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Analysis of Vegetation Dynamics and Responses to Inter-annual Changes of Climatic Variables in Dry Afromontane Forest Fragments, Northern Ethiopia

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Abstract Understanding the current changes and dynamics of different vegetation communities under the background of climate change provides basis for ecological restoration in drylands. The spatiotemporal variations of vegetation growth and their relationships with climatic variables across the arid and semi-arid parts of northern Ethiopia have not yet been well researched. This study analyzed the trends (changes) in vegetation greenness of the dry Afromontane forests of northern Ethiopia and examined their relationships with the climatic variations for the period 2000-2016, based on space-based vegetation index derived from the Moderate Resolution Imaging Spectroradiometer (MODIS13Q1) product and gridded high-resolution climate datasets. A simple linear regression model, correlation analysis, and trend analysis (using Mann-Kendall test and Theil-Sen median trend analysis) were used to assess vegetation dynamics and their responses to climate variability. Results of the study showed a general decreasing trend in vegetation greenness and slight warming trends, with considerable spatiotemporal variations. The NDVI-rainfall relationships were positive in both study sites, implying that rainfall is the main factor which determines vegetation growth in the study region. Future works may need to concentrate on time-series data with better quality (e.g. high resolution) and incorporate land use change and other eco-climatological factors into the study to better account for the spatiotemporal vegetation variability.

Keywords Climate Change, Dry Afromontane Forest, Normalized Difference Vegetation Index, Trend Analysis, Vegetation Dynamics

1. Introduction

Dryland vegetation has enormous socio-economic and ecological benefits. Nevertheless, they are already at greater risk mainly due to threats from climatic and anthropogenic factors [1, 2]. Recent studies claimed that the effects of anthropogenic disturbances on forest ecosystems seem to outweigh the climate-induced impacts [3, 4]; but, projections into future scenario also show serious repercussions of climate change in the dry tropics [5]. In addition to the human-induced land use changes, climate will continue to play an important role in the dynamics of dryland systems [6, 7]. Climate change may directly affect the growth and population dynamics of trees growing in drylands [8, 9], mainly through variations in rainfall and temperature [10]. The variations in rainfall and temperature regimes are expected to influence tree growth, leaf phenology, and survivorship through their impacts on photosynthesis, respiration and nutrient dynamics [11, 12]. [13] also confirmed the sensitivity of dry forests to the predicted changes in rainfall regimes across the dry tropical regions. But, the future of these ecosystems remains uncertain in the face of the changing climate.

The effects of climate change are expected to be even pronounced in the dry tropics given their high sensitivity to the climate anomalies, such as frequent occurrences of extreme heat, increasing aridity and erratic rainfall patterns. The climate in the tropics and sub-tropics will get warmer and drier, with some exceptions in East Africa, the Sahel, the Guinean coast and southern Sahara where there is a likelihood of increment in rainfall, but with a high level of uncertainty [14]. This will likely result in various drastic transformations, including losses of biodiversity, species

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range shifts, altered tree productivity, and an overall extinction risks to the already endangered species living in the highly fragmented environments [15, 12, 16]. This will possibly alter the balance and functioning of the ecosystem, with subsequent negative impacts on the livelihoods of the forest-dependent people. Many dry forests and woodlands in the tropics are expected to be highly vulnerable to climate-induced forest dieback [17, 18]. This is particularly true for countries such as Ethiopia, where much of its landmass (over 72% of the total land area) is categorized under dryland area [19]. Therefore, understanding the response of dryland vegetation to climate change is emerging as a major research agenda [20]. In this regard, knowledge of the current changes and dynamics of various vegetation communities in the face of climate change has crucial roles in planning sustainable forest management strategies.

A common approach used to detect the response of vegetation to climate change is the satellite-derived vegetation index (VI). The Normalized Difference Vegetation Index (NDVI) is among the most widely used VI [21, 22]. The NDVI, a normalized ratio of the near-infrared and red spectral reflections, is often directly related to percentage of ground cover, photosynthetic activity of plants, surface water, leaf area index and amount of biomass [23]. Thus, analysis of NDVI trend and its relationships with climatic variables help in understanding the temporal trend of vegetation's biophysical characteristics at different spatial scales and hence have crucial implications for research on climate and vegetation dynamics [24]. Previous studies have proven the wide applicability of undertaking correlation analyses between NDVI time-series and climatic variables for examining vegetation dynamics and their responses to climate change in varied bioregions [25-29, 20]. Although these several studies conducted hitherto demonstrated the existence of close relationship between vegetation dynamics and climate change, such studies have to be replicated across various spatial and temporal scales. This helps to investigate the emerging complex relationships and to properly understand the extent to which climate change is affecting ecosystem structures and functioning.

In general, the NDVI has been used as a proxy for analysing vegetation dynamics and it is expected to show large temporal and spatial variations in different climatic regions and for different vegetation types [30-32, 29]. NDVI data derived from NOAA/AVHRR have been widely used to quantify vegetation activity [33, 22]. Recently, the NDVI dataset derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) improved the spatial resolution of the previous products and enabled a thorough examination of vegetation dynamics at various scales [34, 35]. Thus, this study examined vegetation dynamics in the dry Afromontane forest remnants of northern Ethiopia using the MODIS NDVI (2000-2016) and further investigated if such vegetation trends can be explained by the long-term climate trends. Since the decline in dryland forest productivity can be interpreted as a sign of widespread drought stress, we expected NDVI to be positively correlated with moisture availability.

