helped us to avoid unwanted dataset. High resolution data needs a large amount of workstation storage.

However, after collecting all year (2016 to 2018) NDVI values we put our Region of interest (ROI) to make sure that all the stations remain in that selected region (Fig:1).

Region of Interest

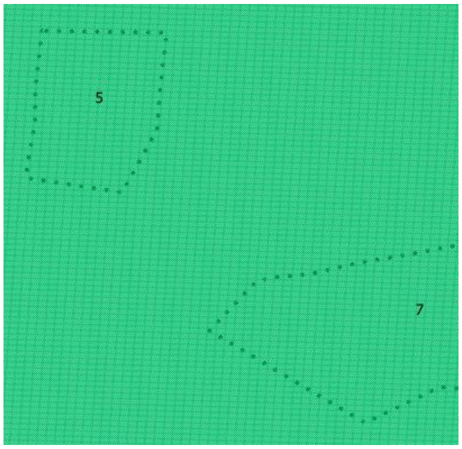


Extracted Sentinel with ROI

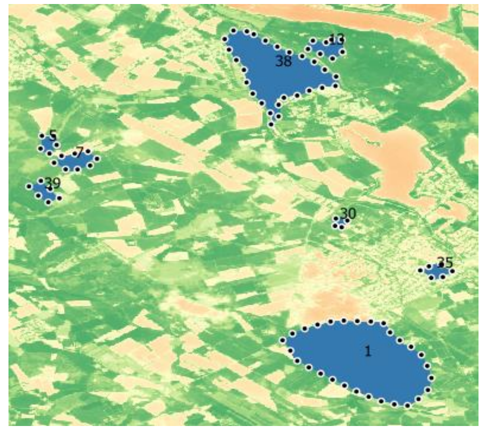
Figure-1: Sentinel Image, Extracted Image with ROI

Consequently, we needed to process our NDVI image for raster pixel to polygon. The tool generates a polygon feature from a group of cells that have the exactly same values, and not from each individual cell. In this stage, we should remember that raster images can consume a large amount of storage space. So, we selected our previously extracted NDVI image to convert.

Subsequently, we intersected the NDVI to select our ROI attributes (1, 38, 13, 30, 35, 5, 7, and 39); which is given to our group (Fig-2).



Raster pixel to polygon



Intersected ROI

Figure-2: Raster Pixel to Polygon, Intersection

After getting the intersected data, now we can find the NDVI mean value of each ROI attribute for each year of 2016, 2017 and 2018. To determine the density of green on a patch of land we needed to calculate the mean value.

