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RESEARCH PAPER

# Multi-sensor Satellite Drought Analysis using Landsat and MODIS Time-Series Based on NDVI and Rainfall

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**A B S T R A C T:**
Iraq's climate is prone to frequent droughts, which have severely influenced the country in the past two decades. A study conducted using remote sensing and geographical information systems analyzed the spatiotemporal patterns of drought in Iraqi Kurdistan - specifically Erbil for 19 years from 2003 to 2021. The research found that the region had experienced severe drought episodes during this time, with an increase in severity and frequency, especially in 2008, 2012, and 2021. These years were noticeable by a decrease in vegetation area cover and lower average precipitation. The study utilized the Normalized Difference Vegetation Index (NDVI), Rainfall, and Rainfall Anomaly to produce multi-temporal classified drought maps, which showed that climate conditions played a significant role in the change of the vegetated cover area. The research also estimated the effect of rainfall variability on vegetation cover in Erbil, concluding that rainfall anomalies led to changes in the NDVI. The correlation matrix between rainfall anomalies and NDVI anomalies confirms that irregular rainfall patterns result in modifications to the NDVI. Productivity was found to increase with wet anomalies and decrease with dry anomalies. Overall, the study provides valuable insights into the impact of drought on agricultural productivity in the Iraqi Kurdistan Region (IKR)-Erbil and emphasizes the importance of implementing effective strategies to mitigate the impact of drought on agriculture in the region.

KEY WORDS: Climate conditions, Drought; NDVI, and Rainfall Anomaly.
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## 1. INTRODUCTION :

Drought is a complex natural disaster, which is often difficult to detect, predict, and alleviate (Aadhar and Mishra, 2017). Its occurrence causes significant harm to society and the environment, highlighting the importance of understanding the spatial-temporal pattern of drought (Dubovyk, 2017). Environmental factors such as high temperature, low humidity, rainfall timing and characteristics, a significant role in the occurrence of droughts, especially during crop growing seasons (Gaznayee, 2020). Although drought has no universal definition currently, drought is commonly defined as a deficit in precipitation and terrestrial water storage that adversely affects agriculture, environment, and economy (Lloyd-Hughes, 2014; Yan et al., 2018).

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During drought periods, severe water stress can occur in a region due to lack of precipitation, high evapotranspiration rates, overexploitation of water resources, and/or combination of those factors (Bezdan et al., 2019; Kamal and Hakzi, 2022). Remote sensing techniques can help map, assess, and monitor drought at different scales. (Dubovyk, 2017). Several methods and indicators have been created to tackle and control drought status. Although insufficient precipitation is the main cause of drought, human activities can also contribute to its occurrence (Perez et al., 2016; Shamsipour et al., 2011). Drought events are usually associated with high temperatures and low humidity levels, which have become more frequent in recent years, mainly due to climate change (Keyantash and Dracup, 2004).

Drought development occurs in two stages: meteorological drought, which occurs when there is a prolonged lack of precipitation, and agricultural drought, which results from reduced soil moisture and limited vegetation cover (UNESCO, 2014). Several studies have described the drought situation in Iraq (Fadhil, 2011). The lack of rainfall, which is the primary cause of severe drought in Iraq, was considered in the Iraqi report of 2009 by the Coordination of Humanitarian Affairs, UNAMI and IAU office (Andrieu, 2017). This has resulted in a decrease in the levels of groundwater and river flows and the depletion of water sources such as springs, deep and shallow wells, as mentioned in the UNDP report of 2012 (UNDP, 2012).

In the period between 2003 and 2021, Iraq experienced multiple severe droughts due to various reasons, including low average precipitation, higher temperature rates, lower water income from neighboring countries, and poor water utilization efficiency, as reported by (Al-Quraishi, 2019; Gaznayee et al., 2022; Wu et al., 2019). In addition, UNESCO recorded severe droughts in Erbil, IKR in 1999 and 2008. (UNESCO, 2014). Between 1999 and 2002, Erbil experienced a period of low precipitation and droughts. Subsequently, another drought event was observed between 2007 and 2011 (Awchi and Jasim, 2017). While there are several remote sensing methods available for drought monitoring, some studies have also examined the impact of drought on vegetation, with NDVI being one of the earliest vegetation indices used for drought monitoring since the 1980s. (Harun et al., 2015; Mohammed and Scholz, 2017; Yao et al., 2011). Numerous studies have explored the spatiotemporal patterns of drought, but most of them have focused on the methods of detecting drought and assessing the relationship between agricultural drought and rainfall averages or crop yields using the Landsat time-series dataset, as per (Harun et al., 2015). In order to identify drought patterns at a meteorological and vegetative scale, it is necessary to conduct a thorough analysis of seasonal drought dynamics (Zewdie and Csaplovics, 2015). The focus should be on drought during the agricultural growing season as rainfall affects aquifer recharge, agricultural activities, and ecological changes (Gaznayee, 2020). When using NDVI to analyze weather impact on vegetation in vegetated regions, it is recommended to separate weather components from an ecosystem component as the fluctuation in weather-related NDVI cannot be easily detected due to the smaller integrated area of the weather component (Abdel-Hamid et al., 2020; Schucknecht et al., 2013). To conduct a comprehensive drought analysis, parameters such as rainfall, soil moisture, potential evapotranspiration, vegetation condition, groundwater, and surface water levels should be considered (Sruthi and Aslam, 2015). By studying changes in vegetation cover using NDVI data, both the trend in occurrences of drought and changes in vegetation cover in the study area can be analyzed. (Al-Quraishi et al., 2021). Typically, the correlation between drought indices is weak due to the non-linear relationship between drought measuring parameters. Therefore, they do not usually predict similar patterns (Owrangi et al., 2011; Vicente-Serrano et al., 2010). To study changes in vegetation cover and drought occurrences in a particular area, NDVI data can be used. However, NDVI is not entirely error-free and may have issues such as data errors during the growing season and saturation effects on dense vegetation. Thus, combining it with other parameters can increase accuracy (Wan and Wang, 2004). Therefore, it is always better to merge it with other parameters to ensure more accuracy (Heydari et al., 2018). Rainfall anomalies index (RAI), both dry and wet, can significantly affect agricultural productivity and cropland expansion. Droughts or dry spells can lead to decreased yields and crop failures, while excessive rainfall or floods can result in waterlogging, soil erosion, and pest infestation (Dutta et al., 2015a). Droughts or dry spells can lead to decreased yields and crop failures, while excessive rainfall or floods can cause waterlogging, soil erosion, and pest infestation. These models can help identify the threshold levels of rainfall anomalies beyond which the impact on crop yields becomes more severe (Salehnia et al., 2017). On the other hand, in drier regions, farmers may have to rely on irrigation or switch to more drought-resistant crops, which can limit cropland expansion(Dutta et al., 2015b). The (NDVI) Anomaly in crop-growing regions for selected years is a visualization that shows changes in vegetation health in regions where specific crops are grown. Anomalies caused by weather conditions, such as drought or heavy rainfall (Amri et al., 2011; Anyamba and Tucker, 2001).