2. Materials and Methods

2.1. Study Area

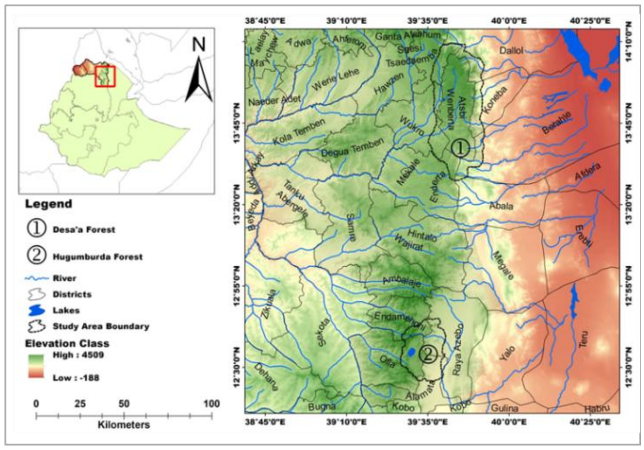

Figure 1. Location of the Study Area

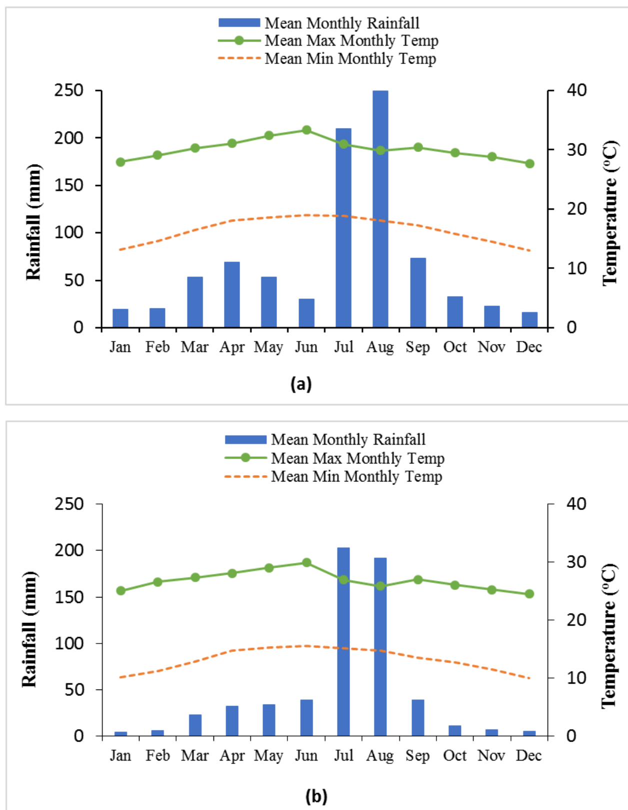

Figure 2. Mean Monthly Rainfall and Mean Monthly Temperature (Maximum and Minimum) Records (1980-2016) of the Study Areas, (a) Hugumburda and (b) Desa'a, Northern Ethiopia

The study was conducted in Desa'a (13°40′ to 13°50′ N, 39°47′ E) and Hugumburda (12°38′ N, 39°32′ E) forests, the two major dry Afromontane forest remnants in northern Ethiopia. These forests are mainly located along the western escarpment of the Great Rift Valley facing the Afar depression [36]. The area falls in the semi-arid agro-ecological zone of Tigray region (Figure 1) where the climate is influenced by topography and exposures to rain-bearing winds [37].

The regional climate shows a distinct seasonality in rainfall with a unimodal rainfall pattern. The mean annual rainfall was estimated at 532 mm in Desa'a [38] and 981 mm in Hugumburda [36]. The core rainy season occurs between June and September, while the remaining extended periods are more or less dry (Figure 2).

Large areas of these forests are characterized by shallow soils and frequent rock outcrops. The dominant soil types are Leptosols, Cambisols, Vertisols, Regosols, and Arenosols [36]. The study sites are generally characterized by rugged topography. These forests are broadly classified as dry Afromontane forests and are dominated by *Juniperus procera* and *Olea europaea subsp. cuspidata.*

2.2. Data Sources and Processing

2.2.1. NDVI Data

NDVI data derived from the Moderate Resolution Imaging Spectroradiometer (MODIS13Q1) product from NASA (USGS) was used for the period 2000-2016 as a proxy for vegetation growth and change detection. The MODIS NDVI product has a spatial resolution of 250 m and a temporal resolution of 16 days composites and was downloaded from http://earthexplorer.usgs.gov/. This product is based on the MODIS sensor on-board NASA's Terra (EOS AM) and Aqua (EOS PM) satellites. The land imaging component of the MODIS sensor combines characteristics of AVHRR (Advanced Very High Resolution Radiometer) and Landsat sensors to provide improved monitoring of the earth's surface at global scales. The NDVI data acquired from the MODIS 16-days composite datasets from 2000 to 2016 were calculated by the amount of reflectance in near-infrared (ρ_2: Band 2, 858 nm) and red (ρ_1: Band 1, 645 nm) portions of the electromagnetic spectrum. These have a spatial resolution of IFOV 250 m.

$$NDVI_{MODIS} = {(\rho_2 - \rho_1)} \Big/ {(\rho_2 + \rho_1)} \quad (1)$$

Then, the NDVI values were corrected by a scale factor (0.0001). The NDVI time-series were aggregated to monthly, seasonal and annual averages to detect the NDVI trends in the given time period. These values measure the seasonal and temporal pattern of vegetation greenness, vigour, or productivity. Intra- and inter-annual dynamics in leaf phenology is often assessed using NDVI [39]. Thus, annual and season NDVIs were generated by computing averages of the respective monthly NDVI values. The dynamics in NDVI values is used to assess the intra- and inter-annual dynamics in vegetation growth [40]. The mean NDVI values were calculated in ArcGIS 10.3 using zonal statistics.

2.2.2. Climate Data

The availability of weather stations in the study sites is extremely low and the existing climate records were fragmentary (i.e., short climatic records containing missing values for several months and/or years). This imposed difficulties for understanding the temporal and spatial climate variability of the study region, which is characterized by a complex topography. Therefore, high-resolution climate datasets from AgMERRA (at 0.25-degree resolution) [41] and the latest version of the Climate Research Unit time-series (CRU TS 4.01) datasets (at 0.5-degree resolution) [42] were used in this study. These global grid datasets are widely used climate data sources in several studies. Especially, the climate data developed by the Climate Research Unit (CRU) of the University of East Anglia have been widely used in several studies given its global coverage, long temporal scale (since 1901) and abundance of climatic variables [43]. These global grid datasets were used to derive temperature (minimum and maximum) and rainfall data and to supplement any fragmentary climate data. The combined climate data spans the period 1901-2016. For the NDVI-climate analyses, the climate data from 2000 to 2016 was used in accordance with the MODIS NDVI data.

2.3. Data Analysis

2.3.1. Trend Analysis

The study employed a combination of three commonly used methods of trend analysis, the least-square linear regression, the Mann-Kendall test, and the Theil-Sen's slope trend test, to detect and characterize the trends in vegetation dynamics and climatic variables in the study region. These methods are widely used in analysing patterns of directions and magnitude (rates of changes) of the trends of NDVI and climatic time-series datasets [44, 30, 31]. The slope of the regression equation (developed using the linear least square fitting of the long-term NDVI series) was applied to analyse the direction of vegetation change [45, 46, 39, 20].

$$Slope = \frac{n \times \sum_{i=1}^{n}(i \times Y_i) - (\sum_{i=1}^{n} i)(\sum_{i=1}^{n} Y_i)}{n \times \sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2} \quad (2)$$

Where, n is the accumulative number of years during the study period (n = 17 years in this study), variable i stands for the year number, and Y_i is the value of the dependent variable in the i^{th} year. In general, if the slope > 0, the variation of the dependent variable exhibits an increasing trend, whereas if slope < 0, it represents a decreasing trend.

The Mann-Kendall test, a non-parametric rank-based test, analyses the strength of the trend patterns using Z statistic values [40, 20]. The mathematical equations for calculating Mann-Kendal test statistic (S), Variance of S [VAR(S)] and the standardized test statistics Z are as follows:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(X_j - X_k) \quad (3)$$

$$sgn(X_j - X_k) = \begin{cases} 1 \; if \; X_j - X_k > 0 \\ 0 \; if \; X_j - X_k = 0 \\ -1 \; if \; X_j - X_k < 0 \end{cases} \quad (4)$$

The mean of S is E[S] = 0 and the variance, VAR(S) is:

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

$$Z = \begin{cases} \frac{S-1}{\sqrt{VAR(S)}} \; if \; S > 0 \\ 0 \; if \; S = 0 \\ \frac{S+1}{\sqrt{VAR(S)}} \; if \; S < 0 \end{cases} \quad (6)$$

Where, X_i and X_j are the time-series observations, n is the length of the time-series, p is the number of the tied groups in the dataset and t_j is the number of data points in the j^{th} tied group.

The Theil-Sen method calculates the non-parametric (rank-based) median slope of the fitted trend line of the NDVI time-series and serves as an indicator of magnitude or quantitative rate of change in the vegetation greenness over time [44, 30, 31]. In this test, first a set of linear slopes are calculated as follows:

$$d_k = \frac{X_j - X_i}{j - i} \quad (7)$$

For $(1 \leq i < j \leq n)$, where d is the slope, X denotes the variable n is the number of data, and i and j are indices. The Sen's slope is then calculated as the median from all slopes: b = Median d_k. The intercepts are computed for each time-step t as given by the following equation:

$$a_t = X_t - b * t \quad (8)$$

The corresponding intercept is as well the median of all intercepts. This function also computes the lower and upper confidence limits for the Sen's slope.

2.3.2. NDVI-Climate Relationship

After estimating the trends in NDVI, rainfall, and temperature, the study further analysed the relationships between NDVI values and climatic variables (rainfall and temperature). The correlations between NDVI and climatic variables were analysed during 2000-2016. The strength of the linear association between NDVI values and climatic variables was assessed by calculating the Pearson's product moment correlation coefficient [30, 31, 20, 45, 40, 44]. The formula for the Pearson's r is given as follows:

$$r_{xy} = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \quad (9)$$

Where, n is the sample size, X_i and Y_i represent observations of independent and dependent variables, respectively, and $\bar{X}$ and $\bar{Y}$ are the corresponding average values. r_{xy} is the coefficient for the two samples, which indicates the degree of correlation between the two factors, and its value is in the range of [-1, 1]. When r > 0, it means that they are positively correlated, whereas when r < 0, they are negatively correlated. In general, the larger the absolute value of the correlation coefficient, the stronger is the correlation between each variable.

A 95% significance level was used to determine the strength of the relationships. Various studies revealed that correlation analyses between NDVI time-series and climatic variables are widely applied for examining vegetation dynamics and their responses to climate change in varied bioregions [25-29, 20]. Before undertaking the analyses, each time-series data was standardized by subtracting the mean of the time-series and dividing by the standard deviation. R programming language software (mainly in R commander) was used for all the statistical data analyses. R programming language is powerful and license free software capable of performing a wide variety of statistical tests ranging from simple to sophisticated analyses with little programming. It is highly extensible with user-submitted packages for specific functions. A script developed in the R environment allows easy reproducibility of analysis. It has a lot of functionalities and vast package ecosystem making it highly flexible and powerful for dealing with data management, analysis and graphic presentations. In general, R software is a well-developed, simple and effective programming language which is compatible with all computer operating systems. It includes an integrated suite of software facilities for data manipulation, calculation and graphical display. Therefore, R programming language remains the best analytical tool for various statistical tests, including linear and non-linear modelling, classical statistical tests, time-series analysis, classification, and clustering, among others. Consequently, R software was chosen for analysing the time-series datasets used in this study. Accordingly, this study used specific functions in the trend package within the time-series package for the data analyses. The mathematical basis for these analyses are presented in the aforementioned equations. In general, analyses results are statistically significant at P<0.05 unless stated otherwise.

3. Results

3.1. Trends in Vegetation Greenness

Table 1 presents a summary of descriptive statistical parameters of the NDVI values in both study sites for the period 2000-2016. The mean NDVI values recorded were 0.6878±0.0155 (± SE) and 0.5800±0.0244 (± SE) in Hugumburda and Desa'a, respectively (Table 1). The variability of annual NDVI values, as measured by the coefficient of variation, was higher in Desa'a site than Hugumburda site.