3.1.3 NDVI Analysis and Comparison of Three Consecutive Years

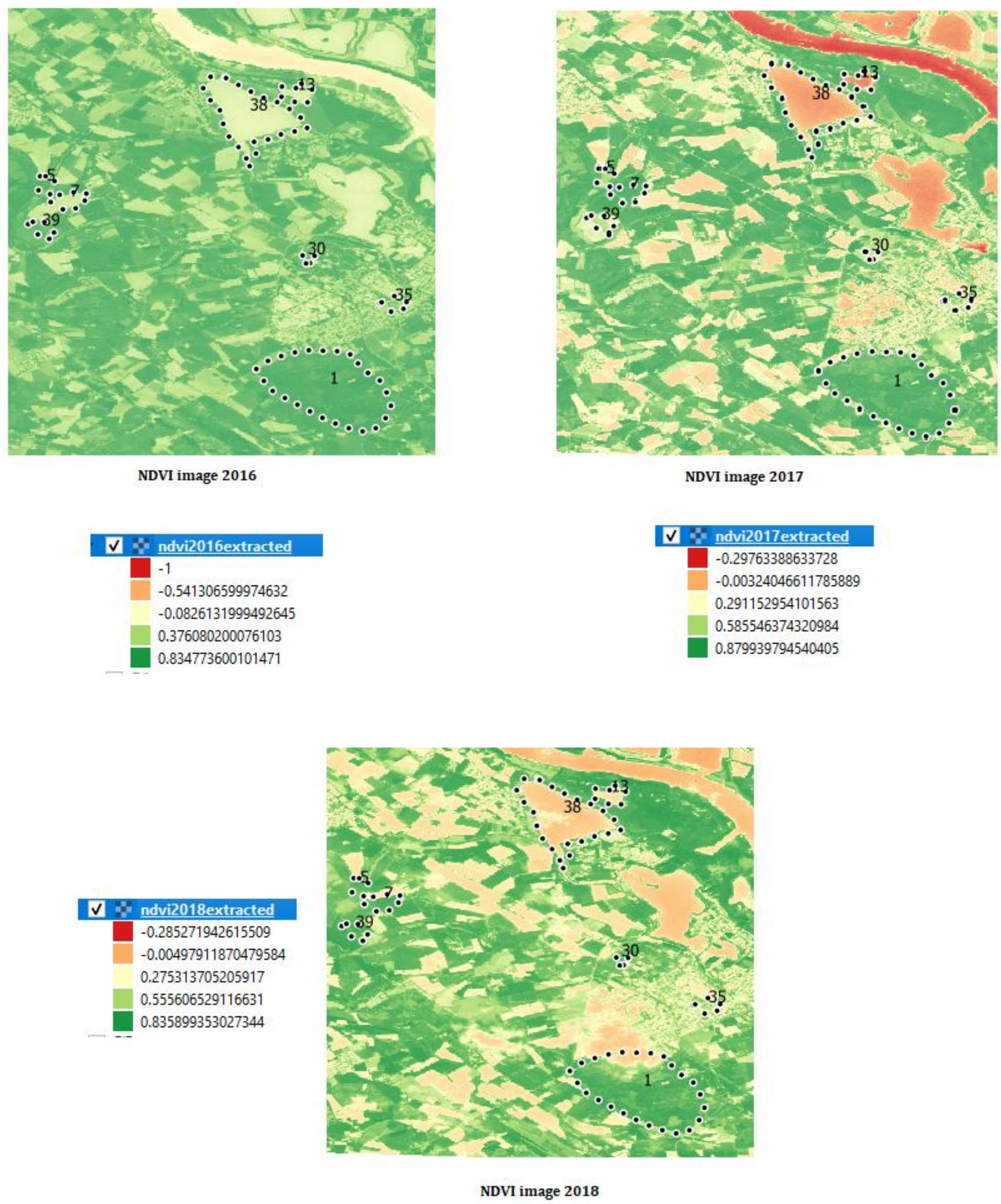


Figure-3: NDVI Analysis and Comparison of Three Consecutive Years (2016, 2017 & 2018)

The determination of NDVI is restricted to certain predefined regions of interests (ROIs). If we look through our ROI attribute-1, it had a high value of vegetation; almost the whole covered area was green in 2016. Compared to that, there is a little bit of change found in 2017, we can observe least amount of moderate value which is the gray colored area, but the vegetation declined in 2018 for attribute-1, it also covered with a considerable measure of moderate value (almost 20%) of NDVI.

ROI attribute 30 & 35 denotes that, moderate density of vegetation is noticeable in 2016, whereas it decreased more in 2017. Although a slight anomaly observed, but not a significant amount of changes noticed for those two regions of interest attributes in 2018.

Considering vegetation for 5, 7 & 39, the density is high for 5 and 39 in 2016, but low consistency was visualized in 2017. Opposite happened for ROI 7, because in 2016, the amount of vegetation was low but it filled up with a high rate in 2017. Overall, most of the areas were green for ROI 5, 7 & 39, but low density also covered certain areas of ROI 5 & 7 in 2018.

In 2016, attribute 13 & 38 were less green and represented low density of vegetation. Very low values of NDVI traced at 13 & 38 in 2017, which corresponds to uncultivable areas of rock, sand, or urban. A moderate value represents low density of vegetation which we got for ROI attribute 13 in 2018, but region-38 showed Very low values of NDVI.

Whenever we will compare the above mentioned three consecutive years' NDVI analysis, we can discover that the greenery in 2018 is comparatively less which can be one of the reasons for drought. So, this analysis says drought affects vegetation and the Normalized Difference Vegetation Index (NDVI) shows the effects on vegetation.

