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Clarifying the impact of climatic parameters on vegetation in Moulvibazar district

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MAKESENS
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ABSTRACT

In this research, the temporal trends of vegetation from 2000 to 2019 as well as meteorological variables contribution to vegetation change were investigated using the GLAM NDVI, rainfall and temperature data. The MAKESENS revealed that the vegetation growth rate was slow, particularly on a yearly time scale. On the other hand, the rainfall and temperature had a major impact on vegetation growth on a monthly-time scale with a time lag. The lagged effect of rainfall and temperature on vegetation was shown to be a promotion (based on cross-correlation analysis). There was high value of r (0.804) between vegetation and rainfall for a certain lag period, which was significant ($P \leq 0.05$) as per the cross-correlation. Rainfall had a 4-month lag effect on vegetation development, while temperature had a 5 (r = 0.74), − 2 (r = 0.84), − 3 (r = 0.68) month lag effect on vegetation growth. This study's findings revealed changes in vegetation and highlighted the importance of rainfall and temperature in regulating vegetation dynamics. Finally, this study recommended that the effect of more climatic variables on vegetation should be investigated in the context of human activities to better conserve the environment.

1. INTRODUCTION

Vegetation is demonstrated by the Normalized Differential Vegetation Index (NDVI) (Tucker 1979) and is also a common tool for depicting biodiversity transition (Nemani et al. 2003). The evolution of satellite sensor technologies has resulted in obtaining these changes more efficiently and effectively (Shen et al. 2016). To a large extent, these technologies have been used in identifying the location of surface vegetation (Chu et al. 2019) over a long period with high spatial and temporal resolution (Rasmus and Simon 2012). Eastman et al. (2013) used NDVI to assess the validity of remote sensing data, especially for evaluating green vegetation and understanding the moisture content of the vegetation in a given region (Delbart et al. 2005; Jackson et al. 2004).

NDVI is also used in drought and ecosystem monitoring (Gu et al. 2008; Gu et al. 2007). As a result, several studies have shown that NDVI is capable of studying vegetation changes at different scales. NDVI was employed to investigate the spatiotemporal distribution of vegetation (Liu and Lei 2015, Zhang et al. 2013). Furthermore, Shilong et al. 2011 investigated vegetation temporal trends in Eurasia's temperate and boreal regions using the NDVI.

Generally, vegetation connects water, soil, environment, and other natural substances (Nemani et al. 2003). At various scales, the NDVI–climate relationship has been well described in many studies. In regions with abundant water supplies, global warming promotes vegetation growth, while in areas with limited water resources, vegetation growth is seriously hampered (Feng et al. 2016). Rainfall and temperature, which have major effects on vegetation growth and distribution, are the two most important factors affecting vegetation change (Pei et al. 2019; Xu et al. 2015). Nowadays, there are noticeable changes in global climate and environment (Na et al. 2018). The climatic and anthropogenic influences on variations in vegetation patterns and functions are major concerns in ecosystem research (Li et al. 2019). The temperature increased plant activity in the Northern Hemisphere (Mao et al. 2013; Piao et al. 2015), while rainfall had a significant

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impact on NDVI in arid and semi-arid areas (Camberlin et al. 2007; Piao et al. 2011). Also, the early greening of the meadow steppe vegetation is aided by spring climate warming, whereas, the issue of weather change was mitigated by the water shortage of traditional steppe and desert steppe vegetation (Zhao et al. 2015). Rainfall, on the other hand, has a major impact on the variation of vegetation at the inter-annual time scale, whilst, at the monthly time level, the vegetation development is affected by both temperature and rainfall (Liu and Wang 2012).

As a result, the primary concern of researchers is the relation between vegetation and climate due to its clear indicative effect on the ecological system (Eastman et al. 2013). For example, lag period and variation of vegetation due to climatic parameters was investigated by Wu et al 2015. The cross-correlation method of comparing a data set at consecutive lags is applied to assess the time lag effect (Davis 2002). Time series measurements must be taken at corresponding times in a cross-correlation study, i.e., two variables must be calculated at the same time (Posavec et al. 2017). A time series is generated when a collection of observations is organized in a systematic order based on their dates of occurrence. A trend, on the other hand, is a consistent change over time in the time series characteristics (Patra 2008). Detecting the existence of trends can be done using a variety of methods. Sun et al. 2021, for instance, investigated the seasonal changes in the normalized difference vegetation index (NDVI) and then evaluated the spatiotemporal pattern of vegetation using Sen's tendency estimation as well as the Mann–Kendall significance test. Multiple regression, Sen's, and Mann–Kendal methods were used to quantify the effects of rainfall, temperature, and human activities on vegetation (Li et al. 2019). A computer software model named MAKESENS is used for trend analysis which is relying on the nonparametric Mann-Kendall test for trend and nonparametric Sen's method for trend magnitude (Salmi et al. 2002).

Around 63 percent of Bangladesh's tea is produced in Moulvibazar (Islam and Al-Amin 2019). Since vegetation estimation and site characterization are still in their infancy in Bangladesh, the study of vegetation in context of rainfall and temperature has yet to be investigated in this rapidly growing town of Moulvibazar. Therefore, understanding vegetation evolution and change characteristics as a result of climate change necessitates a detailed study of the vegetation-rainfall, temperature relationship.

The study purposes were to analyze the temporal variability and trend of NDVI and other meteorological parameters in the Moulvibazar district. Apart from this, another one is to investigate the relationship between NDVI and climatic factors. This research in particular, investigates the impact of climatic variables on vegetation variation and the subsequent vegetation lag caused by climatic factors. The study clarified the relationship between NDVI and climatic variables, evaluated the correlation at different time scales, and estimated the timing of NDVI response to climatic variables, all of which are important for future studies.

2. MATERIALS and METHOD

2.1. Study Site Description

Moulvibazar district is located at Sylhet division in Bangladesh's north-eastern region (Kabir et al. 2014). The climate in Moulvibazar is humid subtropical. Monsoons, high temperatures, high humidity, and heavy rainfall characterize the climate of Moulvibazar. The hot season begins in early April and lasts until July. Moulvibazar has a mean annual temperature of 24.7 °C. A total of 2,805 mm of precipitation occurs each year (Wikipedia 2020). This town (Fig. 1) has a landscape with a Holocene flood plain, a low raised terrace, and sporadic hillocks from the geomorphological context (Rahman et al. 2018).

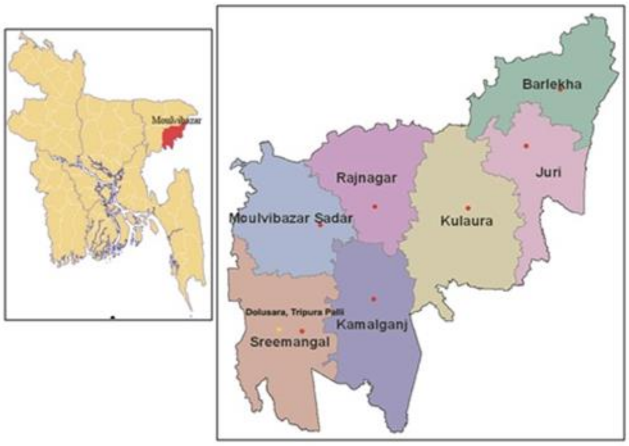


Figure 1. Moulvibazar district

The research used the Global Agriculture Monitoring (GLAM) Terra MODIS 8-day NDVI data in CSV format (https://glam1.gsfc.nasa.gov/) from 2000 to 2019 to investigate the vegetation's temporal distribution. For any given year, this website provides MODIS NDVI images and graphs. The annual NDVI trend can also be compared to the long-term average (NDVI Anomalies) on this website (ARSET Advanced NDVI Webinar Series 2020). NASA Goddard Space Flight Center's GIMMS (Global Inventory Monitoring and Modeling Studies) division, USDA FAS (US Department of Agriculture Foreign Agricultural Service), the South Dakota State University Geographic Information Science Center of Excellence and the University of Maryland-Department of Geography initiated a collaborative research project named GLAM (Becker-Reshef et al. 2010). The project, which started in 2002, is co-financed by USDA-FAS and NASA. It provides timely, easily accessible, remotely sensed data which is scientifically validated for crop condition monitoring and production assessment (USDA FAS 2020). The meteorological data (precipitation and temperature) from 2000 to 2019 within the study area were collected from the Power Data Access Viewer-NASA POWER (https://power.larc.nasa.gov/data-access-viewer/) to examine their impact on vegetation.