Using a linear regression analysis, we showed the changes in NDVI trends during 2000-2016 in the dry Afromontane forest remnants of northern Ethiopia. The NDVI changing patterns were analysed based on the slope which is the gradient of the trend line (Figure 1). Results of the monthly NDVI values showed an increasing trend towards the main rainy season in the region. Although variations were noticed across the study periods, we, generally, observed a gradual increment in NDVI starting from June towards the end of the main growing season (September) and starts to drop thereafter. In both study sites, the maximum NDVI values were recorded in August and September. The NDVI trends of both study sites during 2000-2016 as estimated by means of the least-squares linear regression, Theil-Sen's slope trend test and the Mann-Kendall test score are presented in Figure 3 and Table 2.

Table 1. Descriptive Statistics of NDVI Values (2000-2016)

Variable	Hugumburda site			Desa'a site		
	Mean NDVI	Max NDVI	Min NDVI	Mean NDVI	Max NDVI	Min NDVI
Range	0.2868	0.2305	0.4270	0.4524	0.4296	0.3684
Minimum	0.6353	0.6905	0.4769	0.4943	0.5396	0.3703
Maximum	0.9220	0.9210	0.9039	0.9468	0.9692	0.7387
Mean	0.6878	0.7443	0.5338	0.5800	0.6385	0.4534
SE Mean	0.0155	0.0125	0.0238	0.0244	0.0231	0.0203
Median	0.6772	0.7292	0.5166	0.5609	0.6143	0.4424
SD	0.0640	0.0516	0.0979	0.1006	0.0954	0.0836
CV	9.31	6.93	18.35	17.34	14.94	18.43

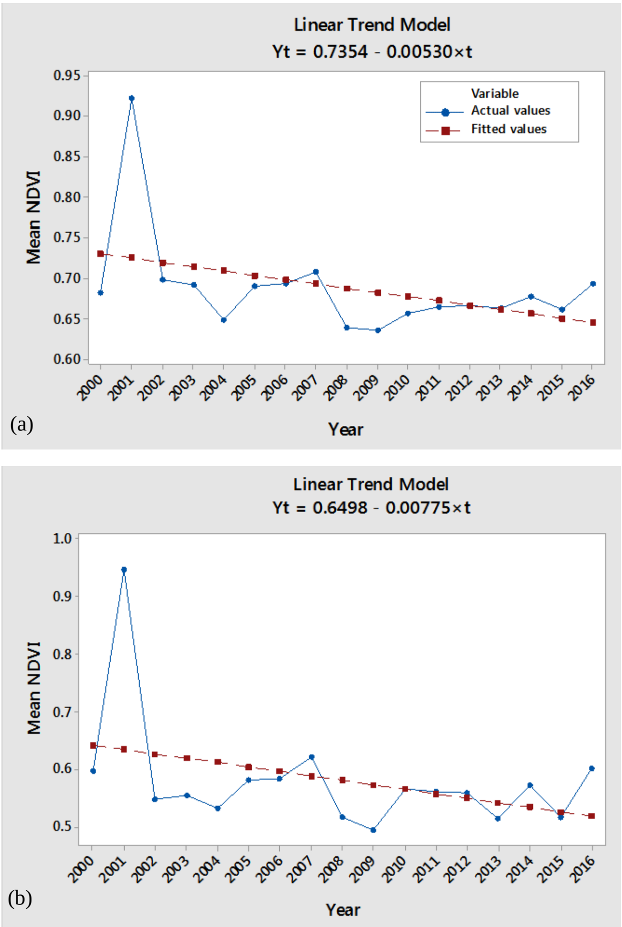

Figure 3. Trend Analysis Plot (2000-2016) for Mean Annual NDVI Changes in two Sites, (a) Hugumburda and (b) Desa'a Sites, in Northern Ethiopia. The Dotted Lines Represent LOWESS Smoothing Line

The study further analysed the inter-annual NDVI trends using the Mann-Kendall test and Thiel-Sen median trend analysis method. The inter-annual trend of NDVI values for the period 2000-2016 alternated between greening (increasing) and browning (decreasing) trends in both study sites, with a peak value recorded in the year 2001.

Overall, the results showed a decreasing trend of vegetation greenness across the study periods in both study sites. Nevertheless, the changes in annual NDVI values were not significant at the 5% significance level, with the exception of the minimum NDVI value in Desa'a site which showed significant vegetation degradation. Based on the results of the Theil-Sen slope, the annual change rates were -0.002 for Hugumburda and -0.003 for Desa'a. In general, results of the Mann-Kendall test and Theil-Sen median trend analysis (Table 2) confirmed that the overall trend of vegetation greenness is slightly decreasing with time even though an increasing trend was also noticed in certain areas. The degree of vegetation degradation is more serious in Desa'a site as compared to that of Hugumburda site.

Table 2. Mann-Kendall and Sen's Slope Tests Results of NDVI Changes for the Period 2000-2016

Site	NDVI values	Mann-Kendall's tau (τ)	Sen's slope (s)	P-value
Hugumburda	Mean NDVI	-0.2058824	-0.001558673	0.26610
	Max NDVI	-0.2941176	-0.003084956	0.10820
	Min NDVI	-0.1176471	-0.0009434204	0.53660
Desa'a	Mean NDVI	-0.1617647	-0.002970642	0.38700
	Max NDVI	-0.2647059	-0.003640219	0.14940
	Min NDVI	-0.3970588	-0.005439763	0.02902*

*Significant Trend at 5% Significance Level of Two-tailed Tests

3.2. Trends in Climatic Variability

Table 3 presents a summary of descriptive statistics of the climatic variables in both study sites for the period 1980-2016. Higher amount of mean annual rainfall (848.7 mm) was recorded in Hugumburda site than in Desea site. The coefficient of variation (CV), which measures dispersion around the mean, was also computed to determine the variability of annual rainfall and temperature in the study sites. The variability of annual rainfall was higher in Hugumburda compared to that of Desa'a site, whereas the variation for both maximum and minimum temperature was higher in Desa'a site (Table 3).