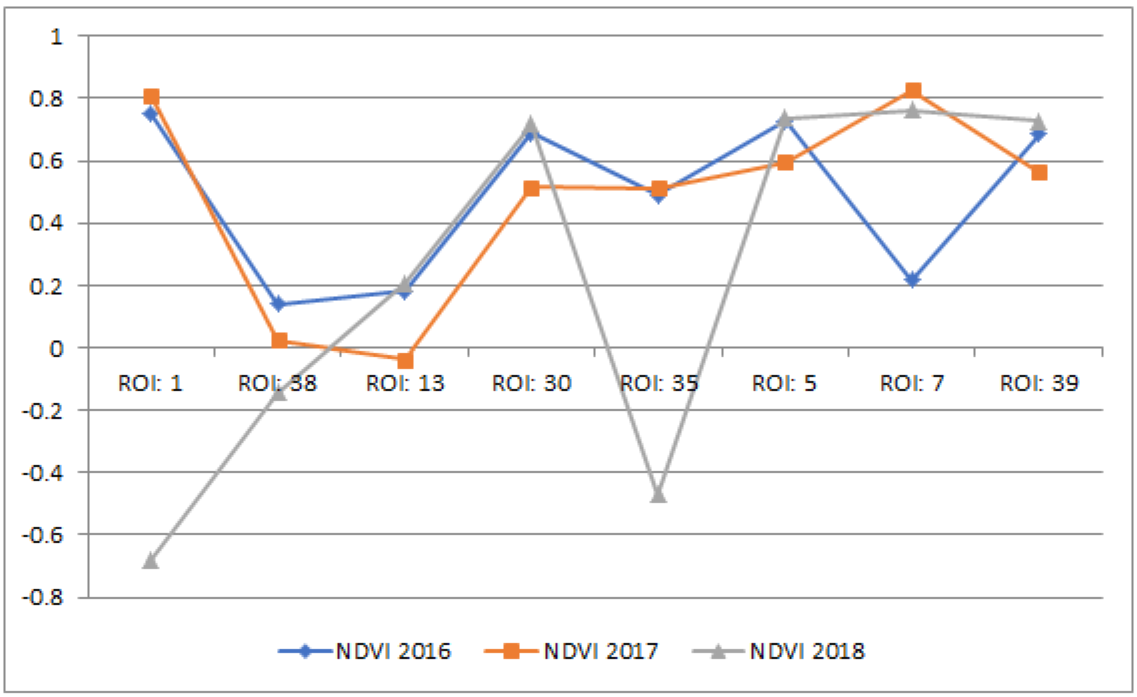


Figure-4: Mean Value of NDVI

Figure-4 analyses the mean of value of NDVI of three years (2016, 2017 & 2018). ROI-1 had the highest value (approximately 0.77) of specified vegetation in 2016, but ROI-13 got the moderate value (about 0.19) which represents low density of vegetation. In 2017, the greenery was very high (almost 0.8), but a rapid decline found for ROI-13 and was near to -0.1 that corresponds to uncultivable areas of rock, sand, or urban. Region of Interest attribute-38 also denotes the water cover.

The highest covered area of greenery in 2018 was in ROI-7 attribute, the vegetation fell down very sharply in 2018 for ROI-1 (about -0.7) and ROI-35 (-0.5) which refers to uncultivable areas of rock, sand, or urban.

3.2 CP & AT Analysis

We have aggregated the measurements for the data from May to June of every year (2016, 2017 and 2018) and used daily time series to derive average cumulative precipitation and temperature. The sensing dates (10-06-2016, 26-05-2017 and 10-05-2018) of our images are between May and June of each year. For precipitation analysis, we have shown time in month in the horizontal axis and precipitation rate in millimeter in the vertical axis. For measuring daily temperatures, in the horizontal axis, we have used time in month. On the other hand, temperature is calculated in Celsius in vertical axis.

3.2.1 Relationship between CP and Drought

In the below mentioned images, we have analyzed the cumulative precipitations of four stations. Three different colors have been used to specify the years (i.e, blue for 2016, orange for 2017 & green for 2018).

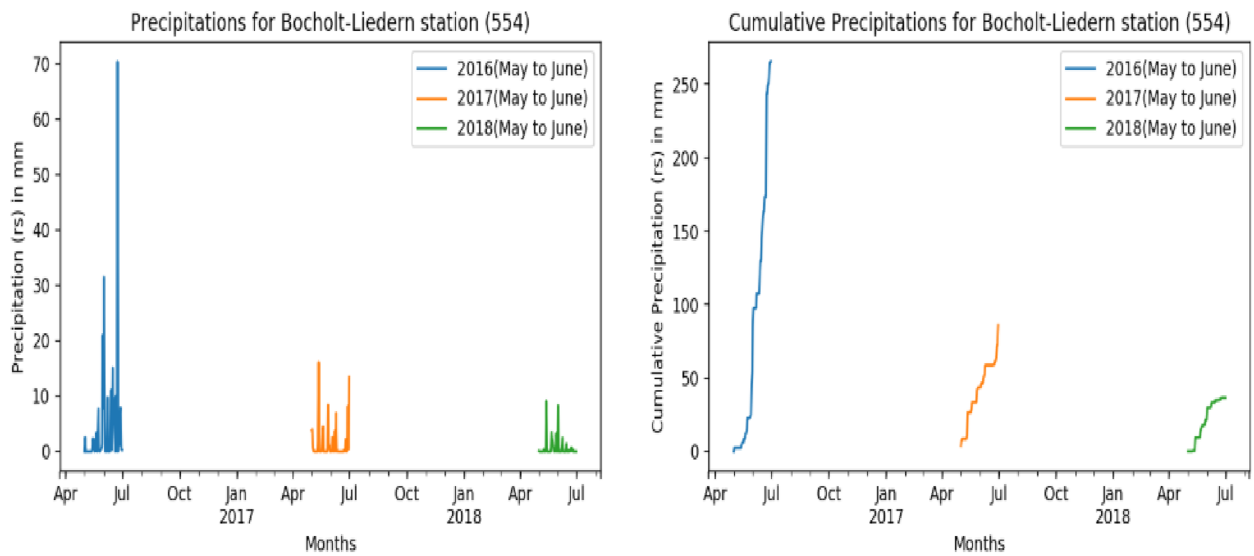


Figure-5: Precipitations/Cumulative Precipitations for Bochlt-Lidern Station (554)

Figure-5 illustrates the changes in the precipitations and cumulative precipitations since May until June (2016 to 2018) for Station-554. Overall, cumulative precipitations in 2016 experienced an upward trend and reached to the highest value among all of the years. Although, a little bit fluctuation observed through the whole period, but at the end of June, it went up to around 234 mm. Looking through the year of 2017, it can be easily noticed that, the cumulative precipitations rate declined significantly and rose to the highest 99 mm (approximately). The least value of CP found in 2018, it had only about 48 mm cumulative precipitations at last.