This study aims to analyze the relationship between rainfall and NDVI and examine drought events in Erbil over a 20-year period. By analyzing precipitation, vegetation growth, and crop data, the study provides valuable insights into drought frequency, duration, and extent, including agricultural drought. These findings are important for planners and policy-makers in developing agricultural strategies that consider historical drought patterns. Understanding the correlation between rainfall and NDVI and monitoring their changes over time can help identify vulnerable regions and implement targeted interventions to mitigate the impact of drought on agriculture.

## 2. MATERIALS AND METHODS

### 2.1. THE STUDY AREA

The research area mentioned encompasses the entirety of the Erbil governorate in northern Iraq, which consists of two physiographic regions: the mountains and foothills. The city of Erbil is situated within the coordinates of latitudes 35°40'0"N to 36°20'10"N and longitudes 43°20'0" E to 44°20'0" E, with an altitude ranging from 400 to 500 meters above sea level. The governorate has a total area of approximately 15,038.93 km2 and is divided into ten districts, including Mergasur, Soran, Choman, Rawanduz, Shaqlawa, Khabat, Dashti Hawler (Qushtapa), Koysinjaq, and Makhmur. Precipitation in Erbil is not uniformly distributed, with the northern areas receiving more precipitation than the southern areas.

The mean annual precipitation in Erbil is 363 mm. (Hakzi, 2022; Razvanchy and Fayyadh, 2022). During winter, the average temperature each day is 5°C, which is considered chilly. On the other hand, the temperature can escalate to 35°C during summer, representing a significant difference in temperature between the two seasons. Furthermore, in the southern regions of the area, the temperature can rise to as high as 50°C, which is an incredibly high temperature. Notwithstanding these temperature extremes, the average temperature for the year is about 21°C, implying that the temperature fluctuates considerably across the seasons but is relatively mild when averaged out. Additionally, there are notable variations in temperature within a day and throughout the year, indicating significant temperature changes.The region affected by a Mediterranean climate, which typically features wet winters and dry summers. This climate type is often associated with regions bordering the Mediterranean Sea, but it can also be found in other parts of the world with similar conditions Figure (1).

The timeframe selected for the study was from 2003 to 2021 due to the repeated occurrence of drought episodes. Landsat images, which have a 30-meter spatial resolution, were obtained from the United States Geological Survey (USGS) website https://glovis.usgs.gov. These images were acquired during April or May of each year since most vegetation growth occurs during this time. The ASTER Global Digital Elevation Model (ASTER GDEM) V2 dataset, with a 30-meter spatial resolution, was obtained from the National Aeronautics and Space Administration (NASA) Reverb homepage (https://www.nasa.gov/) and was used as Digital Elevation Model. (DEM) data for the study. Rainfall data was obtained from the CHIRPS rainfall estimate, produced by the Climate Hazards Group at the University of California, Santa Barbara. CHIRPS is a 35+ year quasi-global rainfall dataset, available at 5 and 10-day accumulations, and can be accessed for free at http://chg.geog.ucsb.edu/data/chirps/(Funk (Funk *et al.*, 2015).The MODIS NDVI CMG data product was retrieved from REVERB, which is managed by the LP DAAC at the USGS/EROS Center in Sioux Falls, South Dakota, USA.

### 2.2. Spectral drought indices

#### 2.2.1. Normalized Difference Vegetation Index (NDVI)

Formula (1) was utilized to calculate the NDVI index of the Landsat images Rouse et al. (1973). The formula for calculating NDVI is:

$$NDVI = (NIR - Red) / (NIR + Red) \quad \ldots\ldots\ldots\ldots\ldots\ldots 1$$

The NIR represents the amount of near infrared light reflected by vegetation, and Red represents the amount of red light reflected by vegetation. The values of NDVI range from -1 to +1, with higher values indicating healthier and more denser_vegetation, while lower values correspond to sparsed or stressed vegetation, bare soil, or water (Akbar et al., 2019; Al-Shwani, 2009).

#### 2.2.2. NDVI Anomaly in crop-growing regions for selected years

The first formula provided is used to perform a linear transformation on pixel values to

map them from a range of Pmin to Pmax to a new range between -100 and 100. This can be useful to enhance the contrast in an image or to standardize values across different images. (Legesse and Suryabhagavan, 2014).
The formula is:

***100*([2*(Px-Pmin)/(Pmax-Pmin)]-1) ………………2***

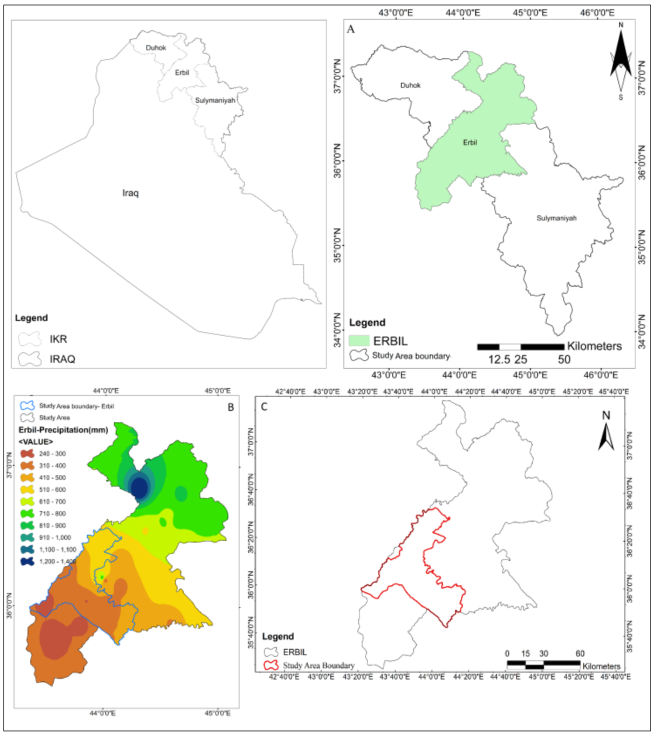


**Fig1:** The location map of the Erbil Province. (A), Location of Erbil Provence study area, (B) The map of the geographical distribution of annual rainfall (mm/year) in Erbil during 1998-2021, and (C) The location map of the study area.

where Px is the pixel value, Pmin and Pmax are the minimum and maximum values in the raster, respectively. The transformed value will be between -100 and 100, with values below 0 indicating that the pixel value is below the midpoint of the range, and values above 0 indicating that it is above the midpoint. The second formula is used to computed an NDVI anomaly percentage, which is the difference between the maximum NDVI value in a raster in a given year and the average of the maximum NDVI values over a period of years (e.g., 2003-2021). The formula is:

***[{(NDVImax_2003)-(mean_NDVImax)}/ (mean_NDVImax + NDVImax_2003)] * 100…………………………………3***

where NDVImax_2003 is the maximum NDVI value in the raster for the year 2003, mean_NDVI max is the average of the maximum NDVI values over the period of years(2003-2021), and NDVI max_2003 + mean NDVI max is the denominator to normalize the anomaly as a percentage. To identify areas with anomalous vegetation growth or to detect changes in vegetation over time (Yang et al., 2017). This visualization, the NDVI Anomaly is used to show changes in vegetation cover in IKR-Erbil during periods of significant drought.

Estimating drought patterns and their effects on vegetation can be made more insightful by using Landsat and MODIS time-series datasets from 2003-2021. By analyzing NDVI, NDVI anomaly, and their correlation with rainfall and rainfall anomaly through Multi-sensor Satellite. techniques, valuable insights can be obtained. Landsat provides high-resolution images at a relatively low temporal frequency (around 16 days), while MODIS provides moderate-resolution images at a high temporal frequency (around 1-2 days). To assess the impact of drought on vegetation, NDVI and NDVI anomaly calculated for each Landsat and MODIS image. The rainfall and rainfall anomaly data for the same period were obtained from meteorological databases. Comparing the NDVI anomaly to 'normal' plant health can provide a useful measure of drought (Liu and Negrón Juárez, 2001). The data used in this visualization was collected by the MODIS instrument on NASA's Terra satellite, and periods with no available data were excluded.

### 2.2.3. Rainfall Anomaly Index (RAI)

Rainfall anomaly refers to the deviation of actual rainfall from the long-term average rainfall in a particular region or location over a specific period. It is a measure of how much more or less rain has fallen than what is typical for that area and time of year. Positive rainfall anomalies indicate that there has been more rainfall than the long-term average, while negative rainfall anomalies indicate that there has been less rainfall than the long-term average(Dutta et al., 2015b; Salehnia et al., 2017; Yang et al., 2017).

$RAI = 3\left[\frac{N-\bar{N}}{\bar{M}-\bar{N}}\right]$ For positive anomalies …………………4

$RAI = -3\left[\frac{N-\bar{N}}{\bar{X}-\bar{N}}\right]$ For negative anomalies ……………………5

The formula for calculating rainfall uses several variables, including N, which represents the current month/year's rainfall in millimeters. $\bar{N}$ represents the historical average monthly/yearly rainfall in millimeters, while $\bar{M}$ and $\bar{X}$ are the average of the ten highest and lowest monthly/ yearly precipitations in the historical record, respectively. Positive anomalies are values above average, while negative anomalies are values below average. If a year has low rainfall values, it is considered a drought year with negative deviation from the mean seasonal rainfall. The Rainfall calculation formula is as follows:

**Anomaly Index: RAI =(R –μ)/ $a$ ……………………….6**

Where, RAI = Rainfall Anomaly Index; R= Rainfall; μ= Long term average; and rainfall a = Standard Deviation

**Table (1)** Classification of Rainfall Anomaly Index.

| RAI range | Classification |
|---|---|
| Above 4 | Extremely humid |
| 2 to 4 | Very humid |
| 0 to 2 | Humid |
| -2 to 0 | Dry |
| -4 to -2 | Very dry |
| Below -4 | Extremely dry |

### 2.3. Statistical Analyses

#### 2.3.1. Correlation Coefficient (r)

To determine the extent of statistical relationships between RAI and NDVI anomaly values, correlation coefficients (r) were computed. Bivariate correlations (specifically the Pearson Correlation Coefficient) were used to identify the variables that exhibited significant statistical associations with each other (Babbie, 2009).

## 3. RESULTS & DISCUSSION

### 3.1. NDVI

The NDVI has been extensively utilized to investigate the correlation between changes in vegetation growth rate and spectral vegetation variability. An Erbil region has been experienced a significant reduction in vegetation cover over the years 2008, 2012, and 2021, largely due to extreme and severe droughts that caused a decreased in agricultural land (Figure 2, 3, and 4).

This decline in vegetation cover is based on a 19-year average of the area covered by vegetation. The severe drought episodes that affected Iraq, including Kurdistan, in 2008, 2012, and 2021, along with a significant decrease in average rainfall, were the main contributing factors to this decline, as illustrated in Figures 2, 3, and 4. The maps demonstrate how the drought impacted vegetation density in Erbil, with some parts of southern Erbil experiencing severe effects, However, in the northern region, areas with increased precipitation showed a corresponding increase in NDVI values.

The NDVI results reveal that the intensity of drought in Erbil increases gradually towards the southwest, as indicated in (Figures 2, 3, and 4).
Erbil experienced a significant decrease in annual precipitation averages in 2008, 2012, and 2021, as compared to the precipitation averages from 2003 to 2021. However, there were certain areas with high precipitation averages and supplementary irrigation systems, which had a positive impact on NDVI values as seen in (Figures 2, 3, and 4).
Additionally, during growing seasons in the southern region of Erbil, low precipitation and high temperatures contribute significantly to the reduction of NDVI values and vegetation cover, as indicated by the correlation coefficient statistics which will be discussed later. By examining the consecutive NDVI maps, the onset and duration of drought for a 19-year period can be easily observed. Based on the results presented in Figures 2, 3, and 4, it can be concluded that the study area experienced drought episodes over the study period, particularly in 2008, 2012, and 2021. The correlation between NDVI, NDVI anomaly, and rainfall analyzed to identify areas and periods of drought. Negative correlations between NDVI / NDVI anomaly and rainfall/rainfall anomaly indicated that vegetation health is declining in response to reduced rainfall, which could be indicative of drought.

### 3.2.The RAI and NDVI.

The study used precipitation data from 2003 to 2021 to examine precipitation trends and variations over a 19-year period. The normal precipitation at a given station was determined by calculating the mean precipitation over 19 years.

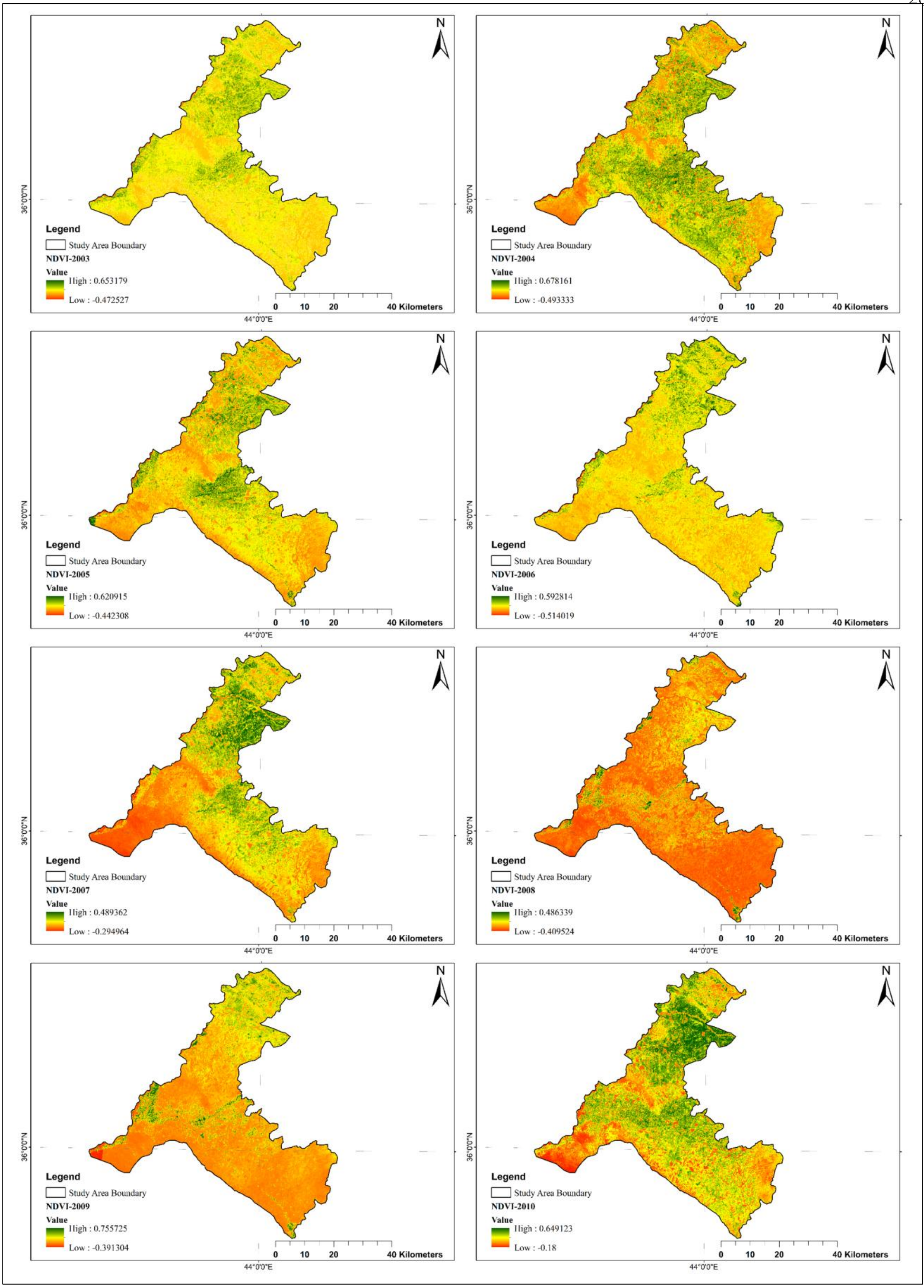


Figure 2: Spatio-temporal variation of the NDVI-based vegetation from 2003 to 2010.

Maps of precipitation patterns were created for the study area based on the amount of annual precipitation per month, 3-month, and average periods. The maps identified months and years that suffered from low annual precipitation, especially in 2007-2008, 2011-2012, and the years 2020-2021, which corresponded to drought periods. These results are consistent with a previous study by (Gaznayee et al., 2022).

The amount of rainfall per year had an impact on the distribution and density of vegetation cover, reductions in precipitation played a significant role in vegetation loss during the study period. Drought periods were identified by comparing a twenty-year moving average to the reference period's average, and the results for the Erbil region were presented separately. Although there were some differences in trends across sites during the reference period, all locations experienced a decrease in precipitation over the last decade due to severe drought, especially in 2007-2008, 2011-2012, and 2020-2021 (Figure 5, 6, 7, 8, and 9). Nearly all sites, from north to south, were considered drought-prone areas, some currently experiencing drought while others were highly vulnerable. It's important to consider differences in water availability when evaluating drought occurrence in the past or present. This means that drought in Erbil, where mean precipitation is below the average year, could have a stronger impact on water resources. This observation, where both monthly and annual moving average precipitation values are below average, indicates that large areas in Erbil are experiencing drought (Figure 6, 7, 8, and 9).

To eliminate the impacts of rainfall patterns, it was necessary to implement appropriate measures. The graphs in Figure 5, 6, 7, 8, and 9 show the amount of rainfall for a selected year and the long-term average (19 years, 2003-2021) in light blue. These results provide insights into the rainfall patterns in a specific region and year. The right figure displays anomalies for one- and three-month-time spans, indicating whether the current year's rainfall is above or below the long-term average.

The (Figure 5, 6, 7, 8, and 9) figures useful for understanding when the rainfall season occurs, NDVI, NDVI anomaly and how the selected year compares to the long-term average, especially during crucial crop development periods. The first plot also highlights that one-month anomalies are more unpredictable than three-month anomalies and can reach more extreme values.

The results describe the use of long-term NDVI data to study vegetation health during drought and wet years in an Erbil area. The study also examines the performance of Landsat Time serious and the National Oceanic and Atmospheric Administration-Advanced Very High-Resolution Radiometer (AVHRR) NOAA-AVHRR derived NDVI data and showed that there are visible differences in NDVI between the northern and southern parts of Erbil due to uneven distribution of monsoonal rainfall. The study observed that the diversity in NDVI indicates spatial variation in vegetation health within the area, which has occurred mainly due to uneven distribution of monsoonal rainfall. The study also identifies years of drought, including 2008, 2009, 2012, and 2021, based on a comparison of NDVI data from those years to normal conditions in other years. Analyzing the correlation between NDVI (Normalized Difference Vegetation Index), NDVI anomaly, and rainfall is vital for identifying regions and time periods affected by drought. NDVI is a widely used index that utilizes remote sensing to assess vegetation cover and health, providing valuable information about the state of vegetation in a given area(Table2). Rainfall, on the other hand, is a crucial factor for supporting vegetation growth, particularly in regions where crops are cultivated.

When examining the relationship between NDVI and rainfall, negative correlations indicated the impact of reduced rainfall on vegetation health. A decrease in NDVI values or NDVI anomaly (deviation from the long-term average) suggests that vegetation is undergoing stress or deterioration due to insufficient water availability in year 2008 and 2021. This observation often signifies the presence of drought conditions. By studying the anomalies in rainfall and NDVI, researchers can pinpoint specific areas and timeframes that are susceptible to drought. Negative correlations between NDVI/NDVI anomaly and rainfall/rainfall anomaly emphasize the dependence of vegetation health on precipitation patterns. Crop-growing regions are of particular interest in this analysis since they heavily rely on adequate rainfall for successful agricultural production.

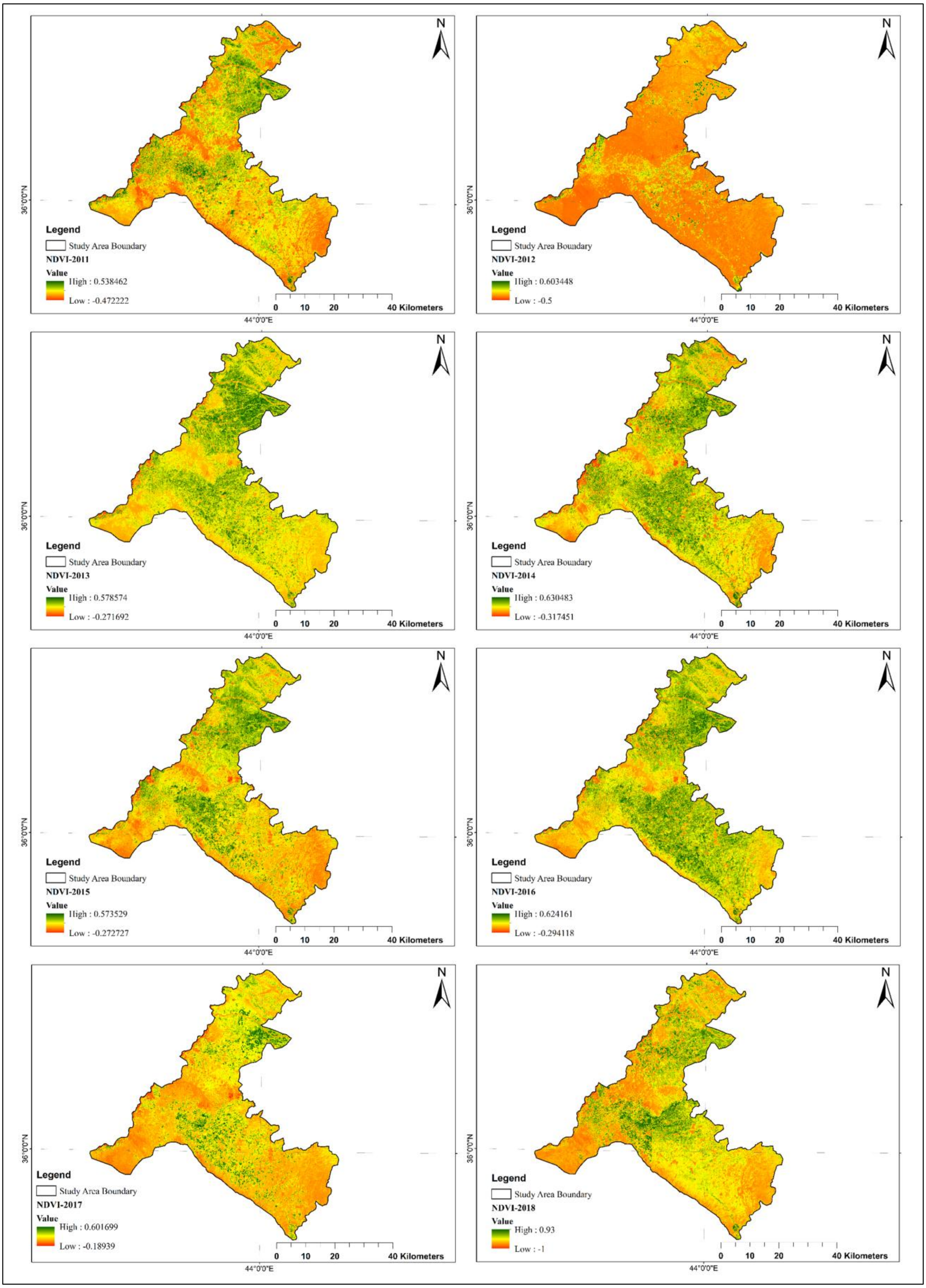


**Figure 3:** Spatio-temporal variation of the NDVI-based vegetation from 2011 to 2018.

Through an examination of selected years, these studies observe the variations in NDVI anomaly in crop-growing regions and its correlation with rainfall anomalies in (Table2). These findings offer valuable insights for farmers, policymakers, and researchers in comprehending the dynamics of drought and its impact on agriculture.

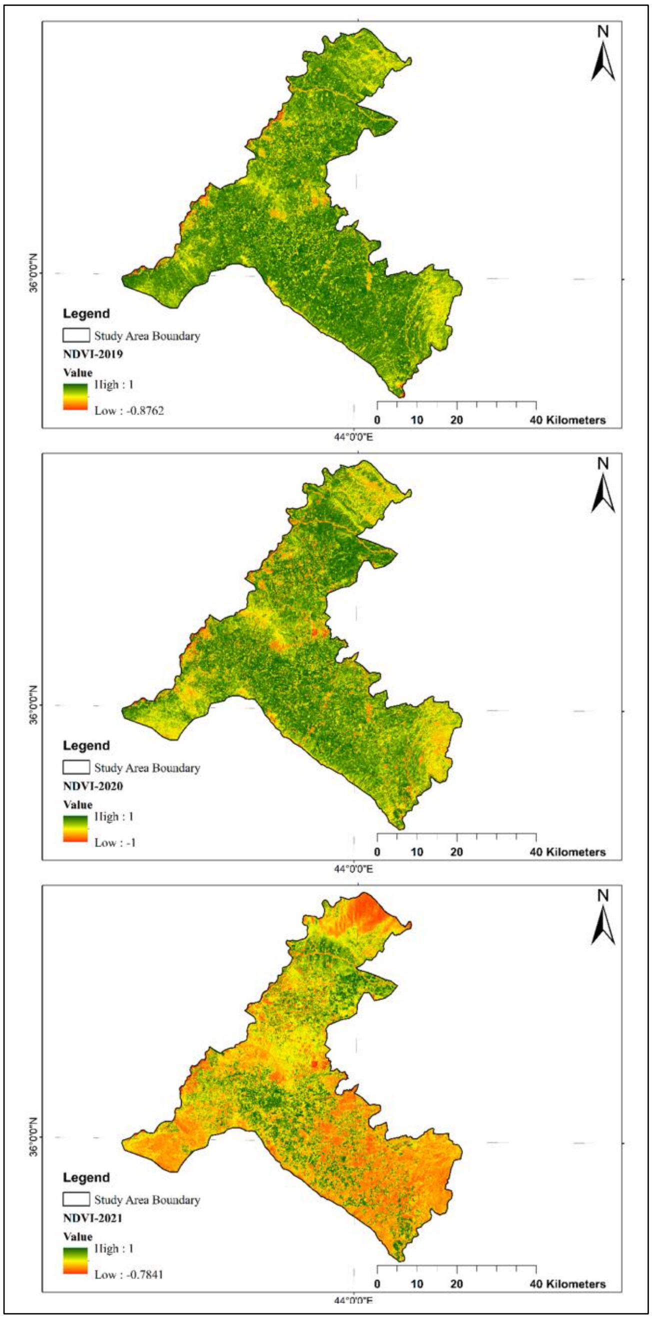


Figure 4: Spatio-temporal variation of the NDVI-based vegetation from 2019 to 2021.

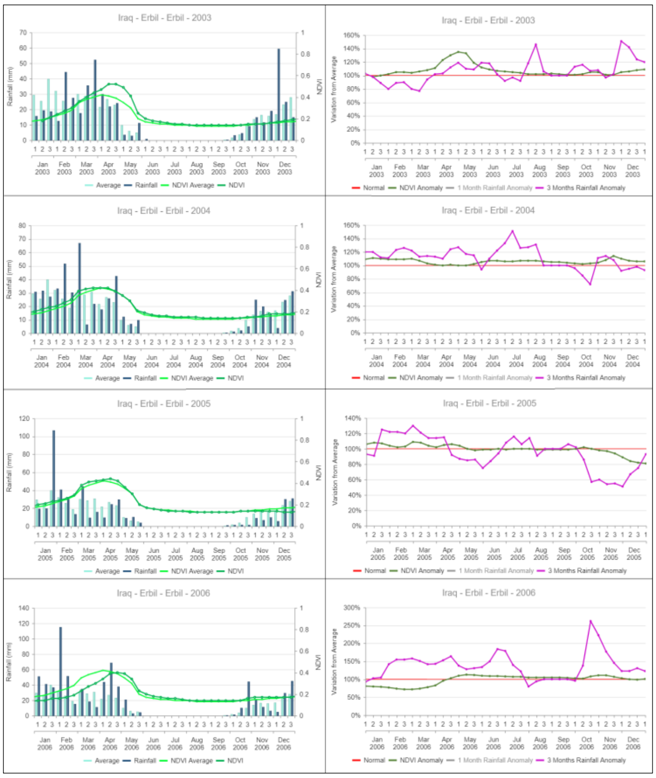


**Fig 5.** Spatial pattern changes of Rainfall, Rainfall Anomaly, NDVI and NDVI anomaly
for (2003-2006) years.

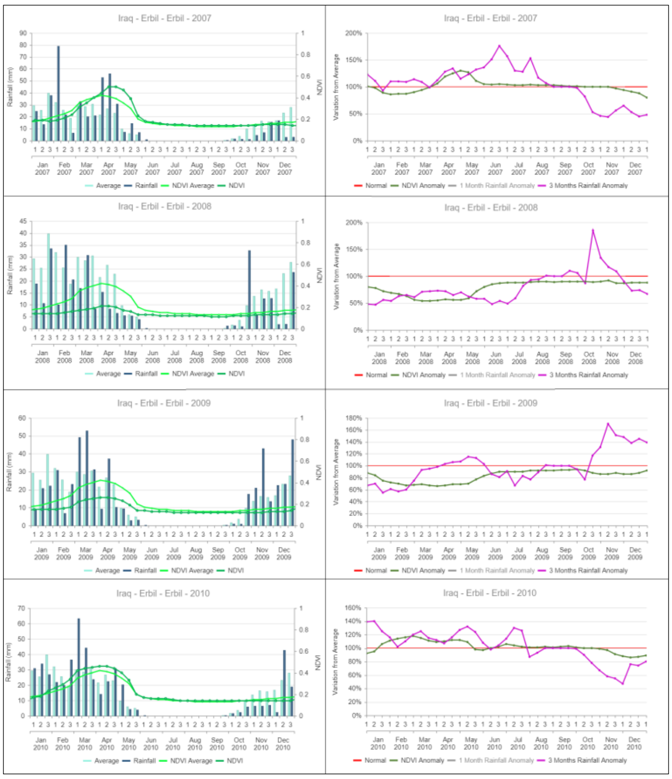


**Fig 6.** Spatial pattern changes of Rainfall, Rainfall Anomaly, NDVI and NDVI anomaly
for (2007-2010) years.

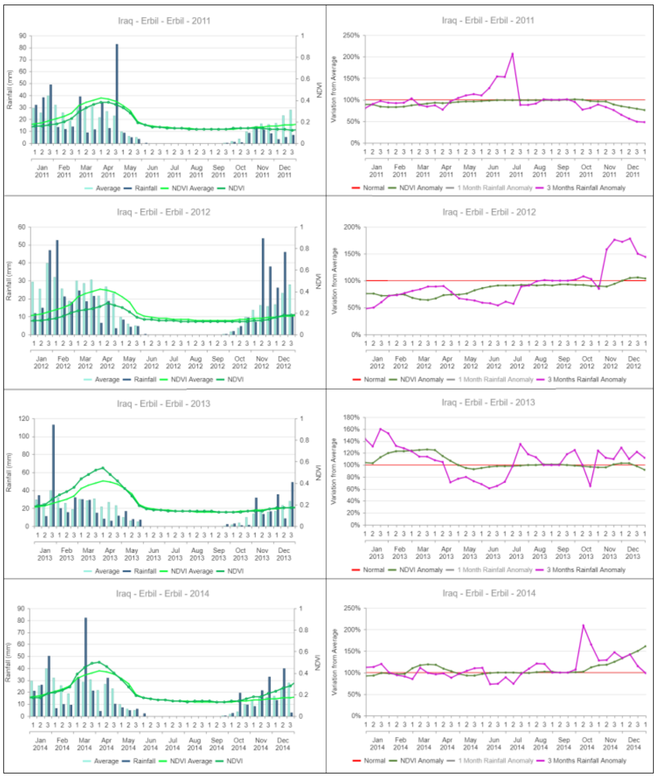

**Fig 7.** Spatial pattern changes of Rainfall, Rainfall Anomaly, NDVI and NDVI anomaly for (2011-2014) years.

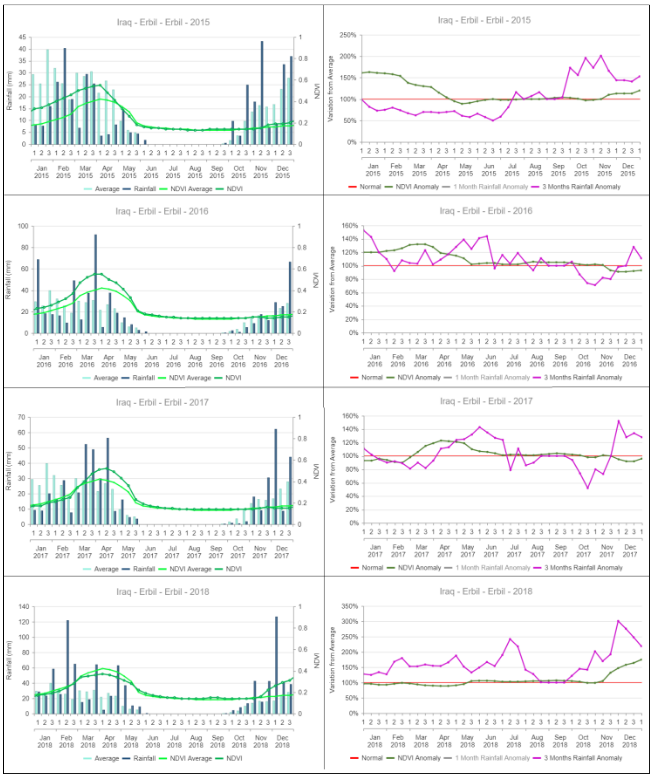

**Fig 8.** Spatial pattern changes of Rainfall, Rainfall Anomaly, NDVI and NDVI anomaly for (2015-2018) years.

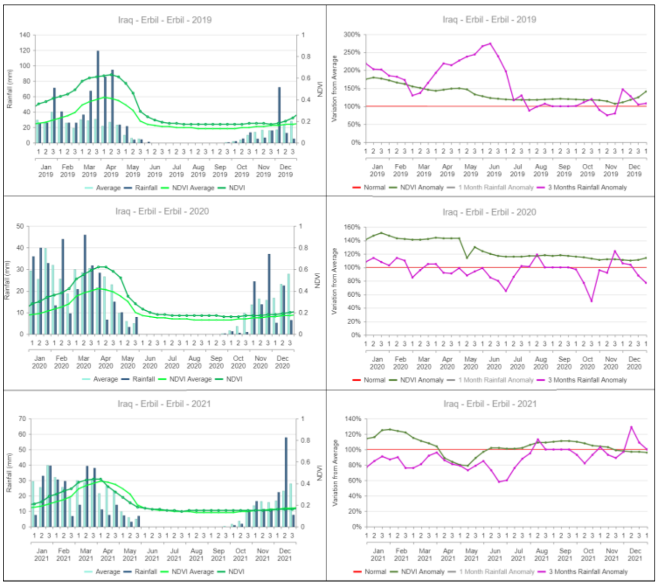

**Fig 8.** Spatial pattern changes of Rainfall, Rainfall Anomaly, NDVI and NDVI anomaly for (2019-2021) years.

## 4. DISCUSION

According to a study result from 2010, 2021 experienced the second largest shortage of rainfall, only surpassed by the extreme drought year of 2008. The finding also suggests that vegetation indices obtained from AVHRR can indicate plant health and growth, and can also help detect weather-related dangers such as seasonal changes (Science et al., 2010).

As a result, there exists a robust relationship between rainfall and vegetation indices like NDVI, with a minor time lag ranging from 1 to 12 weeks before the vegetation exhibits a response, as evidenced by the observations.(Mzuri et al., 2021). The research discovered that in the southern regions, the NDVI values were lower compared to the north, indicating less vegetation coverage. In addition, the study found that there was a significant decrease in average yearly rainfall in 2008, 2012, and 2021 when compared to other years from 2003 to 2019 as explained by (Gaznayee et al., 2022). The results also indicated that insufficient rainfall and high temperatures significantly reduced the vegetation cover and NDVI values in the southern parts of Erbil, particularly during the growing season.

**Table (2) Correlation matrix (Pearson) between Rainfall Anomaly and NDVI Anomaly**

| Variables | 2003N | 2004N | 2005N | 2006N | 2007N | 2008N | 2009N | 2010N | 2011N | 2012N | 2013N | 2014N | 2015N | 2016N | 2017N | 2018N | 2019N | 2020N | 2021N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **2003R** | 0.090 | 0.053 | 0.070 | -0.032 | 0.050 | 0.177 | -0.019 | 0.037 | 0.196 | -0.009 | -0.037 | -0.037 | -0.022 | 0.109 | 0.109 | 0.041 | 0.168 | 0.168 | -0.022 |
| **2004R** | -0.103 | -0.158 | -0.214 | -0.067 | 0.190 | 0.013 | -0.200 | -0.002 | **-0.270** | 0.016 | 0.175 | -0.140 | -0.026 | **-0.236** | **-0.236** | 0.165 | 0.066 | 0.066 | -0.003 |
| **2005R** | **-0.282** | **-0.447** | **-0.342** | **-0.392** | **-0.234** | -0.163 | **-0.360** | **-0.479** | -0.166 | **-0.364** | **-0.276** | -0.099 | **-0.464** | **-0.365** | **-0.365** | **-0.411** | -0.150 | -0.150 | **-0.260** |
| **2006R** | **-0.500** | **-0.502** | **-0.582** | **-0.410** | **-0.374** | **-0.558** | **-0.485** | **-0.458** | **-0.493** | **-0.401** | **-0.368** | **-0.496** | -0.221 | **-0.331** | **-0.331** | **-0.264** | **-0.531** | **-0.531** | **-0.544** |
| **2007R** | -0.205 | **-0.354** | **-0.254** | **-0.397** | -0.187 | -0.069 | **-0.430** | **-0.371** | -0.119 | **-0.265** | **-0.260** | -0.118 | **-0.384** | **-0.351** | **-0.351** | **-0.325** | -0.036 | -0.036 | -0.222 |
| **2008R** | **-0.234** | -0.113 | -0.198 | -0.003 | -0.217 | **-0.360** | 0.021 | -0.107 | -0.186 | -0.085 | -0.121 | -0.206 | 0.009 | 0.014 | 0.014 | -0.085 | **-0.435** | **-0.435** | -0.195 |
| **2009R** | **-0.226** | **-0.387** | **-0.341** | **-0.326** | 0.013 | 0.036 | **-0.384** | **-0.296** | **-0.292** | **-0.331** | -0.126 | -0.206 | **-0.293** | **-0.424** | **-0.424** | -0.140 | 0.088 | 0.088 | **-0.226** |
| **2010R** | -0.224 | -0.183 | -0.069 | **-0.310** | **-0.399** | -0.197 | **-0.268** | **-0.339** | -0.004 | **-0.254** | **-0.339** | -0.085 | **-0.356** | -0.204 | -0.204 | **-0.475** | -0.205 | -0.205 | **-0.263** |
| **2011R** | -0.027 | 0.102 | -0.009 | 0.169 | -0.093 | **-0.252** | 0.200 | 0.104 | -0.030 | 0.095 | 0.026 | -0.109 | **0.254** | **0.234** | **0.234** | 0.163 | **-0.303** | **-0.303** | -0.050 |
| **2012R** | **0.483** | **0.475** | **0.500** | **0.308** | 0.179 | **0.379** | **0.567** | **0.411** | **0.478** | **0.296** | 0.213 | **0.468** | **0.265** | **0.392** | **0.392** | **0.255** | **0.375** | **0.375** | **0.424** |
| **2013R** | **0.410** | **0.518** | **0.432** | **0.480** | **0.305** | **0.257** | **0.404** | **0.600** | **0.276** | **0.505** | **0.325** | **0.298** | **0.503** | **0.524** | **0.524** | **0.413** | **0.336** | **0.336** | **0.406** |
| **2014R** | **0.413** | **0.321** | **0.315** | **0.409** | **0.616** | **0.526** | **0.328** | **0.391** | 0.215 | **0.321** | **0.487** | **0.280** | **0.287** | 0.144 | 0.144 | **0.473** | **0.500** | **0.500** | **0.488** |
| **2015R** | 0.209 | -0.010 | 0.035 | 0.031 | **0.367** | **0.306** | 0.010 | 0.071 | 0.025 | -0.113 | 0.125 | 0.076 | -0.016 | -0.105 | -0.105 | 0.203 | **0.400** | **0.400** | 0.167 |
| **2016R** | 0.224 | **0.245** | **0.303** | 0.064 | -0.129 | 0.118 | **0.238** | 0.147 | **0.364** | 0.099 | -0.069 | **0.239** | 0.030 | **0.262** | **0.262** | -0.094 | 0.104 | 0.104 | 0.142 |
| **2017R** | 0.124 | **0.392** | **0.307** | **0.399** | 0.077 | -0.018 | **0.290** | **0.378** | 0.122 | **0.338** | 0.159 | 0.092 | **0.342** | **0.370** | **0.370** | **0.256** | -0.030 | -0.030 | 0.158 |
| **2018R** | **0.410** | **0.319** | **0.427** | **0.488** | **0.661** | **0.575** | **0.292** | **0.378** | **0.335** | **0.284** | **0.444** | **0.232** | **0.241** | 0.157 | 0.157 | **0.419** | **0.498** | **0.498** | **0.456** |
| **2019R** | **0.257** | 0.109 | 0.194 | 0.151 | **0.419** | **0.488** | 0.026 | 0.153 | 0.196 | 0.154 | **0.245** | 0.192 | -0.005 | -0.028 | -0.028 | 0.182 | **0.488** | **0.488** | **0.300** |
| **2020R** | 0.096 | 0.192 | **0.252** | 0.163 | 0.064 | 0.213 | **0.301** | 0.128 | 0.191 | 0.179 | 0.210 | **0.231** | 0.044 | 0.001 | 0.001 | -0.007 | 0.115 | 0.115 | 0.210 |
| **2021R** | 0.056 | 0.084 | 0.144 | 0.105 | 0.061 | 0.186 | **0.271** | 0.082 | 0.097 | 0.156 | 0.215 | 0.217 | 0.040 | -0.055 | -0.055 | -0.013 | 0.094 | 0.094 | **0.623** |

**Values in bold are different from 0 with a significance level alpha=0.05**
**R**=Rainfall Anomaly
**N**=NDVI Anomaly

However, in northern regions, some areas encountered an increase in rainfall, resulting in a rise in the temporal and spatial patterns of vegetation greenness. The connection between precipitation and vegetation dynamics in Erbil was examined using the analysis of NDVI time series and rainfall estimates at varying spatial resolutions. Additionally, it was demonstrated that NDVI could be utilized to assess the impact of weather on vegetation and evaluate its health and productivity. A significant shift in NDVI values was detected during 2008 and 2021, which give support to the findings of a study by (Almamalachy et al., 2019). The study findings depict the consequences of drought on the density of vegetation in the Erbil Province. The impact was severe in the southern parts of the region, as revealed by the NDVI maps spanning 19 years. Notably, the years 2008, 2012, and 2021 were particularly affected by drought (Hakzi, 2022). The variability in NDVI was governed by meteorological factors, such as temperature, precipitation, and relative humidity. The study also attributed spatial variability in NDVI to climate, soil, and topography (Gaznayee et al., 2022). The vegetative cover in the southern region exhibited a decline over the study period due to land degradation processes resulting from drought, which is a significant challenge in the area. (Al-Quraishi, *et al*, 2020; Al-Quraishi, *et al*, 2021; Mzuri, 2021; Gaznayee *et al.*, 2022). In conclusion, the research underscores the importance of monitoring and managing drought episodes in the region to preserve vegetation cover and agricultural output by demonstrating the significant impact of drought on vegetation density in Erbil.

## 5. CONCLUSION

In conclusion, the study conducted in Iraqi Kurdistan, specifically Erbil, using remote sensing and geographical information systems, shed light on the spatiotemporal patterns of drought over a period of 19 years. The research highlighted the occurrence of severe drought episodes in the region, with an increasing trend in severity and frequency, particularly in 2008, 2012, and 2021. These years witnessed reduced vegetation cover and lower average precipitation. The analysis of the Normalized Difference Vegetation Index (NDVI), rainfall, and rainfall anomaly revealed that climate conditions played a significant role in the changes observed in the vegetated cover area. The study also found that irregular rainfall patterns led to modifications in the NDVI, confirming a strong correlation between rainfall and vegetation indices. The productivity of the region was found to be influenced by wet and dry anomalies, with an increase in productivity during wet periods and a decrease during dry periods.

The research also highlighted the discrepancy in vegetation dynamics between the southern and northern regions of Erbil. While the southern areas experienced reduced vegetation cover due to insufficient rainfall and high temperatures, some northern regions witnessed an increase in rainfall and subsequent greening of vegetation. The study emphasized the importance of monitoring and managing drought episodes in the region to safeguard vegetation cover and agricultural productivity. The findings contribute valuable insights into the impact of drought on the density of vegetation in Erbil, emphasizing the need for effective strategies to mitigate the adverse effects of drought on agriculture in the area.

Furthermore, the study corroborated previous research by demonstrating the link between precipitation and vegetation dynamics using NDVI time series analysis. It also emphasized the role of meteorological factors and spatial variability in influencing NDVI values. The research highlighted the challenges posed by land degradation processes resulting from drought, particularly in the southern region of Erbil.

In conclusion, the study's findings emphasize the significance of addressing drought episodes in order to protect vegetation density and agricultural output in Erbil. Monitoring and managing drought conditions using remote sensing techniques and informed strategies can aid in mitigating the adverse impacts of drought on the region's ecosystems and socio-economic systems.

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**Conflict of Interest (1)**

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