2.2. Methods

Initially, the PNG (Portable Network Graphics) formation, which was downloaded from the website https://glam1.gsfc.nasa.gov/, was used to evaluate the oversimplified view of NDVI in the Moulvibazar region. The annual trend of climatic factors and NDVI was then determined using the MAKESENS software. Furthermore, the monthly trend of NDVI was examined in this regard. The correlation was also examined to analyze the influence of climatic variables on vegetation, and the lag period was determined using the cross-correlation process. The website https://exceluser.com/1069/ provided the ready-to-use cross-correlation excel spreadsheet.

2.2.1. The oversimplified view of NDVI in Moulvibazar

For Moulvibazar, an image of NDVI with NDVI anomaly was taken from the GLAM website (https://glam1.gsfc.nasa.gov/) (Fig. 2). An NDVI anomaly is the difference between the average NDVI for a given month in a given year and the average NDVI for the same month over a fixed number of years. This method can be used to compare the health of vegetation in a given month and year relative to what is considered natural, which can be a good indicator of drought or deteriorating vegetation health (ARSET Advanced NDVI Webinar Series 2020).

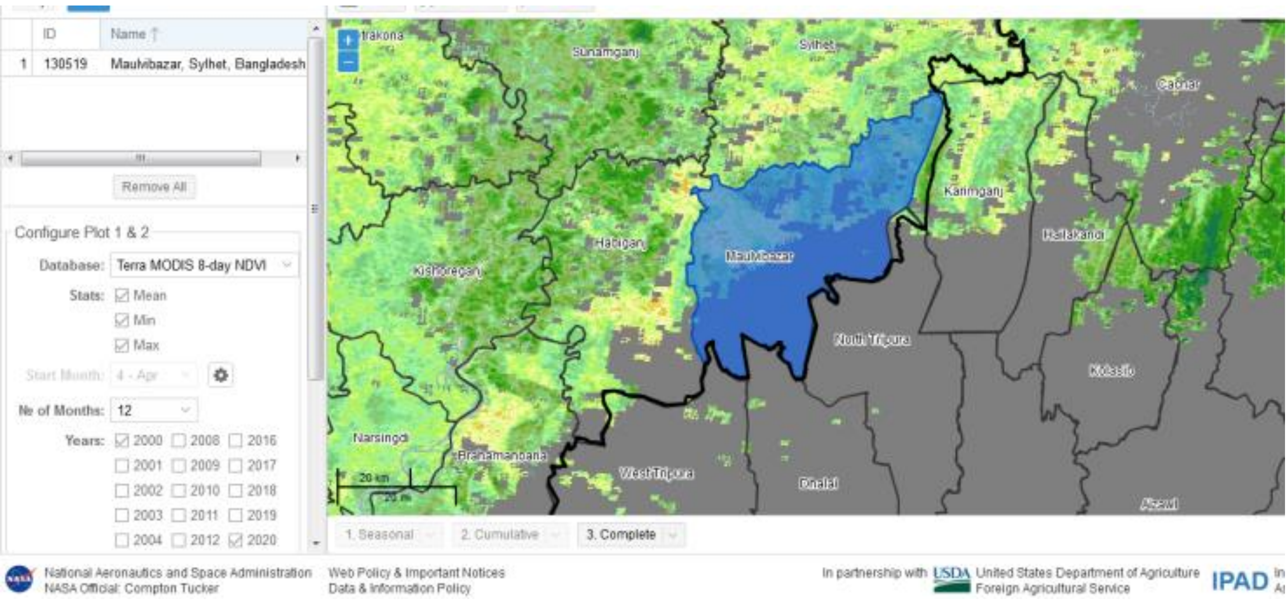


Figure 2. Selection of Moulvibazar district

2.2.2. Trend analysis

For analyzing the sloping pattern of time-series, Sen et al. proposed the Sen's estimation process (Li et al. 2019; Meng et al. 2020). It is a computational method that has the advantage of not being influenced by a lack of data. The MAKESENS method was then employed to calculate the NDVI time series' sloping pattern. The following is the formula:

$$f(t) = Qt + B \tag{1}$$

The $f(t)$ was a monotonically increasing or decreasing time function, the constant was B and the slope was Q. To obtain the slope estimate Q in Eq. (ii), all data value pairs' slopes were first estimated (Li et al. 2019; Meng et al. 2020; Salmi et al. 2002):

$$Q_i = \frac{x_j - x_k}{j - k} \tag{2}$$

Here j and k are the years, and x_j and x_k are the annual values of these years where $j > k$. If the time series had n values x_j the slope Q_i is estimated by $N = n\ (n-1)/2$. Sen's slope estimator was the median of these N values of Q_i (Salmi et al. 2002).

Sen's tendency estimation approach does not provide statistical significance tests for the trend, so the MAKESENS method was used to assess the trend. Since it is nonparametric statistical test, this technique is widely used to detect a monotonic pattern in climate. The MAKESENS method (Li et al.,2019; Meng et al. 2020; Salmi et al. 2002) was as follows:

$$Z = \begin{cases} \frac{S-1}{\sqrt{VAR(S)}} & if\ S > 0 \\ 0 & if\ S = 0 \\ \frac{S+1}{\sqrt{VAR(S)}} & if\ S < 0 \end{cases} \tag{3}$$

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(x_j - x_k) \tag{4}$$

$$sgn(x_j - x_k) = \begin{cases} 1 & if\ x_j - x_k > 0 \\ 0 & if\ x_j - x_k = 0 \\ -1 & if\ x_j - x_k < 0 \end{cases} \quad (5)$$

$$VAR(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p=1}^{q} t_p(t_p - 1)(2t_p + 5)\right] \quad (6)$$

Where S denoted the test statistic and VAR(S) denoted variance of S. q was the number of tied groups and in the pth group, tp was the number of data values. For time series with less than ten data points, the S test was used, and for time series with ten or more data points, the standard approximation (Z) was used.

The number of annual values in the data series under investigation was denoted by the letter n. For four different significance levels in MAKESENS, the two-tailed test was used α: 0.1, 0.05, 0.01, and 0.001. An upward (downward) trend is indicated by a positive (negative) Z value (Salmi et al. 2002).

2.2.3. Relationship and Lag Time Analysis

The lag relationship between hydrothermal factors and vegetation is more pronounced. Therefore, studying the NDVI–climate relationship on a monthly time scale may be more realistic. Climate change affects vegetation in a variety of ways. Vegetation does not always react to climate change immediately, indicating that there is a time lag in vegetation due to climate change. The NDVI–climate relationship was investigated on two-time scales in this study: (i) monthly average NDVI and climatic variables from 2000 to 2019, and (ii) annually average NDVI and climatic variables from 2000 to 2019. In the first case, the NDVI and climate factor mean monthly sequences (January to December) from 2000 to 2019 were used as two sets of variables, and the value of correlation coefficients between them was estimated. On the other hand, the yearly average series of NDVI and climatic factors from 2000-2019 were taken for the second case. The value of correlation coefficients between NDVI and climatic factors was determined in the same way as in the first case. The following is the related formula (Wang et al. 2020; Li et al. 2018):

$$R_{xy}\ (r) = \frac{\sum_{i=1}^{n}[(x_i - \bar{x})(y_i - \bar{y})]}{\sqrt{\sum_{i=1}^{n}[(x_i - \bar{x})^2(y_i - \bar{y})^2]}} \quad (7)$$

where R_{xy} is the Pearson correlation coefficients between variable x and variable y, with a value between −1 and 1, n is the sample size, x_i is the value of NDVI in the ith month, and y_i is the mean monthly climate factors in the ith month, where $\bar{x}$ and $\bar{y}$ are the means of the two variables, respectively. In addition, the ANOVA findings were used to test the significance of the correlation coefficients.