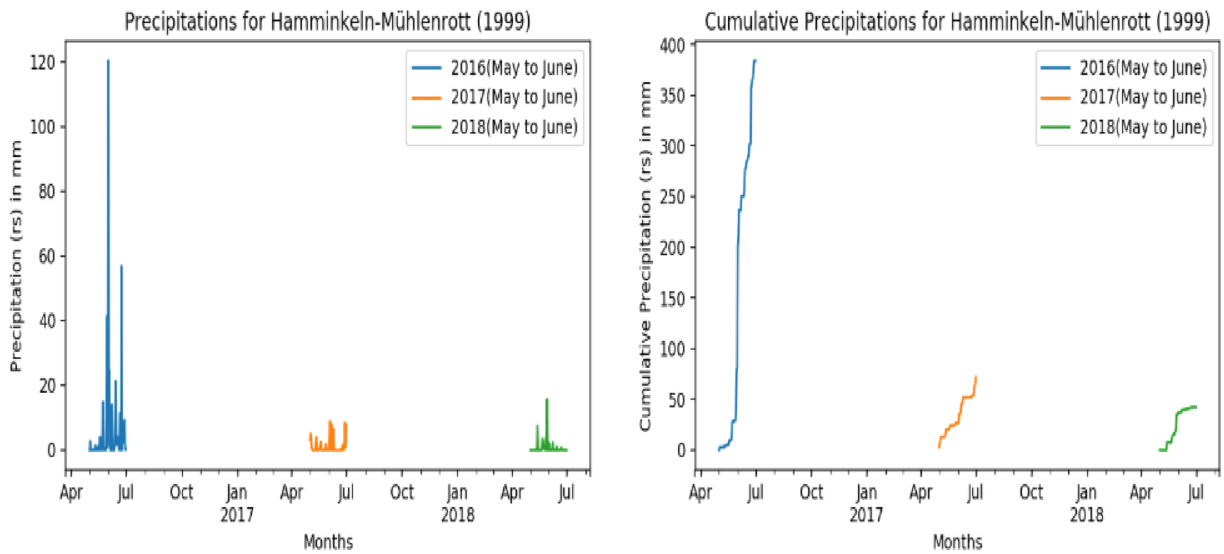


Figure-6: Precipitations/Cumulative Precipitations for Hamminkeln-Muhlenrott Station (1999)

Figure-6 depicts the variation of Precipitations & Cumulative Precipitations from May until June (2016 to 2018) for Station-1999. The cumulative precipitations rate in June, 2016 was highest (about 380 mm). Later on, it declined rapidly in 2107 and peaked at close to 75 mm at the end of June. Although a slight up-down observed till May, 2017, it experienced less value and was almost 48 mm at the end of June.

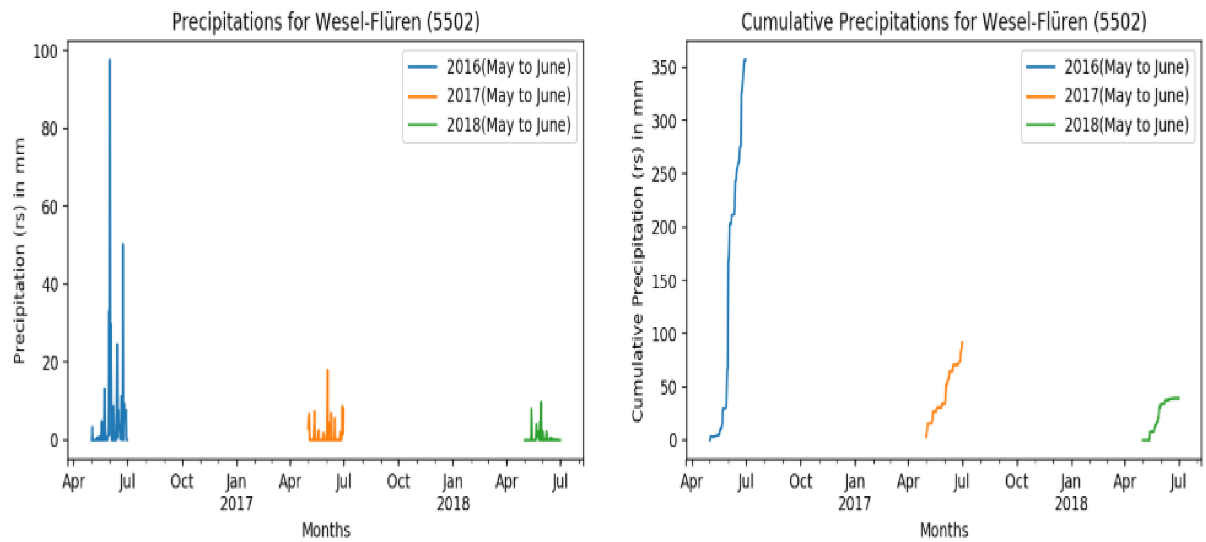


Figure-7: Precipitations/Cumulative Precipitations for Wesel-Fluren Station (5502)

The above Figure-7 represents the change of Precipitations & Cumulative Precipitations from May until June (2016 to 2018) for Station-5502. An upward surge visualized in 2016 for CP and climbed to about 360 mm. After that, a rapid fall occurred in 2017 and at the end of June; the value of cumulative precipitation was approximately 100 mm. In 2018, the CP rate was very low and went up to around 48 mm.