The inter-annual changes in rainfall and temperature (minimum and maximum) in the period 1980-2016 are presented in Figure 4. In Desa'a site, the minimum and maximum temperature recorded were 28℃ (in 2007) and 12℃ (in 2011), respectively. The minimum temperature recorded in Hugumburda site was 15℃ in 2005, while the maximum temperature was 30°C in 2015. In general, temperature showed a slightly increasing but insignificant trend in both study sites. But, the trend in minimum temperature was significant in both study sites ($p<0.05$) (Table 4).

Table 3. Descriptive Statistical Attributes of Rainfall and Temperature for the Period 1980-2016

Variable	Hugumburda site			Desa'a site		
	Rainfall	Tmax	Tmin	Rainfall	Tmax	Tmin
Range	944.0	2.517	1.933	590.7	2.683	1.883
Minimum	455.7	28.642	15.325	352.4	25.175	12.117
Maximum	1399.7	31.158	17.258	943.1	27.858	14.000
Mean	848.7	30.107	16.455	595.3	26.823	13.119
SE Mean	37.1	0.105	0.0740	19.6	0.106	0.0768
Median	819.6	30.133	16.508	583.3	26.892	13.158
SD	225.4	0.640	0.450	119.3	0.645	0.467
CV	26.56	2.13	2.73	20.04	2.40	3.56

Note: Tmax= mean annual maximum temperature, Tmin= mean annual minimum temperature

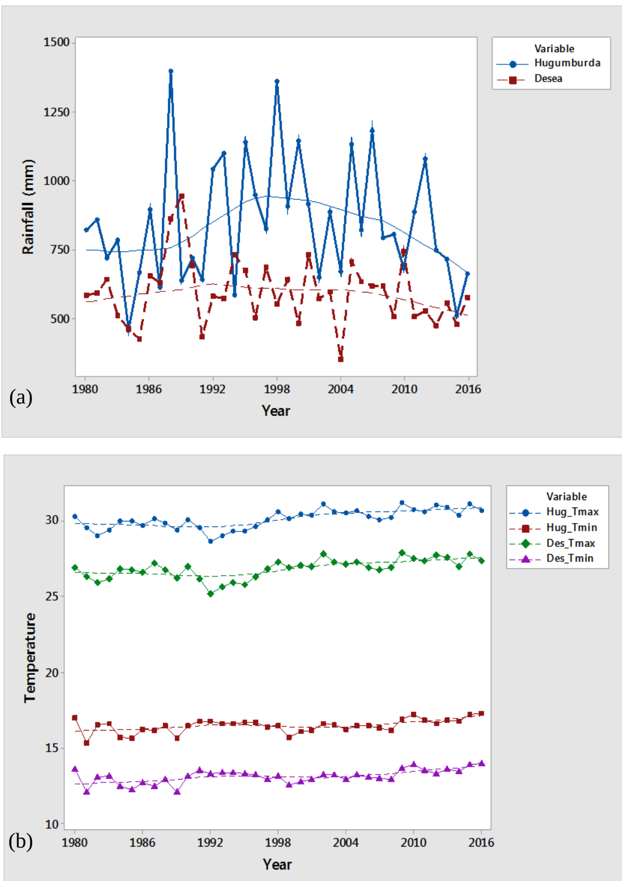

Figure 4. Trend Analysis Plot (with LOWESS Smoothing Curves) for (a) Mean Annual Rainfall and (b) Mean Annual Temperature (Maximum and Minimum) in Hugumburda and Desa'a Sites of the Dry Afromontane Forest Remnants in Northern Ethiopia for the Period 1980-2016

On the other hand, the temporal changes in rainfall showed a negative trend during the study period. Peak values of rainfall were recorded in 2005, 2007 and 2012 in Desa'a site. The maximum value of mean annual rainfall recorded in Desa'a was 943.1 mm, and 1399.7 mm in Hugumburda. It is evident from the figure that considerable spatiotemporal variations in temperature and rainfall were observed in the study region both temporally and spatially.

Table 4. Mann-Kendall and Sen's Slope Tests Results for Rainfall and Temperature (*Significant Trend at 5% Significance Level of Two-tailed Tests)

Site	Climate variable	Mann-Kendall's tau (τ)	Sen's slope (s)	P-value
Hugumburda	Annual RF	-0.3235294	-15.95455	0.07651
	Tmax	0.2533202	0	0.2478
	Tmin	0.51245	0	0.0168*
Desa'a	Annual RF	-0.78266	-5.675	0.4338
	Tmax	0.2435441	0	0.2684
	Tmin	0.5092286	0	0.0177*

3.3. Relationships between NDVI Trends and Climatic Variables

The study analysed the relationships between NDVI trends (2000-2016) and changes in climatic variables (rainfall and temperature) in the semi-arid region of northern Ethiopia. Results of the correlation analysis between the area-averaged mean NDVI values and climatic variables in both study sites are presented in Table 5.

The correlations showed considerable variations spatially over the study periods. Positive correlations were found between the mean NDVI values and rainfall in the vegetated areas of both study sites. The correlations in Desa'a site were significant ($P<0.05$) (Table 5). But, the NDVI values correlated negatively with temperature, and significant correlations (at 5% significance level) were found in April and June-September.

In addition, correlation coefficients (Pearson's r) were calculated between the seasonally-averaged NDVI values and the corresponding seasonal rainfall and temperature to determine the relationship between vegetation dynamics and the seasonal climatic variables. The mean NDVI showed different responses to the changes in the climatic variables.

On a seasonal scale, most positive correlations occurred during the rainy season, exceeding all other seasons (Figures 5 and 6). Negative correlations were observed during the dry season. Spatially, the positive correlations between NDVI and rainfall in Hugumburda site were significantly higher than those in Desa'a site.

The study further analysed the correlations between NDVI and rainfall of the same month in both study sites. Stronger correlations were found between NDVI during August ($r=0.665$, p-value=0.004) and September ($r=0.494$, p-value=0.044) in Hugumburda site, and NDVI during May ($r=0.491$, p-value=0.045) and August ($r=0.346$, p-value=0.174) in Desa'a site.