The response time is known as the lag time that corresponds to the maximum of the cross-correlation function (Cai and Ofterdinger 2016). In this analysis, the mean response time of the NDVI in the study region to climatic events was calculated using a cross-correlation function between climatic factors (rainfall, temperature) and NDVI time-series. In order to estimate lag time, a specially developed cross-correlation Excel spreadsheet program was used. The correlation (r) was estimated by the value of NDVI and climatic parameters. The calculation was done by the value of current and previous 1–5-month climatic parameters with the value of NDVI. Furthermore, r was also calculated by the current as well as the previous 1–5 months' NDVI values with climatic factors.

3. RESULTS

3.1. General View of NDVI

Before conducting in-depth studies on NDVI in Moulvibazar, a general view of NDVI would assist in vegetation assessment. Throughout the study period, the range of NDVI values within the study area was shown in Fig. 3 and 4. The NDVI values ranged from - 1 to 0.90 across the entire study region. Besides that, the graphical representation (Fig. 3) depicted a comparison of the NDVI mean from 2001 to 2018 with the 8-day NDVI values. The graph beneath it (Fig. 4) depicted the fluctuation of negative and positive NDVI anomalies over time. Over Moulvibazar, the highest positive anomaly pattern was observed in 2013 and 2017, while the highest negative anomaly pattern was discovered at the end of 2010. In comparison to the positive anomaly pattern, the study zone had more negative anomalies.

3.2. Annual Pattern of Climatic Factors and NDVI

In Fig. 5, the trend of mean annual climatic factors (rainfall, temperature) and NDVI in the Moulvibazar district (as determined by MAKESENS) was illustrated. The trends of NDVI and rainfall (except temperature) were statistically significant at different levels (Table 1). The trend's alternative hypothesis was rejected in temperature, as shown by the blank cell of significance. The NDVI and rainfall both showed a significant upward trend based on positive Z values, with an increased rate of 0.003/year and 0.149 mm/year, respectively (Table 1). The NDVI trend was significant at a level of 0.05 for the entire observation period, while the rainfall time series trend was significant at a level of 0.1. In the case of temperature, however, the rate was zero.

3.3. Monthly Pattern of NDVI

The trends (by MAKESENS) of mean monthly NDVI were shown in Fig. 6. The trends were statistically significant at different levels excluding in months January, June, September, and October (Table 2). The null hypothesis of the trend was accepted in these months, as shown by the significance blank cell. Depending on the positive Z values, the NDVI displayed a noticeable upward trend, which varied between 0.002 and 0.007 per month.

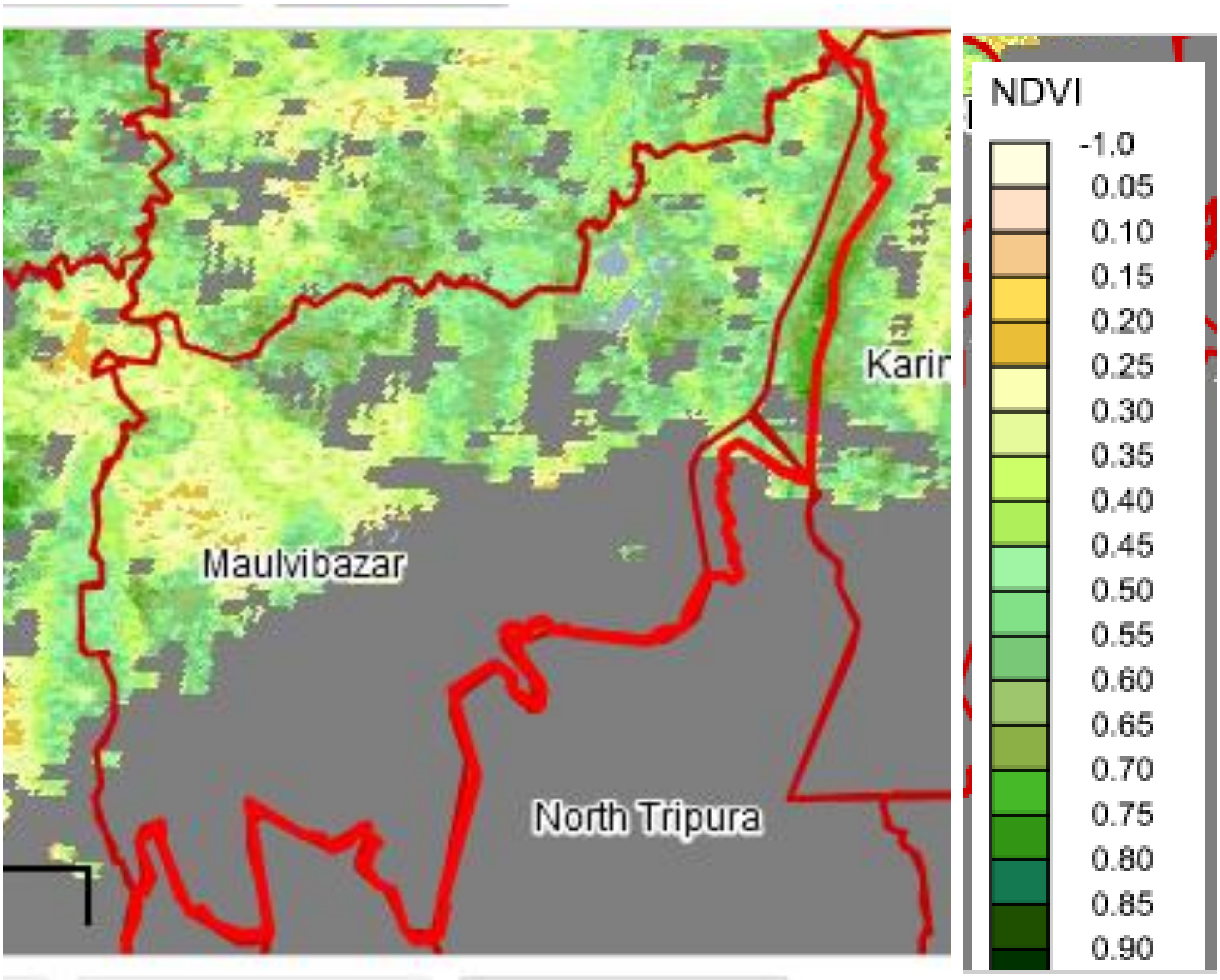


Figure 3. NDVI value in Moulvibazar

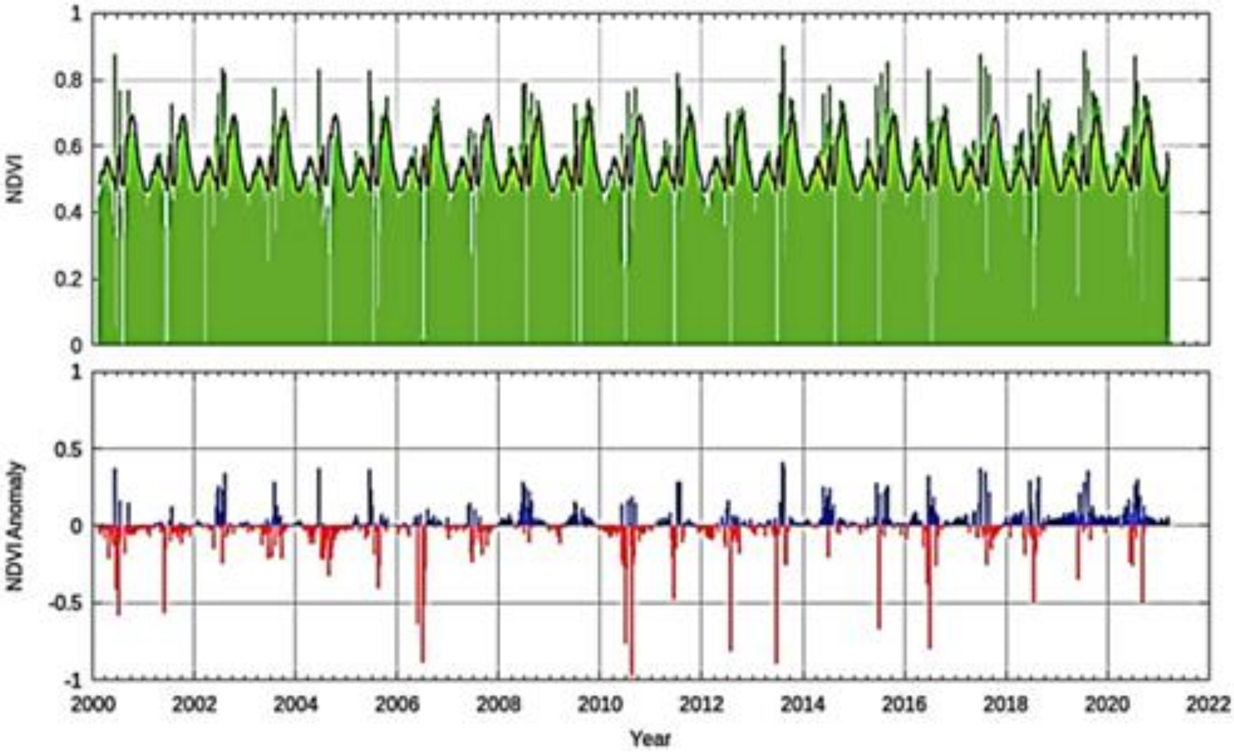


Figure 4. NDVI and NDVI anomaly in Moulvibazar

Table 1. Annual trend of climatic factors and NDVI

Events	First Period	Last Period	Test Z	Rate of Change per Year, Q	Constant, B	Significance of Trend, **α**
NDVI	2000	2019	2.37	0.003	0.50	0.05
Rainfall (mm)	2000	2019	1.78	0.149	5.18	0.1
Temperature (°C)	2000	2019	0.00	0.000	24.40	

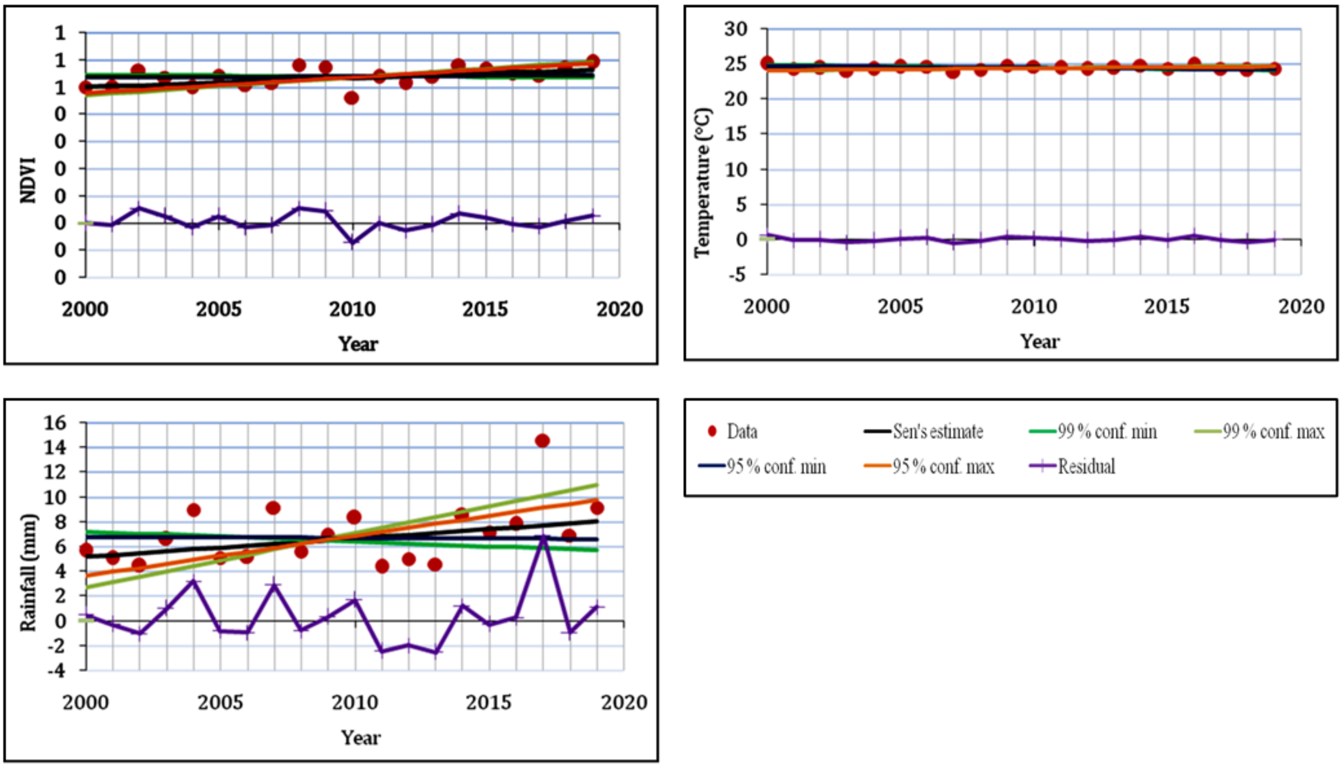
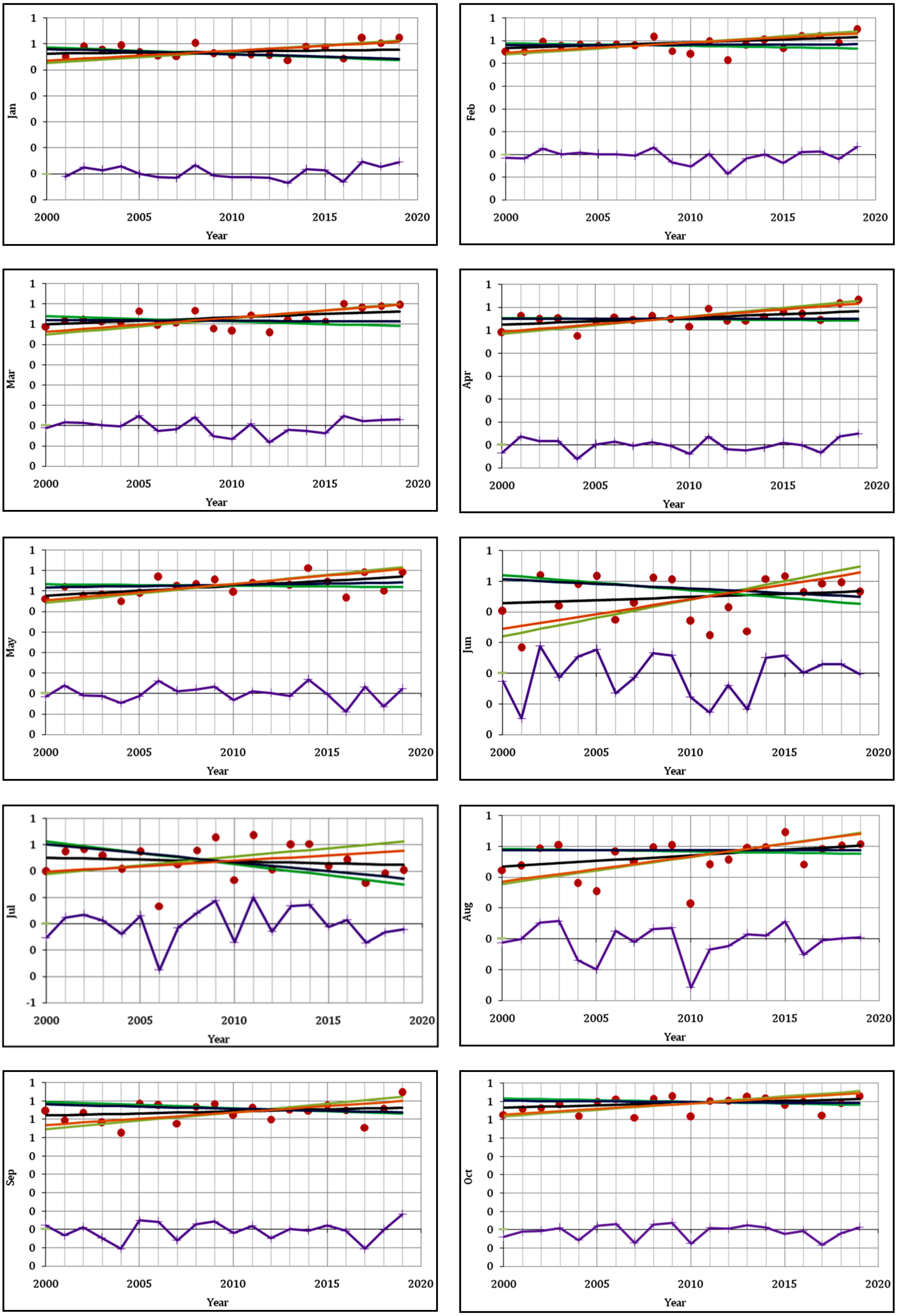


Figure 5. Trends of mean annual NDVI and climatic factors

Table 2. Monthly trend of climatic factors and NDVI

Month	First Period	Last Period	Test Z	Rate of Change per Year, Q	Constant, B	Significance of Trend, **α**
Jan	2000	2019	0.91	0.001	0.46	
Feb	2000	2019	2.04	0.003	0.47	0.05
Mar	2000	2019	1.91	0.003	0.50	0.1
Apr	2000	2019	2.11	0.003	0.53	0.05
May	2000	2019	2.50	0.005	0.48	0.05
Jun	2000	2019	0.55	0.004	0.46	
Jul	2000	2019	-0.49	-0.003	0.50	
Aug	2000	2019	1.98	0.007	0.47	0.05
Sep	2000	2019	1.07	0.002	0.62	
Oct	2000	2019	1.46	0.002	0.67	
Nov	2000	2019	2.08	0.003	0.58	0.05
Dec	2000	2019	2.70	0.002	0.50	0.01


Jan
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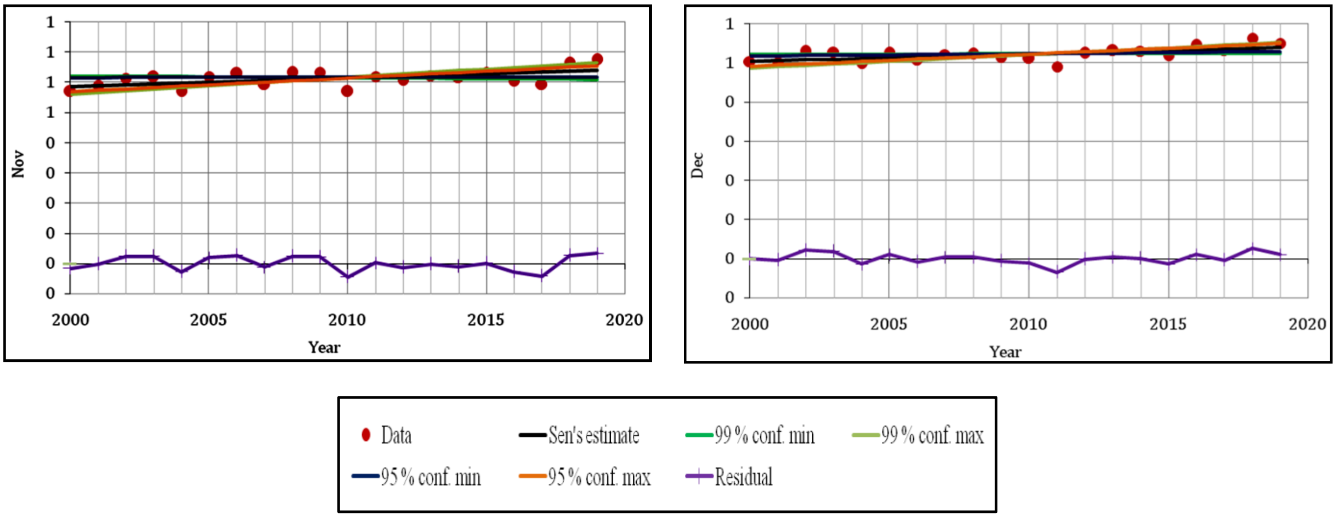

Figure 6. Trends of mean monthly NDVI time series

3.4. Relationships between Climatic Variables and Vegetation

Rainfall and temperature were used in this analysis to demonstrate their impact on NDVI. Rainfall showed an irregular gradient in different years (Fig. 7 (right)), while the distribution of rainfall is highly unequal in month-wise (Fig. 7 (left)) variance. The areas with high rainfall values were observed in 2017 (14.57 mm) (Fig. 7(right)) and in June (15.45 mm) (Fig. 7(left)). On the other side, the low values were distributed mainly in 2011 (4.39 mm) (Fig. 7(right)) and in January (0.16 mm) (Fig. 7(left)). The mean annual rainfall was 6.96 mm (Fig. 7(right)) over the study area and it increased from April to October (Fig. 7(left)) over the study period. The lowest rainfall was observed from November to March (Fig. 7(left)). On the other hand, the temperature also varied (Fig. 8) with the lowest values mainly in January (17.22 °C) and in 2007 (23.92 °C), and with the highest values mainly in July (27.78 °C) and in 2000 (25.07 °C). The areas with high temperature values were noticed from March to October, whereas, low temperature values were observed from November to February (Fig. 8 (left)). From 2000 to 2019, the mean NDVI value in the study region showed distinct characteristics (Fig. 7 and 8). The NDVI fluctuated in a small range maintaining a stability in the region with the lowest value of 0.47 (July) and 0.46 (2010), and the highest value of 0.68 (October) and 0.59 (2019). Almost similar results in the case of annual NDVI with the highest (2017) and lowest (end of 2010) values were also found from section 3.1 (Fig. 4). Every year, the lower values of NDVI were appeared between January and February. On the other side, the higher values were appeared from July to October indicating NDVI changed in a predictable pattern (Fig. 7 (left) and 8 (left)). From the analysis, the highest NDVI was noticed in October while the highest rainfall was found in June. So, the monthly NDVI value was increased corresponding to rainfall with about 4 months lag. Similarly, the monthly NDVI value was increased corresponding to temperature with about 6 months lag. However, the annual relationship was found uneven in both cases.

The correlations R^2 (r) between the climatic parameters and NDVI were evaluated at two-time scales to determine the effects of each on vegetation: (i) one is monthly (Fig. 9(left), 10(left)), and (ii) another is annually (Fig. 9(right), 10(right)). As shown in Fig. 9 and 10, an insignificant correlation was observed with positive value, indicating that both rainfall and temperature had less impact on vegetation over the study area. According to the above results, NDVI with a certain lag time showed frequent changes as climatic factors changed on a regular basis.

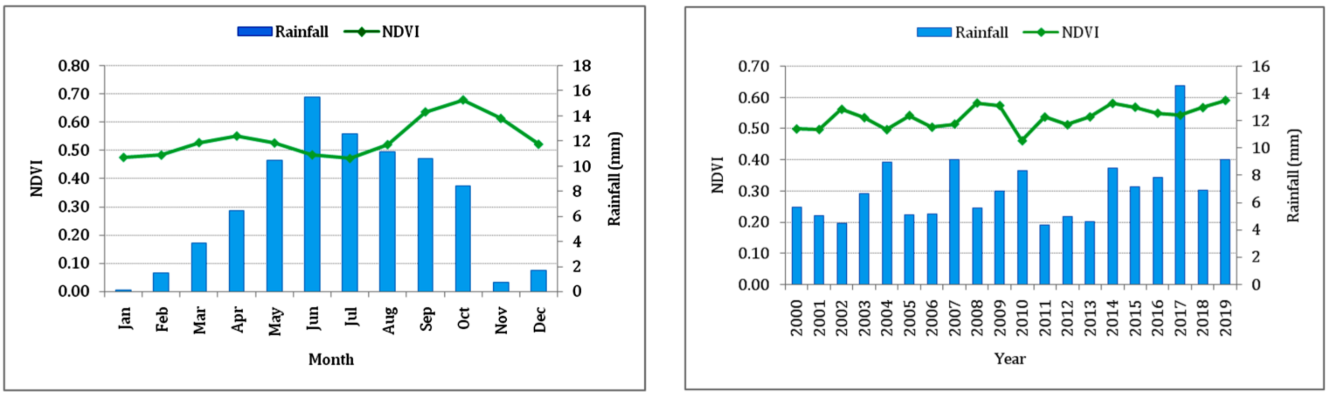

Figure 7. Changes in NDVI and rainfall: (left) monthly average, (right) yearly average

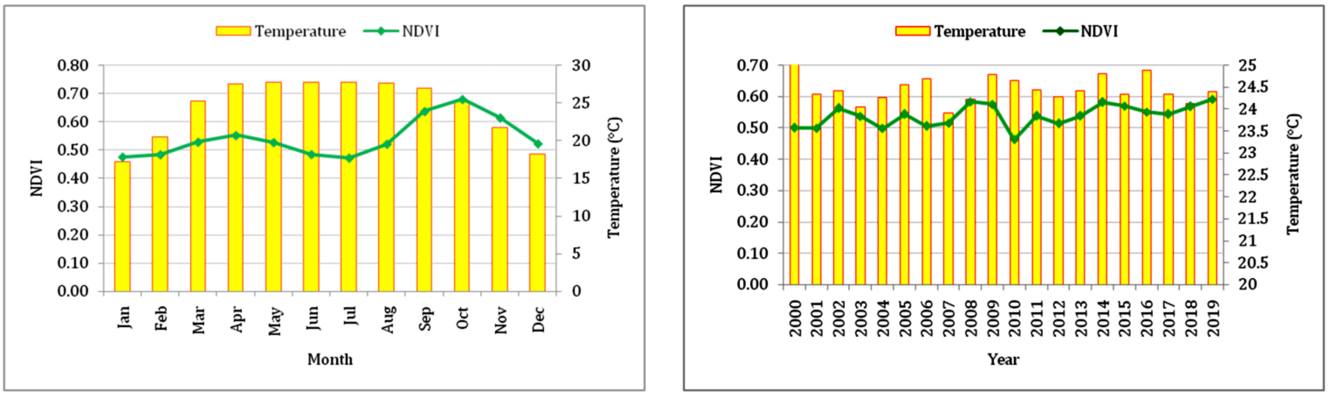

Figure 8. Changes in NDVI and temperature: (left) monthly average, (right) yearly average

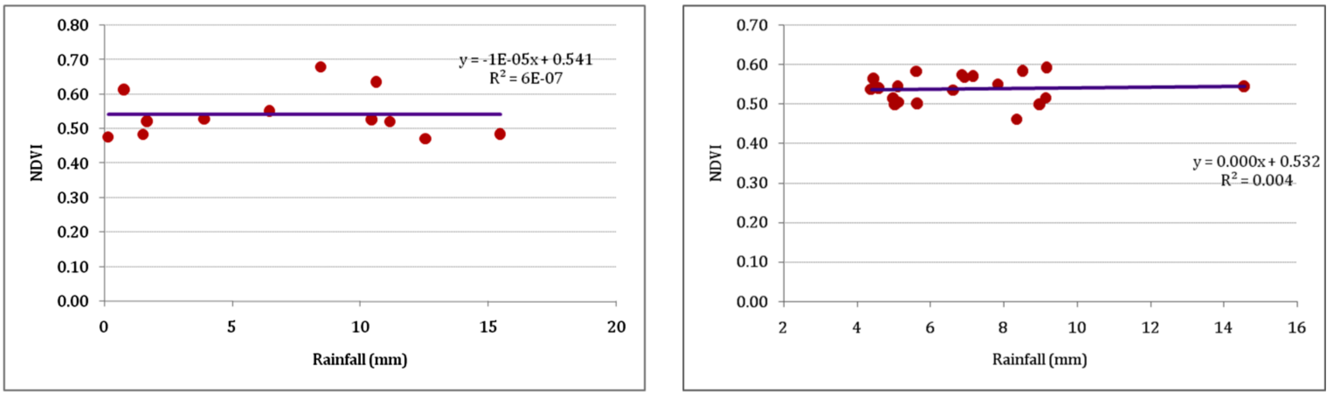

Figure 9. Relation between vegetation and Rainfall: (left) monthly, (right) yearly

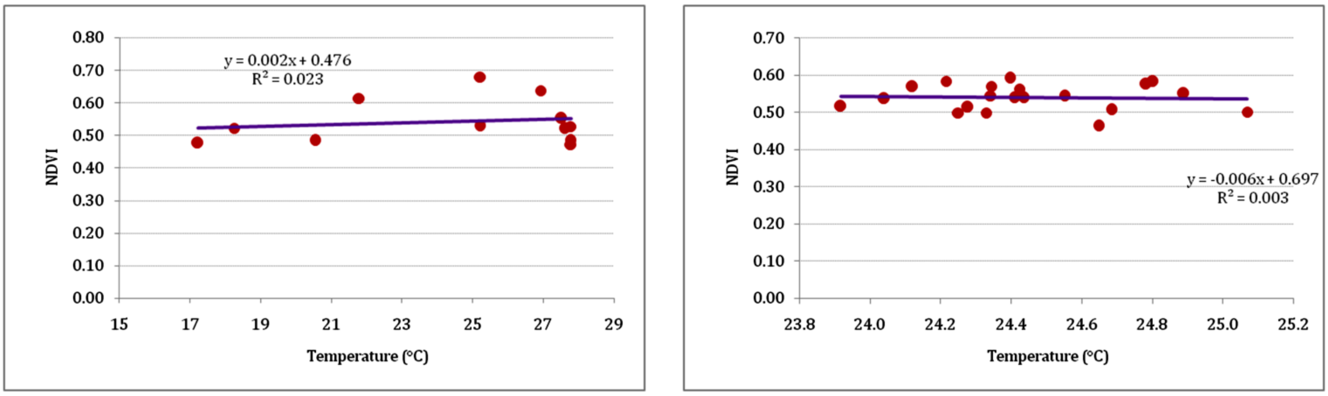

Figure 10. Relation between NDVI and Temperature: (left) monthly, (right) yearly

3.5 Analysis of Lag Period

Since the relationship between monthly NDVI values and climate factors was inconsistent in annual analysis (Fig. 9(right) and 10(right)), the lag between monthly NDVI values and climatic factors was investigated. Fig. 11 depicted the values of the correlations between NDVI and rainfall as well as temperature from 2000 to 2019. The current and previous months' NDVI and climate variables were compared, and the month with the highest correlation coefficient was chosen as the lagged month. At subsequent lags, both positive and negative comparisons are made, with the zero-lag representing the alignment of two data sets at their source.

In terms of rainfall, the study discovered a clear positive relationship (Fig. 11(left)) between NDVI and rainfall in May (r = 0.804, P[1]=0.016), suggesting that vegetation was lagged by four months in receiving rainfall from May. In case of temperature (Fig. 11(right)), the lagged months of NDVI were March, April and June. However, the significant positive correlation in month June (r = 0.74, P = 0.05) and March (r = 0.84, P = 0.002), April (r = 0.68, P = 0.045) indicated that there was monthly lag (5 months, — 2 – 3 months) vegetation due to temperature.

[1] P indicates significance level. If P exceeds 0.05, then it will be insignificant.

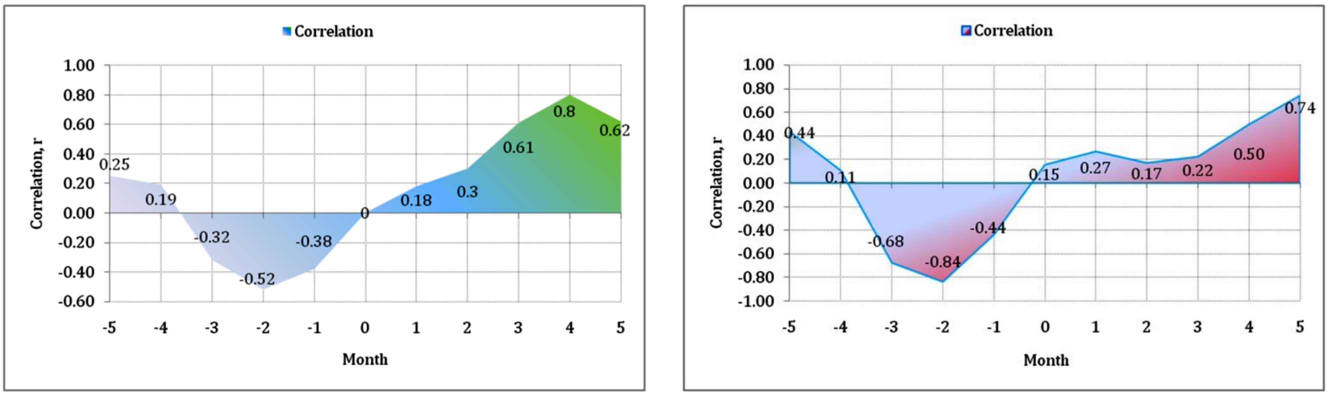

Figure 11. Correlation coefficients between climatic factors: (left) rainfall, (right) temperature and vegetation

4. DISCUSSION

Over the last few decades, vegetation is influenced largely by the effect of human disturbance (Yu et al. 2018), rainfall and temperature change (Li et al. 2019). As a result, studying vegetation change and how it responds to climate change would provide vital information for management of environmental resources (Sun et al. 2021; Li et al. 2019).

The highest (0.59) and lowest (0.46) NDVI values were reported in this analysis in 2019 and 2014, respectively. The NDVI values were ranged from – 1 to 0.09 across the sample region. Various factors promoted the development of vegetation, in which reainfall and temperature playing a significant role (Jiang and Wang 2016). Significant climate change has resulted in the rising of current vegetation pattern (Wang et al. 2005). The NDVI–climate relationship has been difficult to uncover. Some research looked at the influences of rainfall, temperature and anthropogenic activities on arable land in a quantitative way (Shi et al. 2016). Studies have found that the most significant factors influencing vegetation growth were climatic parameters (Pei et al. 2019).

Climate conditions, on the other hand, impact certain places at different time scales. A distinctive relationship between vegetation and climatic factors was observed in different case of annual and monthly time scales. According to MAKESENS there were significant increasing trends (P < 0.05) observed in vegetation growth and rainfall. Similarly, a significant upward trend was also found in vegetation coverage on the Loess Plateau (Sun et al. 2015). In terms of an annual basis trend, the rate of vegetation growth was 0.003. Meanwhile, based on the monthly trend, a growth rate of 0.002 to 0.007 was observed. The increasing rate of rainfall, on the other hand, was 0.149 mm/year, which suggested a low growth rate of rainfall on annual basis.

The highest NDVI value was found in October, while the highest rainfall was identified in June in this study. The explanation for this could be that there was sufficient moisture condition for the development of vegetation as there was too much rain in June, with some of it remaining in the subsurface in October. On the other hand, the highest temperature was recorded in July, and the highest NDVI growth was recorded in October. The reason for this could be that decomposition and mineralization of organic matter would be accelerated as the enzymatic activities of photosynthesis would be stimulated due to rise of temperature (Wan et al. 2005).

NDVI was influenced by temperature and rainfall, and cross-correlation analysis revealed a time lag for climate influences. In general, cross-correlation was defined as the degree to which two series were correlated in terms of lag between them, as well as the method of comparing them at successive lags (Davis 2002). Generally, time lags occurred as different climatic variables changed (Davenport and Nicholson 2007). The NDVI reached at a high value of r (0.804) due to rainfall for a certain lag period, which was significant ($P < 0.05$) according to the cross-correlation. Rainfall had a 4-month lag effect on vegetation development, while temperature had a 5 (r = 0.74), − 2 (r = 0.84), and − 3 (r = 0.68) month lag effect on vegetation growth. Sun et al. 2021 also discovered that rainfall in the end of growth period had a lag of 1-2 months on vegetation development, whereas the temperature in the middle of the growth period had a lag impact of one month.

5. CONCLUSION

The current study used the MAKESENS software, cross-correlation, and ANOVA significance test to investigate the trends of NDVI and their lag period due to climatic conditions. The NDVI's temporal variation revealed that vegetation growth was low, particularly on the yearly-time scale (0.003/year). Furthermore, an assessment revealed that vegetation growth on the monthly-time scale was strongly dominated by rainfall and temperature. Finally, the delayed impact of rainfall and temperature on vegetation was revealed. Rainfall from January to April had a four-month lag effect on vegetation growth, while temperature had a 5, - 2, - 3 months lag on vegetation growth. This study's findings revealed changes in vegetation and highlighted the importance of rainfall and temperature in regulating vegetation dynamics.

This study was limited to find out the temporal variation of vegetation. Instead of considering spatiotemporal data, only MODIS NDVI temporal data were used in this scenario. The effect was assessed using two climatic variables (temperature and rainfall), though there were many other variables, including human activity, which were not addressed. Therefore, to better preserve the environment, the effects of climatic conditions on NDVI should be analyzed under the circumstance of global climate change. Meanwhile, the human activities on vegetation should be analyzed quantitatively.

Author contributions

Mst. Mahbuba Khatun: Conceptualization, Methodology, Software, Data curation, Writing-Original draft preparation. **Debajani Chakraborty:** Validation, Writing-Reviewing and Editing. **Ifterkharul Alam:** Visualization, Investigation.

Conflicts of interest

The authors declare no conflicts of interest.

REFERENCES

ARSET Advanced NDVI Webinar Series (2020). Winter 2016, Session 3, MODIS NDVI Time Series. Available online: accessed on November 25, 2020, Retrieved from https://appliedsciences.nasa.gov/sites/default/files/202011/ndvipart3exercise.pdf.

Becker-Reshef I, Justice C, Sullivan M, Vermote E, Tucker C, Anyamba A, Small J, Pak E, Masuoka E, Schmaltz J, Hansen M, Pittman K, Birkett C, Williams D, Reynolds C & Doorn B (2010). Monitoring Global Croplands with Coarse Resolution Earth Observations: The Global Agriculture Monitoring (GLAM) Project. Remote Sensing, 2(6), 1589–1609.

Cai Z & Ofterdinger U (2016). Analysis of groundwater-level response to rainfall and estimation of annual recharge in fractured hard rock aquifers, NW Ireland. Journal of Hydrology, 535, 71-84.

Camberlin P, Martiny N, Philippon N & Richard Y (2007). Determinants of the interannual relationships between remote sensed photosynthetic activity and rainfall in tropical Africa. Remote Sensing of Environment, 106(2), 199–216.

Chu H, Venevsky S, Wu C & Wang M (2019). NDVI-based vegetation dynamics and its response to climate changes at Amur-Heilongjiang River Basin from 1982 to 2015. Science of the Total Environment, 650, 2051–2062.

Davenport M L & Nicholson S E (2007). On the relation between rainfall and the normalized difference vegetation index for diverse vegetation types in east Africa. International Journal of Remote Sensing, 14(12), 2369–2389.

Davis J C (2002). Statistics and Data Analysis in Geology. John Wiley & Sons, Inc., New York, Third Edition, ISBN: 978-0-471-17275-8.

Delbart N, Kergoat L, Toan T L, Lhermitte J & Picard G (2005). Determination of phenological dates in boreal regions using normalized difference water index. Remote Sensing of Environment, 97(1), 26– 38.

Eastman J R, Sangermano F, Machado E A, Rogan J & Anyamba A (2013). Global trends in seasonality of normalized difference vegetation index (NDVI), 1982–2011. Remote Sensing, 5(10), 4799–4818.

Exceluser, 2020: Accessed on 25-6-2020, Retrieved from https://exceluser.com/1069/.

Feng X, Fu B, Piao S, Wang S, Ciais P, Zeng Z, Lü Y, Zeng Y, Li Y, Jiang X & Wu B (2016). Revegetation in China's Loess Plateau is approaching sustainable water resource limits. Nature Climate Change, 6, 1019–1022.

GLAM, 2020: Accessed on 25-6-2020, Retrieved from https://glam1.gsfc.nasa.gov/.

Gu Y, Brown J F, Verdin J P & Wardlow B (2007). A five-year analysis of MODIS NDVI and NDWI for grasslanddrought assessment over the central Great Plains of the United States. Geophysical ResearchLetters, 34(6).

Gu Y, Hunt E, Wardlow B, Basara J B, Brown J F & Verdin J P (2008). Evaluation of MODIS NDVI and NDWI for vegetation drought monitoring using Oklahoma Mesonet soil moisture data. Geophysical ResearchLetters, 35(22).

Islam M N & Al-Amin M (2019). Life behind leaves: Capability, poverty and social vulnerability of tea garden workers in Bangladesh. Labor History, 60(5), 571–587.

Jackson T J, Chen D, Cosh M, Li F, Anderson M, Walthall C, Doriaswamy P & Hunt E R (2004). Vegetation water content mapping using Landsat data derived normalized difference water index for corn and soybeans. Remote Sensing of Environment, 92(4), 475– 482.

Jiang C & Wang F (2016). Environmental Change in the Agro-Pastoral Transitional Zone, Northern China: Patterns, Drivers, and Implications. International Journal of Environmental Research and Public Health, 13, 165.

Kabir M H, Hasan N, Rahman M M, Rahman M A,Khan J A, Hoque N T, Bhuiyan M R Q, Mou S M, Jahan R &Rahmatullah M (2014). A survey of medicinal plants used by the Deb barma clan of the Tripura tribe of Moulvibazar district, Bangladesh. Journal of Ethnobiology and Ethnomedicine, 10(19).

Li C, Wang J, Hu R, Yin S, Bao Y & Ayal D Y (2018). Relationship between vegetation change and extreme climate indices on the Inner Mongolia Plateau, China, from 1982 to 2013. Ecological Indicators, 89, 101–109.

Li Y, Xie Z, Qin Y & Zheng Z (2019). Estimating Relations of Vegetation, Climate Change, and Human Activity: A Case Study in the 400 mm Annual Precipitation Fluctuation Zone, China. Remote Sensing, 11, 1159.

Liu S L & Wang T (2012). Climate change and local adaptation strategies in the middle Inner Mongolia, northern China. Environmental Earth Sciences, 66, 1449–1458.

Liu Y & Lei H (2015). Responses of natural vegetation dynamics to climate drivers in China from 1982 to 2011. Remote Sensing, 7(8), 10243–10268.

Mao J, Shi X, Thornton P E, Hoffman F M, Zhu Z &Myneni R B (2013). Global Latitudinal-Asymmetric Vegetation Growth Trends and Their Driving Mechanisms: 1982- 2009. Remote Sensing, 5(3), 1484–1497.

Meng X, Gao X, Li S & Lei J (2020). Spatial and temporal characteristics of vegetation NDVI changes and the driving forces in Mongolia during 1982–2015. Remote Sensing, 12(4), 603.

Na L, Na R, Zhang J, Tong S, Shan Y, Ying H, Li X &Bao Y (2018). Vegetation Dynamics and Diverse Responses to Extreme Climate Events in Different Vegetation Types of Inner Mongolia. Atmosphere, 9(10), 394.

Nemani R R, Keeling C D, Hashimoto H, Jolly W M, Piper S C, Tucker C J, Myneni R B & Running S W (2003). Climate-driven increases in global terrestrial net primary production from 1982 to 1999. Science, 300, 1560–1563.

Patra K C (2008). Hydrology and water resources engineering. New Delhi: Narosa Publishing House, Second edition, ISBN:978-81-7319-846-5.

Pei Z, Fang S, Yang W, Wang L, Wu M, Zhang Q, Han W &Khoi D N (2019). The Relationship between NDVI and Climate Factorsat Different Monthly Time Scales: A Case Study of Grasslands in Inner Mongolia, China (1982–2015). Sustainability, 11(24), 7243.

Piao S, Tan J, Chen A, Fu Y H, Ciais P, Liu Q, Janssens I A, Vicca S, Zeng Z, Jeong S J, Li Y, Myneni R B, Peng S, Shen M &Penuelas J (2015). Leaf onset in the northern hemisphere triggered by daytime temperature. Nature Communications, 6, 6911.

Piao S, Wang X, Ciais P, Zhu B, Wang T & Liu J (2011). Changes in satellite-derived vegetation growth trend in temperate and boreal Eurasia from 1982 to 2006. Global Change Biology, 17(10), 3228–3239.

Posavec K, Vukojević P, Ratkaj M & Bedeniković T (2017). Cross-correlation Modelling of Surface Water–Groundwater Interaction Using the Excel Spreadsheet Application. The Mining-Geology-Petroleum Engineering Bulletin, 25-32.

Rahman M Z, Hossain M S, Kamal A S M M, Siddiqua S, Mustahid F & Farazi A H (2018). Seismic site characterization for Moulvibazar town, Bangladesh. Bulletin of Engineering Geology and the Environment, 77, 1451–1471.

Rasmus F & Simon R P (2012). Evaluation of Earth Observation based global long term vegetation trends—Comparing GIMMS and MODIS global NDVI time series. Remote Sensing of Environment, 119, 131–147.

Salmi T, Maatta A, Anttila P, Ruoho-Airola T & Amnell T (2002). Detecting Trends of Annual Values of Atmospheric Pollutants by the Mann-Kendall Test and Sen's Slope Estimates -The Excel Template Application MAKESENS. User Manual, Air Quality, Finnish Meteorological Institute, Helsinki, Finland. Accessed on 25-9-2020, Retrieved from https://en.ilmatieteenlaitos.fi/documents/30106/335634754/MAKESENS Manual_2002.pdf/25bbe115-7f7e-4de3-97d8-5a96ac88499f.

Shen X J, Liu B H & Zhou D W (2016). Using GIMMS NDVI time series to estimate the impacts of grassland vegetation cover on surface air temperatures in the temperate grassland region of China. Remote Sensing Letters, 7, 229–238.

Shilong P, Wang X, Ciais P, ZHU B, Wang T & Liu J (2011). Changes in satellite-derived vegetation growth trend in temperate and Boreal Eurasia from 1982 to 2006. Global Change Biology, 17(10), 3228–3239.

Shi X, Wang W & Shi W (2016). Progress on quantitative assessment of the impacts of climate change and human activities on cropland change. Journal of Geophysical Sciences, 26, 339–354.

Sun H, Wang J, Xiong J, Bian J, Jin H, Cheng W & Li A (2021). Vegetation Change and Its Response to Climate Change in Yunnan Province, China. Advances in Meteorology, 2021, 1-20.

Sun W Y, Song X Y, Mu X M, Gao P, Wang F & Zhao G J (2015). Spatiotemporal vegetation cover variations associated with climate change and ecological restoration in the Loess Plateau. Agricultural and Forest Meteorology, 209, 87–99.

Tucker C J (1979). Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment, 8(2), 127–150.

USDA FAS (2020). GLAM-Global Agricultural Monitoring. Accessed on 21-9-2020, Retrieved from http://www.pecad.fas.usda.gov/glam.cfm (accessed on November 21, 2020).

Wan S, Hui D, Wallace L & Luo Y (2005). Direct and indirect effects of experimental warming on ecosystem carbon processes in a tallgrass prairie. Global Biogeochemical, Cycles, 19(2), GB2014, doi:10.1029/2004GB002315.

Wang X, Chen F H, Dong Z & Xia D (2005). Evolution of the southern Mu Us Desert in north China over the past 50 years: An analysis using proxies of human activity and climate parameters. Land Degradation & Development, 16(4), 351–366.

Wang Y, Shen X, Jiang M & Lu X (2020). Vegetation change and its response to climate change between 2000 and 2016 in marshes of the Songnen plain, northeast China. Sustainability, 12(9), 3569.

Wikipedia, 2020: Moulvibazar. Accessed on 25-6-2020, Retrieved from https://en.wikipedia.org/wiki/Moulvibazar.

Wu D, Zhao X, Liang S, Zhou T, Huang K, Tang B & Zhao W (2015). Time-lag effects of global vegetation responses to climate change. Global Change Biology, 21(9), 3520–3531.

Xu Y, Yang J & Chen Y (2015). NDVI-based vegetation responses to climate change in an arid area of China. Theoretical and Applied Climatology, 126, 213–222.

Yu X, Ding S, Zou Y, Xue Z, Lyu X & Wang G (2018). Review of rapid transformation of floodplain wetlands in northeast China: roles of human development and global environmental change. Chinese Geographical Science, 28(4), 654–664.

Zhang Y, Gao J, Liu L, Wang Z, Ding M & Yang X (2013). NDVI-based vegetation changes and their responses to climate change from 1982 to 2011: a case study in the Koshi river basin in the middle Himalayas. Global and Planetary Change, 108, 139–148.

Zhao X, Hu H, Shen H, Zhou D, Zhou L, Myneni R B & Fang J (2015). Satellite-indicated long-term vegetation changes and their drivers on the Mongolian Plateau. Landscape Ecology, 30, 1599–1611.