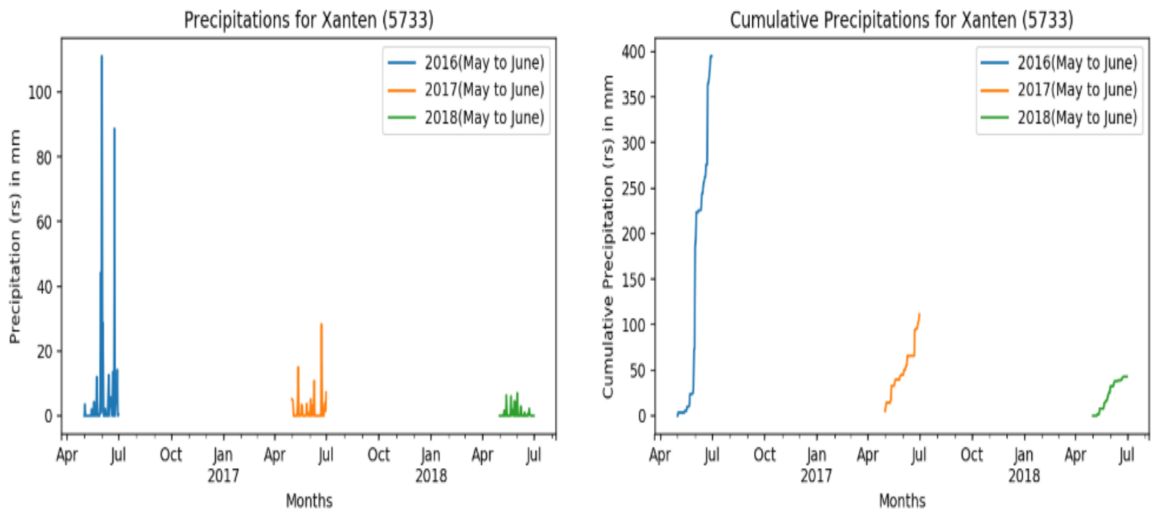


Figure-8: Precipitations/Cumulative Precipitations for Xanten (5733)

Precipitations/Cumulative Precipitations for Xanten (5733) has been described in Figure-8; it denotes that CP rate in 2016 was very high and rose up to around 399 mm in June end. A dramatic fall of Cumulative Precipitations experienced in 2017 and was almost 124 mm and then it had the lowest value of CP in 2018 at period's end (approximately 48 mm)

If we compare the above three graphs, we can determine that the cumulative precipitation rate decreased in the last three consecutive years (2016, 2017 and 2018) which results in drought as agricultural droughts are caused by precipitation shortages. In comparison with the year of 2016 and 2017, the cumulative precipitation (CP) in 2018 is low, and that is why it faced most droughts. Thus, the drought is related to the cumulative precipitation (CP) over the last year and there is a strong relationship between cumulative precipitations and droughts.

3.2.2 Relationship between AT and Drought:

In the below mentioned images, we have analyzed the Daily/Average Temperature (AT) of four stations. Three different colors have been used to specify the years (i.e, blue for 2016, green for 2017 & purple for 2018). As we have not found any data of Xanten, so we have worked on the data of the nearest region.

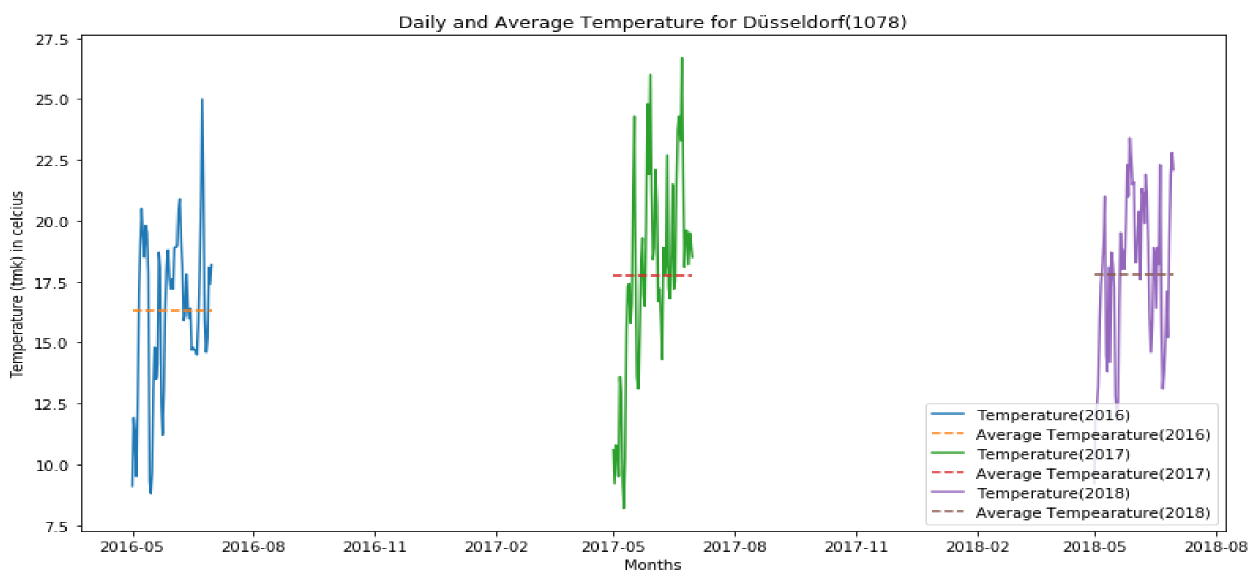


Figure-9: Daily and Average Temperature for Dusseldorf (1078)

Figure-9 depicts that, the average temperature of Dusseldorf (1078) for 2016 (May to June) was about 16.29°C and it was lowest for this region. Then, it increased and became almost 17.75°C in 2017. This graph experienced the highest temperature in 2018 and was around 17.82°C. Thus, it shows enhancement of average temperature.