Table 5. Correlation Coefficients (Pearson's r) for NDVI and Climate Variables

Site	NDVI values	Annual rainfall	Wet season rainfall	Max temperature	Min temperature
		r(p-value)	r(p-value)	r(p-value)	r(p-value)
Hugumburda	Mean NDVI	0.209 (0.422)	0.438 (0.079)	-0.286 (0.266)	-0.343 (0.178)
	Max NDVI	0.270 (0.295)	0.435 (0.081)	-0.279 (0.277)	-0.391 (0.120)
	Min NDVI	0.152 (0.561)	0.383 (0.129)	-0.224 (0.386)	-0.309 (0.227)
Desa'a	Mean NDVI	0.511 (0.036)*	0.397 (0.115)	-0.395 (0.117)	-0.346 (0.174)
	Max NDVI	0.585 (0.014)*	0.481 (0.050)*	-0.443 (0.075)	-0.382 (0.130)
	Min NDVI	0.560 (0.020)*	0.488 (0.047)*	-0.393 (0.118)	-0.427 (0.087)

*At the 0.05 Level was Significantly Correlated

Table 6. Correlations (Pearson's r) between Seasonally-averaged NDVI Values and Corresponding Climatic Variables (Rainfall and Temperature; Tmax = Maximum Temperature, and Tmin = Minimum Temperature); Correlations with p-value <0.05 are Significant

Site	Season	Rainfall (mm)	Tmax (℃)	Tmin (℃)
		r(p-value)	r(p-value)	r(p-value)
Hugumburda	Autumn	-0.490 (0.046)	0.168 (0.519)	0.330 (0.195)
	Winter	0.074 (0.778)	-0.170 (0.514)	0.049 (0.853)
	Spring	0.286 (0.265)	0.037 (0.889)	-0.003 (0.991)
	Summer	0.323 (0.206)	-0.296 (0.249)	-0.303 (0.238)
Desa'a	Autumn	0.038 (0.888)	0.025 (0.926)	-0.022 (0.935)
	Winter	-0.135 (0.606)	-0.305 (0.235)	-0.096 (0.713)
	Spring	0.501 (0.04)	-0.261 (0.312)	0.141 (0.588)
	Summer	0.272 (0.291)	-0.409 (0.103)	-0.134 (0.607)

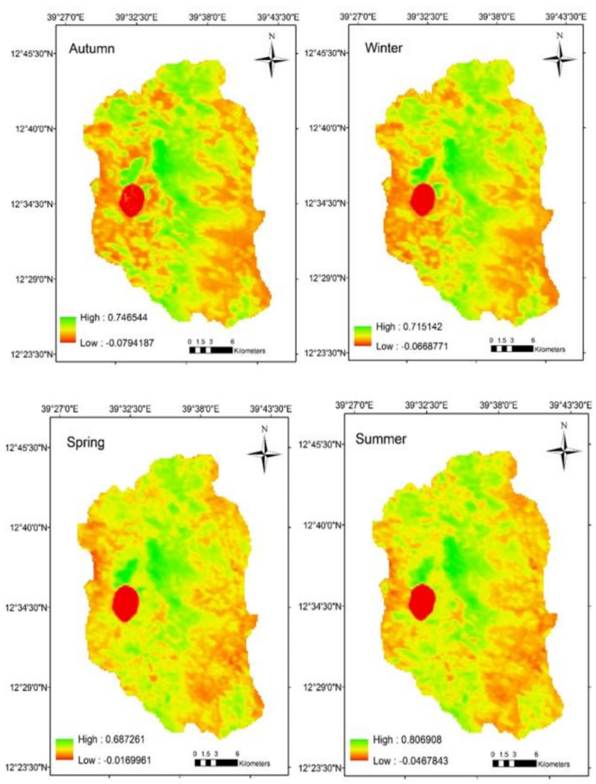

Figure 5. Spatial Distribution of Seasonal NDVI Changes from 2000 to 2016 in Hugumburda Site, Northern Ethiopia

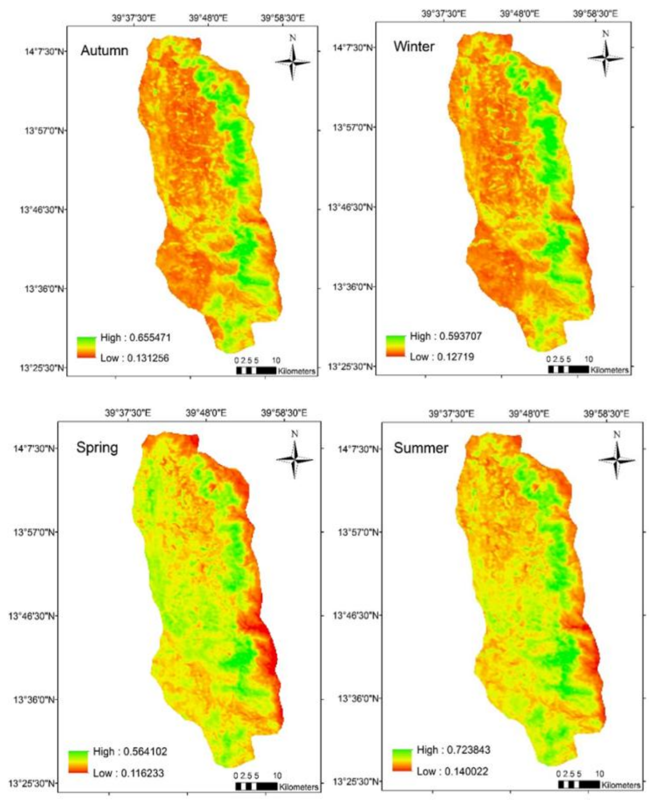

Figure 6. Distribution of Seasonal NDVI Changes from 2000 to 2016 in Desa'a Site, Northern Ethiopia

Figures 5 and 6 show the spatial distribution of NDVI values and were used to determine the overall relationship between vegetation dynamics and seasonal climatic variables during 2000-2016. Higher NDVI values were recorded during the summer season in both study sites confirming that rainfall remains the main factor affecting vegetation growth in the dry Afromontane forests of northern Ethiopia.

4. Discussion

This study analysed the trends in vegetation greenness and climatic variables in the semi-arid region of northern Ethiopia. Besides, correlation analyses were undertaken between the climate datasets and NDVI time-series to analyse vegetation responses to climate variability in the study region. The results showed an overall decreasing (browning) trend of vegetation cover, with considerable spatiotemporal variability. Rainfall remained an overriding factor in determining the spatiotemporal variability in NDVI trends.

4.1. Analyses of Trends

Using a combination of a least-square linear regression analysis, Mann-Kendall test and Theil-Sen median trend analysis, this study examined the changes in trends of NDVI values and the main climatic variables in the dry Afromontane forests of northern Ethiopia. Previous studies [e.g. 44, 20] confirmed that the changes in NDVI trends can best be described using the results of the Mann-Kendall test and the Theil-Sen median trend analysis. Accordingly, the significance level of the changes in NDVI trends was determined using the Z-values at 5% significance level. The results of the Mann-Kendall test were classified into insignificant changes (if $-1.96 < Z < 1.96$) or significant changes (if $Z \geq 1.96$ or $Z \leq -1.96$). Besides, the patterns of trends in NDVI values and climatic variables were classified following the approach of [20] (Table 7).

Table 7. Classification of NDVI Trend Changes using the Sen's Slope and Z-values

Group	S_{NDVI}	Z-values	Description of NDVI trend
1	≥ 0.001	≥ 1.96	Significant improvement
2	0.0001 to 0.001	-1.96 to +1.96	Slight improvement
3	-0.0001 to 0.0001	-1.96 to +1.96	Stable or non-vegetated
4	-0.001 to -0.0001	-1.96 to +1.96	Slight degradation
5	< -0.001	≤ -1.96	Significant degradation

Source: adapted from [20]

The results showed no significant (obvious) trend of both vegetation dynamics and climate variability. The vegetation change alternated between increasing (greening) and decreasing (browning) trends. Similar vegetation dynamics trends were reported by [30]. Besides, slight warming was observed (especially the minimum temperature showed a significant trend) in the study region, while rainfall showed a decreasing trend. The results showed that the trend patterns of NDVI and the climatic variables (rainfall and temperature) were spatially and temporally heterogeneous, alternating between increasing and decreasing trends. However, the results showed an overall decreasing trend of vegetation greenness in both study sites across the study periods (2000-2016). These results indicate that the study region experienced considerable vegetation degradation during the study periods.

Table 8. Results of the Mann-Kendall Test (Z) and Theil-Sen Median Trend (S) Analysis Showing Trend Patterns of NDVI (MaxNDVI = Maximum NDVI, MinNDVI = Minimum NDVI) and Climatic Variables (R ainfall and Temperature; Tmax = Maximum Temperature and Tmin = Minimum Temperature)

Variable	Hugumburda		Desa'a	
	S	Z	S	Z
Mean NDVI	-0.0016	-1.1122	-0.0029	-0.8651
MaxNDVI	-0.0031	-1.6065	-0.0036	-1.4417
MinNDVI	-0.0009	-0.6179	-0.0054	-2.1832
Annual rainfall	-15.955	-1.7713	-5.6750	-0.7827
Tmax	0	1.1558	0	1.1068
Tmin	0	2.3910	0	2.3717

In light with the warming climate and anthropogenic pressures, we expected increasing vegetation degradation in the study region. As expected, a browning trend of vegetation greenness was found in both study sites and this was congruent with the trends in rainfall. The results confirm the assertion that moisture availability during the main growing season remains the primary limiting factor to tree growth in arid and semi-arid regions [30].

Obviously, as confirmed by several studies, the large spatiotemporal variability of NDVI trends are expected across different climatic regions and for different vegetation communities [31]. Some showed an increasing trend in greenness in various bioregions, including the northern high latitudes (e.g. 40, 31] and in the Sahel region [45]. Others have shown decreasing trends in vegetation growth in many parts of the globe, for example, in central Asia [29], and across the boreal forests [47]. Such vegetation changes were reported to be closely linked with the trends in climatic variables. In the high latitudes, greening trends are largely controlled by temperature, while in other regions (e.g. in Africa, China, and the United States) vegetation productivity is highly linked to precipitation anomalies [52, 31]. [46] found vegetation improvement in some areas and at the same time vegetation degradation in others, and both temperature and rainfall were the driving factors. In line with this study, [20] reported a decreasing trend of vegetation greenness for shrubs and sparse vegetation types of desert regions and attributed it to the impacts from increased drought occurrence (i.e., increased temperature and decreased precipitation). Even though the study highlighted drought to be the main factor affecting vegetation degradation, it equally identified human-induced degradation.

4.2. Relationships between Vegetation Dynamics and Climatic Variables

Previous studies have already proven the wide applicability of undertaking correlation analyses between NDVI time-series and climatic variables for examining vegetation dynamics and their responses to climate change in varied bioregions [25-29, 20]. The spatiotemporal patterns of vegetation are continuously changing worldwide owing to the continuous upheavals from climatic and anthropogenic factors. Large temporal and spatial variations in NDVI trends are expected in different climatic regions and for different vegetation types [30, 31]. Thus, this study analysed vegetation dynamics over the past two decades and their responses to the changing climatic variables.

In this study, the correlation between NDVI and climate variables were analysed in the semi-arid region of northern Ethiopia. Results of the correlation analyses revealed a general correspondence between vegetation dynamics and climatic variations. The study region experienced slight warming and decreasing rainfall, and this is congruent with the declining trend in vegetation growth. The decline in vegetation growth can, therefore, partly be explained by the recurrent drought events due to the changes in rainfall and temperature and the complex relation with other factors.