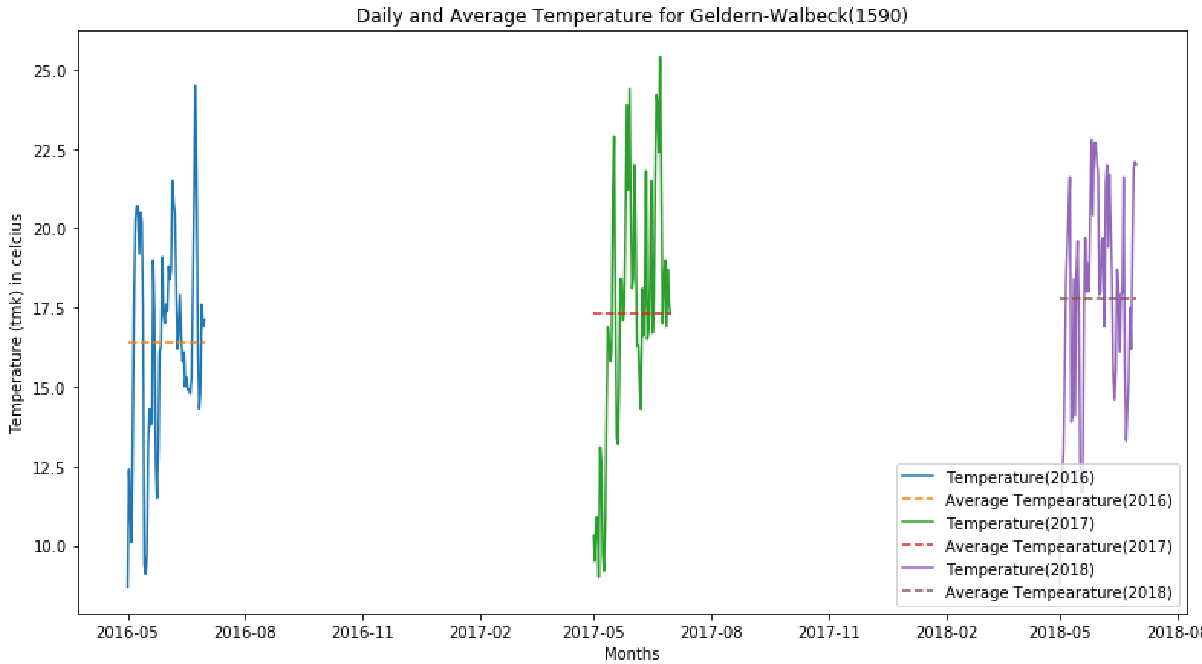


Figure-10: Daily and Average Temperature for Geldren-Walbeck (1590)

Looking at Figure-10, we can notice that the average temperature of Geldren-Walbeck (1590) for 2016 (May to June) was about 16.38°C which was lowest among all of these. Later on, the AT showed an upward trend and reached approximately 17.30°C in the year of 2017. The most significant average temperature was recorded in 2018 and was around 17.81°C. This graph also shows the increase of AT.

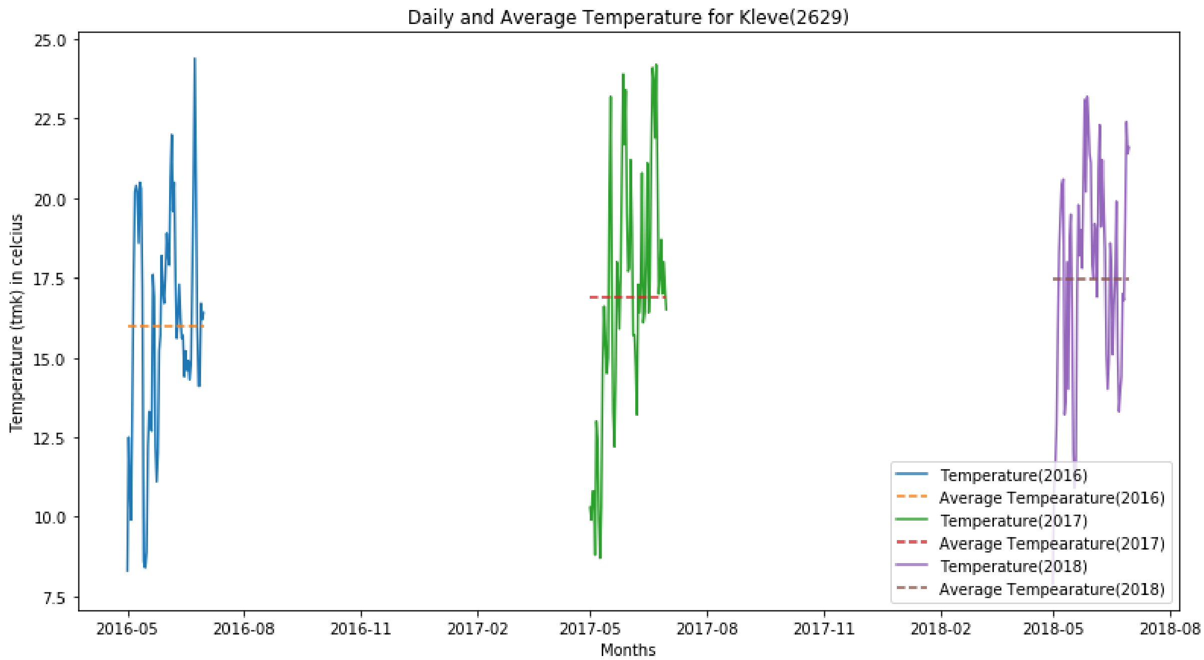


Figure-11: Daily and Average Temperature for Kleve (2629)

The least average temperature of Kleve (2629) observed in 2016 (May to June) was around 15.97°C in Fig-11. In 2017, Kleve experienced approximately 17.30°C. The recorded highest AT in 2018 was around 17.48°C. This graph denotes the growth of average temperature.

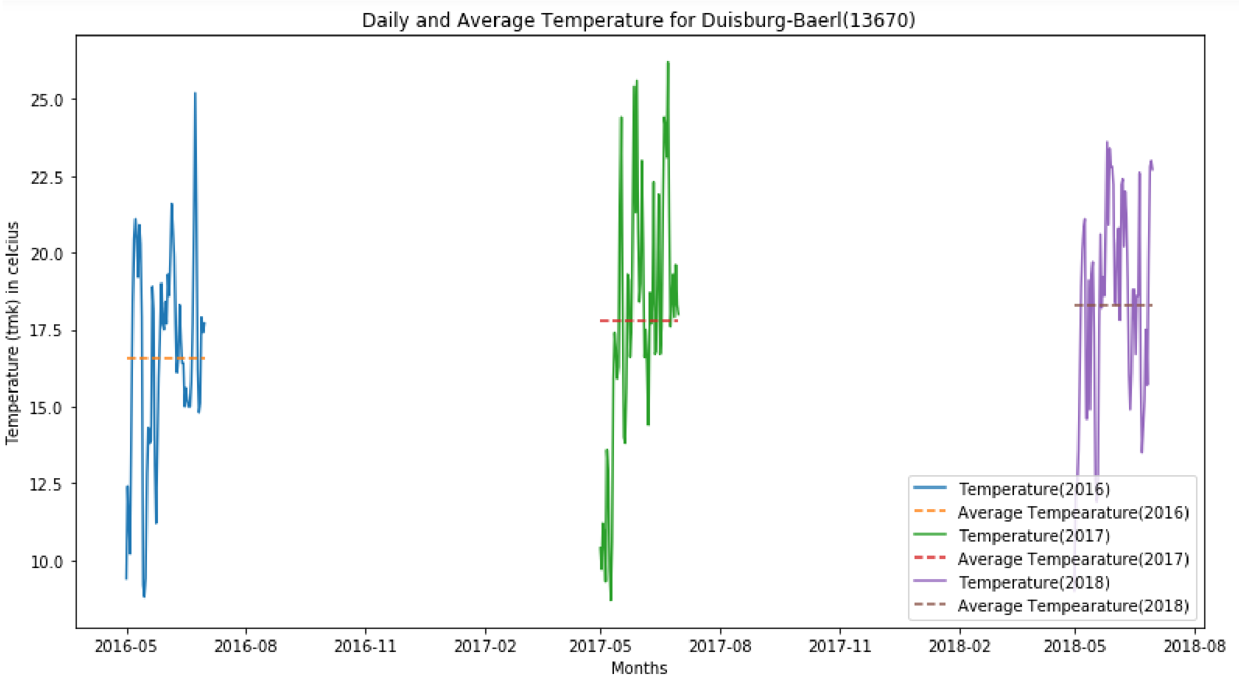


Figure-12: Daily and Average Temperature for Duisburg-Baerl (13670)

In Fig-12, the less AT for Duisburg-Baerl (13670) was recorded about 16.59°C in 2016 (May to June). A rise of average temperature found in 2017 and grew up to around 17.78°C. Highest value counted in 2018 for AT was almost 18.28°C, which means the temperature upturn.

After comparing four regions' average temperature, it is noticeable that AT is increasing day by day. In 2016, we found the lowest value for each area but in 2017 & 2018, temperature increased respectively. This is why; we can say that drought is related to the average temperature (AT) over the last year. There is a correlation between AT and drought.

3.3 Correlation between CP and NDVI

There is a noticeable correlation between Cumulative Precipitations (CP) and Normalized Difference Vegetation Index (NDVI). If we look at CP of 2016, it showed that the precipitation rate was comparatively better and the greenery of different ROI attributes was also in high density. But, the value of CP started declining in 2017 so as the vegetation. At last, in 2018, we experienced the lowest cumulative precipitations and the least green covered area. Thus, analysis says decreased precipitation causes low vegetation.

3.4 Correlation between AT and NDVI

A considerable measure of Average Temperature (AT) has effect on Normalized Difference Vegetation Index (NDVI). The lowest temperature recorded in 2016 whereas it had significant growth in 2018, like the vegetation was high in 2016 but it went down each year and became less green in 2018. Therefore, it is said that there is a correlation between AT and NDVI; because if the temperature goes up, the vegetation index also collapses.