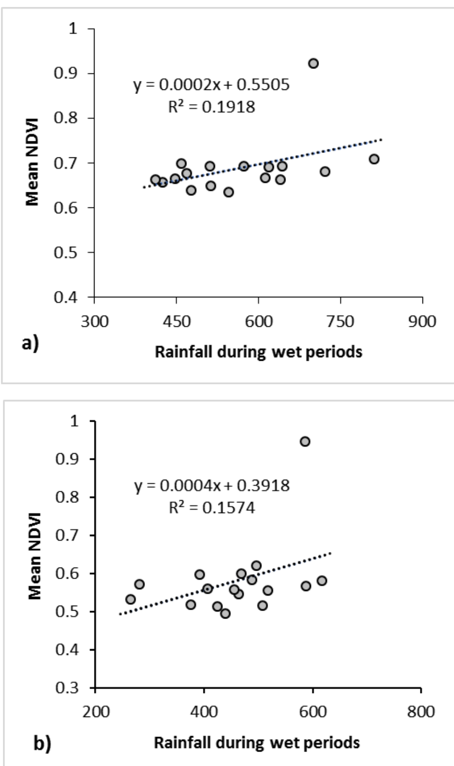

Figure 7. Scatter Diagram of Relationships between Mean NDVI Values and Rainfall (mm) for the Period 2000 to 2016 in two Study Sites, (a) Hugumburda and (b) Desa'a, in the Dry Afromontane Forest Remnants, Northern Ethiopia

In general, the correlation analyses confirmed that the changes in climatic variables had an impact on the regional vegetation dynamics. In both study sites, positive correlations were found between the NDVI values and rainfall, whereas the correlations with temperature were negative (Tables 5 and 6). Strong relations were observed when NDVI values were compared with rainfall during the main growing season (i.e., the core rainy season) (Figure 7). NDVI in June, July and August showed positive and significant relations with rainfall, but it was negatively correlated with temperature. This shows that the NDVI was mainly influenced by the June – August rainfall, with a possible lag effect on September where good correlations were noticed as well. This implies that precipitation is the main limiting factor for vegetation growth in the dry Afromontane forests of the entire study region. These results show similarities with the climate response patterns for the regional NDVI and tree-ring growth of the main tree species of the dry Afromontane forest remnants, showing some common limiting factors for their growth. This finding is consistent with most studies undertaken in arid and semi-arid regions which revealed that precipitation is the main factor in determining the growth of desert vegetation, even for mountain forests and grasslands (e.g. 32, 48]. On the other hand, some other previous studies, mainly from the high latitude regions, have suggested that temperature may be the key factor for vegetation growth [44].

In a study conducted on desert vegetation in Hexi region, China, [48] found a positive correlation between NDVImax and annual precipitation, indicating that precipitation is a key factor for desert vegetation growth in the study region. Nevertheless, the same study confirmed the existence of spatial differences in such relations; non-significant positive correlation was also observed mainly in areas located in the lower reaches of river basins. This can be attributed to the disturbances from human activities. Similarly, [49] found an overall increasing NDVI trend with both temperature and rainfall before the mid or late 1990s in the Mongolian plateau. However, a downward NDVI trend was observed with the significantly decreased precipitation since the mid or late 1990s. [44] found an overall enhancement in vegetation greenness since 1981 in the Tao river basin (in Northwestern China) and was primarily driven by temperature. [50] reported a general increasing trend in NDVI in the study region between 2001 and 2012, while about 35% of the region showed degradation.

In general, earlier studies reported that the NDVI–climate relationship differs with climatic regions and their long-term trends, at inter-annual levels. In arid and semiarid regions, a strong positive NDVI-rainfall relationship is commonly reported [e.g. 24, 31]. Nevertheless, such relationships would be examined on the condition that increasing rainfall could compensate the increasing water requirement along with increasing temperature [31], and the physiological characteristics of the vegetation. In humid regions, temperature controls vegetation dynamics [31]. On the other hand, the complexity in the NDVI-climate relationships may also be explained by the interactive effects from other factors, for instance, anthropogenic activities may have accumulative effects on vegetation dynamics [31, 46].

On the other hand, some studies also noted that the interactions between growing season NDVI and climatic variables are more complex than the expected due to the existence of lag effects of the climatic factors on the NDVI values [39, 47]. For instance, [47] noted a lag effect of 1-2 years in the correlations between NDVI and climatic variables (rainfall or temperature). Thus, this finding should be supported with further studies emphasizing on the water requirements and drought tolerance of vegetation in this ecological region along with impacts from human-induced disturbance. This study analysed only the associations between NDVI, rainfall, and temperature. However, it is obvious that there are other factors that may have an influence on terrestrial vegetation growth, such as relative humidity, nutrients, light intensity and mechanical factors including the occurrence of fire and other damages [50, 51]. These need to be further studied to better understand vegetation dynamics and their responses to the changing climate.

5. Conclusions

Understanding the spatiotemporal vegetation dynamics of a given region is crucial to provide baseline information for advocating ecological restoration and management endeavours, particularly in dry agro-ecologies. This study used simple linear regression model, correlation analysis, and trend analysis (using Mann-Kendall test and Theil-Sen median trend analysis) to assess vegetation dynamics and their responses to climate variability. For this purpose, the MODIS NDVI time-series data and gridded rainfall and temperature datasets were used for the common periods (2000-2016). Results of the study confirmed the general assumption about trends in vegetation greenness in most arid and semi-arid regions of the world; we found a general declining trend in vegetation greenness during the study period, but with considerable spatiotemporal variations. The vegetation change alternated between increasing (greening) and decreasing (browning) trends. Slight warming was observed (especially the minimum temperature showed a significant trend) in the study region, while rainfall showed a decreasing trend. Besides, positive NDVI-rainfall relationships were found in the vegetated areas of both study sites. This implies that the annual changes in NDVI were mainly affected by rainfall, and this conforms to the claim that moisture availability is the main factor in determining the growth of dryland vegetation.

In general, this study confirms the utility of MODIS NDVI time-series data as an index to express vegetation dynamics at the landscape scale. But, it is assumed that the interplay of other factors with climatic variables may affect the estimates on NDVI changes. Therefore, more investigations are needed to accurately clarify and quantify the impacts of various interacting (natural and human-induced) factors on vegetation dynamics. To this end, future works may need to concentrate on time-series data with better quality (e.g. resolution) and incorporate land use change and other eco-climatological factors into the study to better account for the spatiotemporal vegetation variability. For instance, we suggest further studies emphasizing on the water requirements and drought tolerance of vegetation in this ecological region along with impacts of human-induced disturbance.

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