3.5 Correlation between AT and CP

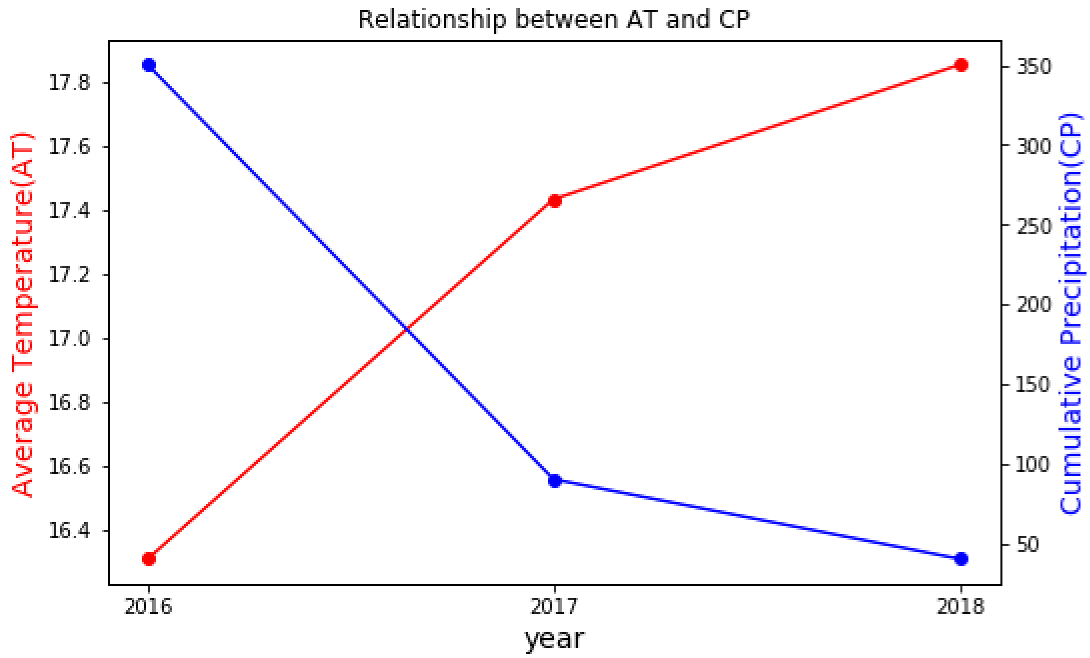


Figure-13: Relationship between AT and CP

After analyzing the three consecutive years (2016, 2107 and 2018), it is remarkable that each year temperature increased and precipitations reduced. So, there must be a correlation between Average Temperature (AT) and Cumulative Precipitations.

4 Conclusions

In conclusion, this project successfully implemented a prototype to conduct drought detection on specific areas in the region of Xanten. This study has presented a methodology to identify agricultural drought based on a combination of three indicators (NDVI, CP & AT). This paper analyzed NDVI, temperature and precipitation changes and investigated the correlations between NDVI, temperature and precipitation for eight different vegetation types during the seasons (May–June) of the period 2016–2018. The data exploration of three years says three indices precipitations, temperature and vegetation are interrelated. When the temperature increases and precipitation declines, the growth of vegetation also falls down and it causes severe drought. All the major steps, which are necessary to get to the results of the rudimentary prototype, are illustrated. Also, an extensive discussion and an outlook are provided. The accuracy of the training process is similar to the results of the related work, but once the model is put to action, it took a huge time to calculate NDVI from QGIS through sentinel. There was no specific data set for Xanten and that is why we took data from the nearest station for cumulative precipitation and average temperature. With more time, a much vaster examination of the achieved results could have been done.

4.1 Outlook

Because of achieving just a rough prototype, lots of future tasks can be considered-

The methods used for drought prediction based on certain drought indicators can be used directly to predict other hazards related to hydro climatic variables, such as flood forecasting, although a difference may exist in the properties of variables of interest; for example, low quintile is of interest for drought prediction while high quintile is of interest for flood prediction.

Advances in drought prediction give opportunities for alternative forms of hazards too. For instance, drought is a very important contributing factor to the incidence of wildfire, thus accurate drought prediction might give helpful data for wildfire risk mitigation.

4.2 Critical Reflection

Throughout the implementation phase of this project, the process of creating the dataset took much longer than expected and thus caused a delay in achieving the final results. The time during that delay could have been used more efficiently to implement the discussed confusion matrix to provide more insights on the ultimate outcome.

A weakness of this report and probably of the other related work is to point out actually uses for scene classification.

Besides these two points, the project worked out as expected. The tools used were sufficient enough to create an appealing visualization in QGIS in order to examine the predictions.

The group work worked out well. Everybody tremendously supported each other.

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Individual Contributions

Asif Al-Samy

- Task-4
- Task-5 (Report Writing)

Marjahan Akter

- Task-3
- Task-5 (Report Writing)

Md. Mehedi Hasan

- Task-1
- Task-2
- Task-5 (Report Writing)

Declaration of Authenticity

We, Asif Al-Samy, Marjahan Akter and Md. Mehedi Hasan, hereby declare that our contribution to the work presented herein is our 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. We will retain a copy of this assignment until after the Board of Examiners has published the results, which we will make available on request.

Signatures: