



# Long-term dynamics of woodland vegetation with response of climate variability in the lowlands of north western part of Ethiopia

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## Abstract

Vegetation is one of the main earth's surface resources. It serves as a bridge among some earth's components like soil, atmosphere and water cycle. It is the most sensitive indicator of seasonal change and environmental degradation. Analysis of terrestrial vegetation dynamics allows a better understanding of climate effects on terrestrial ecosystems. Vegetation growth is influenced by the climate conditions. But, there is a debate whether woodland vegetation decreases or increases in the study area. The area was selected purposely where vegetation is sensitive too much to precipitation (RF) and relative humidity (RH). LANDSAT image has been selected from United State Geological Survey website. Starting 1984–2014 period collection of LANDSAT image with TM, ETM scanner has designed for normalized difference vegetation index (NDVI) analysis. Meteorological data were collected from Ethiopian Methodological Agency. The maximum value of NDVI was computed using ERDAS 2010 and ArcGIS10.2 software. It was analyzed with meteorological data by multiple regression analysis approach using R-statistical package. Statistical analysis result showed that woodland vegetation NDVI value and RH had positive correlation with precipitation while temperature was negative. It indicated that precipitation and woodland vegetation have strong relationship. Precipitation was significant key factor for woodland vegetation. The value of  $R^2=0.71$  and  $P<0.05$  showed us NDVI could contribute significantly for climate variability. Spatial and temporal dynamics of woodland vegetation was found greater in the semiarid area. This was due to sensitivity nature of woodland vegetation and fire experience of the study area. Therefore, woodland's vegetation was highly sensitive to climate factor's variability and seasonal change.

**Keywords** Climate variability · NDVI · Rainfall · Dry land · Dynamics

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## 1 Introduction

Vegetation is one of the main earth's surface resources and serves as a bridge among some earth's components like soil, atmosphere and water cycle. It is an indicator of seasonal change and environmental degradation (Li and Xiao-ling 2006). Vegetation is also tightly linked to the climate factors. Analysis of terrestrial vegetation dynamics allows a better understanding of climate effects on terrestrial ecosystems. Vegetation growth is influenced by climate conditions (temperature and precipitation) and ecosystem disturbances like drought or fire (Na-u-dom et al. 2017; Nemani et al. 2003). Interactions between the atmosphere and land surface strongly influence climate variability and land surface processes (Weiss et al. 2004; Hou et al. 2015). In line with this, effect of prevailing climatic variabilities (precipitation, relative humidity and temperature) on vegetation component or vice versa has been widely validated across different regions of the world (Chuai et al. 2013; Parrini and Erasmus 2003; Li and Xiao-ling 2006). In the semiarid area, vegetation greenness is highly sensitive to regional and local climate variability and Chopra (2006) showed that both precipitation and air humidity were brought pronounced seasonal and annual vegetation changes.

Recently, remote sensing technology and techniques are used to study long-term impacts of climate factor variables with vegetation dynamics (Guo 2002). NDVI is derived from satellite remote sensing data which is one of the main characteristic descriptors of vegetation cover and is widely used to monitor the changing dynamics of vegetation cover, biomass and the ecosystem (Tucker et al. 1991). Moreover, it is vital for the analysis and estimation of environmental and climate change (Johnson 2014). Using NDVI as a proxy for these biophysical variables has allowed relationships between vegetation and meteorological variables over various spatial and temporal scales to be identified in arid and semiarid environments (Weiss et al. 2004). There is evidence that NDVI is sensitive to the brightness and exhibits a curvilinear relationship with greenness, exhibiting saturated signals over high biomass conditions (Huete and Jackson 1988). NDVI is a numerical indicator that uses the visible and near-infrared bands of the electromagnetic spectrum and is adopted to analyze remote sensing measurements and assess whether the target being observed contains live green vegetation or not. It has found a wide application in vegetative studies as it has been used to estimate crop yields, pasture performance, and rangeland carrying capacities among others. It is often directly related to other ground parameters such as percent of ground cover, photosynthetic activity of the plant, surface water, leaf area index and the amount of biomass (Nemani et al. 2003).

Woodlands and deciduous plants in the lowlands of Ethiopia most likely have their own positive effect for climate change mainly for protection of great Saharan desert expansion as green belt (ANPMP 2009). It is also known as a safe guard for enlargement of Saharan Desert (Assefa et al. 2017). Considering this, Ethiopian Government has decided that the area is protected as National Park. Despite this contribution, the woodlands have been faced many challenges, including socioeconomic effects (grazing, wild and induced fire, fuel wood), resettlement and government-initiated agricultural investment (Lemenih and Kassa 2011; Eshete et al. 2011, 2005; Teketay 2004–2005). As results, the extent and productivity of the woodland vegetation have declined coupled with climate change. Besides, Menale and Jungmeier (2011) also identified several challenges around the National Park. The impact of this anthropogenic and natural disturbance on the woodland vegetation attributes and its response for climate variability is not well understood. To date, the impact of grazing and fire have not been included in global studies of woodland vegetation

dynamics (as cited in Andela et al. 2013). In the study area, land use and land cover change and its driver's researches (Muluneh et al. 2018; Aklilu et al. 2014; Fikirte et al. 2017) have been established. However, the effect of vegetation dynamics on climate variability has not addressed. Therefore, main objective of this study was to assess woodland vegetation dynamics using NDVI value and evaluate its impact on climate variability in the study area.

## 2 Materials and methods

### 2.1 Study area description

The study site is typically located in Quara district which is situated near East Sudan approximately 1052 km far from the capacity Addis Ababa. The annual temperature and rainfall of the area range from 25 to 35 °C and 600 to 1200 mm, respectively. The lowland area of the district is one of the widely used investment corridors in Ethiopia, and the population density is scarce (Fig. 1).

Northwest low lands part of Ethiopia is characterized by woodlands vegetation which is highly sensitive to seasonal and annual change. This lowland is mostly covered by woodland vegetation and grassland which are actually affected by agricultural expansion, human-induced and wild fire. Riverine vegetation and seasonal wetland vegetation are other types

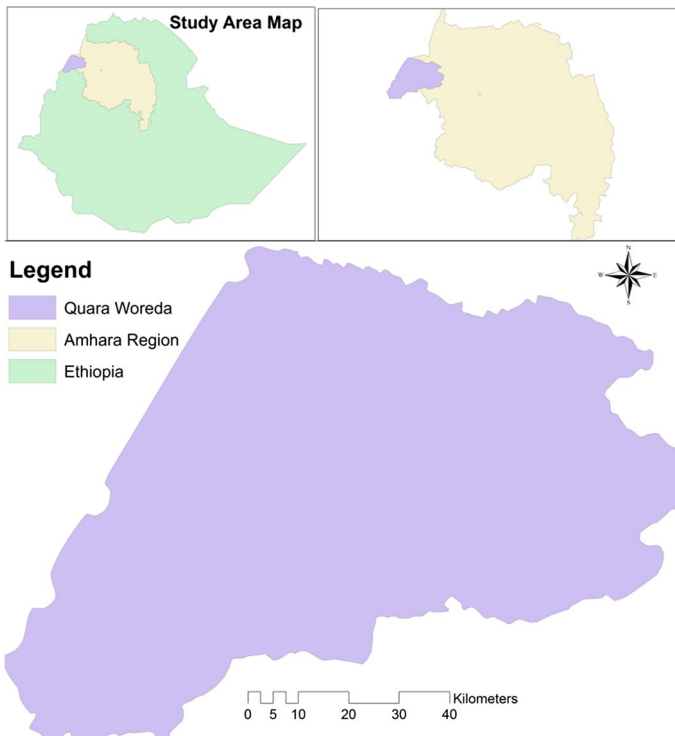


Fig. 1 Study area map

of cover types. Wild and induced fire is highly experienced in the area. This may have negative impact on the vegetation regeneration, growth and greenness. The lowland vegetation attributes were a challenge for satellite data collection and analysis using NDVI. Because, in dry season, most woody plants shade their leaves, whereas the vegetation and grassland even bare lands seem green when the wet season appears. It booms its greenness within short period of time. Thus, quantifying tree canopy cover with remotely sensed data remains a challenge for dry land ecosystems where vegetation is sparse and trees, shrubs, and grasses often coexist at fine spatial scales (Yang et al. 2012).

## 2.2 Satellite data collection

Satellite data were downloaded and collected from United State Geological Survey (USGS) official website via earth explorer. Landsat 4, 5, 7 and 8 in TM, ETM and ETM+ sensor with 30 Meter resolution were selected. The last 30-year Landsat images were applied to analyze spatiotemporal dynamics of woodland vegetation (1984–2014). In this period, different satellite generation products were used and specific period or season of satellite products was selected purposely to reduce cloud effect and reflectance difference due to seasonal variation. Satellite data acquisition date were not consecutive due to some reasons like cloud cover, not accessible for the same month (November) and sensitivity nature of vegetation for the seasonal change. It was really difficult in order to interpret satellite images, because every feature seems green in rainy season, whereas almost all green vegetation seems grass and bare land in dry season that makes it difficult interpretation process. Therefore, November 16–30 was selected as an appropriate season to get clear and unbiased greenness of vegetation. Landsat 7 satellite products were striped (error). Therefore, de-striping technique was employed using ERDAS2010 IMAGINE software. Ground truth and verification data were collected using Garmin (GPSMAP 64 s) GPS in the study area. Specific study area boundary was mapped using ArcGIS 10.1 software from ETHIO-GIS data sources. NDVI values were computed from reflectance of vegetation in specific wave bands (infrared and visible range of wavelength of radiation). ArcGIS 10.1 software was the tool to calculate vegetation NDVI values in its ArcToolbox component.

The formula is shown below.

$$\text{NDVI} = \frac{\text{Band4} - \text{Band3}}{\text{Band4} + \text{Band3}}$$

where Band 4 is near-infrared web band (NIR) and Band 3 is RED web band. NDVI values are ranging between  $-1$  and  $1$  (Abbasova 2010) with an  $\text{NDVI} < 0$  indicating cloud or water and  $> 0.1$  vegetation coverage. But, in our case, about 23 remote sensing Landsat images were taken. The minimum and maximum NDVI values were computed for each year and selected for further analysis related to climate factors data. About  $0.1$  and above NDVI values were considered as vegetation category, even if, there is some confusion over the exact range of the NDVI (Higginbottom and Symeonakis 2014). The maximum NDVI value was intended to integrate with climate factors data (rainfall, relative humidity and temperature) which determines growth and greenness of vegetation.

### 2.3 Meteorological data

Annual precipitation (RF), annual average temperature (Temp) and annual average relative humidity (RH) were collected in Ethiopian Meteorological Agency via University of Gondar, Climate change center. The data were collected in Quara and Metema.

### 2.4 Data analysis

All collected remote sensing and meteorological data were analyzed by R-statistical package. This was done through NDVI value which was calculated using prescribed formula in the methods part in ArcGIS environment, algebra calculator too for intended years. The maximum value of the NDVI was carefully selected and correlated with corresponding annual RF, RH and Temp. By using a map, spatial and temporal dynamics of woodland vegetation in 10-year interval was described and generated in ArcGIS. To quantify the impacts of the vegetation on climate variability, multiple regressions were used. This was also used to explain relationship between NDVI values and climate variables data (RF, Temp, and RH). Maximum NDVI value was considered as dependent variables, and RF, Temp and RH were independent variables in multiple regression process.

## 3 Result and discussion

### 3.1 Result

In multiple regressions with continuous variables, significant relationship was observed between NDVI and climate factors at  $P < 0.05$ . RF, Temp and RH were explained greater than 71% variability in NDVI. Moreover, simple regression value of NDVI with RF, RH, and Temp were calculated as  $R^2 = 0.53$ ;  $P < 0.05$ ,  $R^2 = 0.34$ ;  $P < 0.05$ ,  $R^2 = 0.06$ ;  $P > 0.05$ , respectively. The relationship of NDVI across independent variables was analyzed. The relationship of NDVI with RF was higher than that of both RH and Temp (Figs. 2, 3).

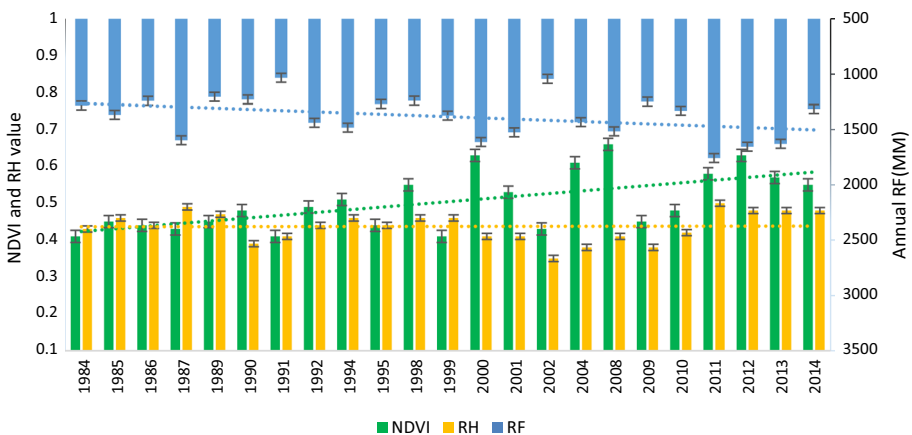


Fig. 2 Relationship among rainfall, relative humidity and normalized difference vegetation index

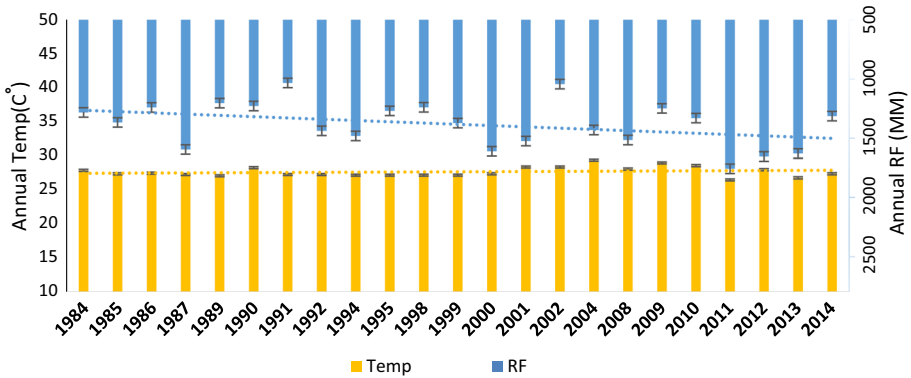


Fig. 3 Relationship between annual rainfall and temperature

Log data analysis resulted as: Temp is nearly constant trend with weaker relationship with NDVI than RF and RH.

Annual precipitation and annual average temperature resulted incremental trend for the last 30 years, but the temperature was almost constant, with only slight increment (Fig. 3). In terms of correlation, NDVI was positively correlated with RF, RH and Temp which is presented in (Table 1).

For the last three decade, woodland vegetation was not showed only growth but also the density of the vegetation was increased. Landsat remote sensing data analysis result exhibited that the computed maximum and minimum NDVI value of woodland vegetation was 0.66 and 0.11, respectively. In the first period (1984), it was 0.41, whereas at the recent period (2008) and (2014) it was 0.66 and 0.56, respectively. Spatiotemporal dynamics of vegetation was detected for the last 30 years in the study area. Significant spatial and temporal woodland vegetation dynamics was observed.

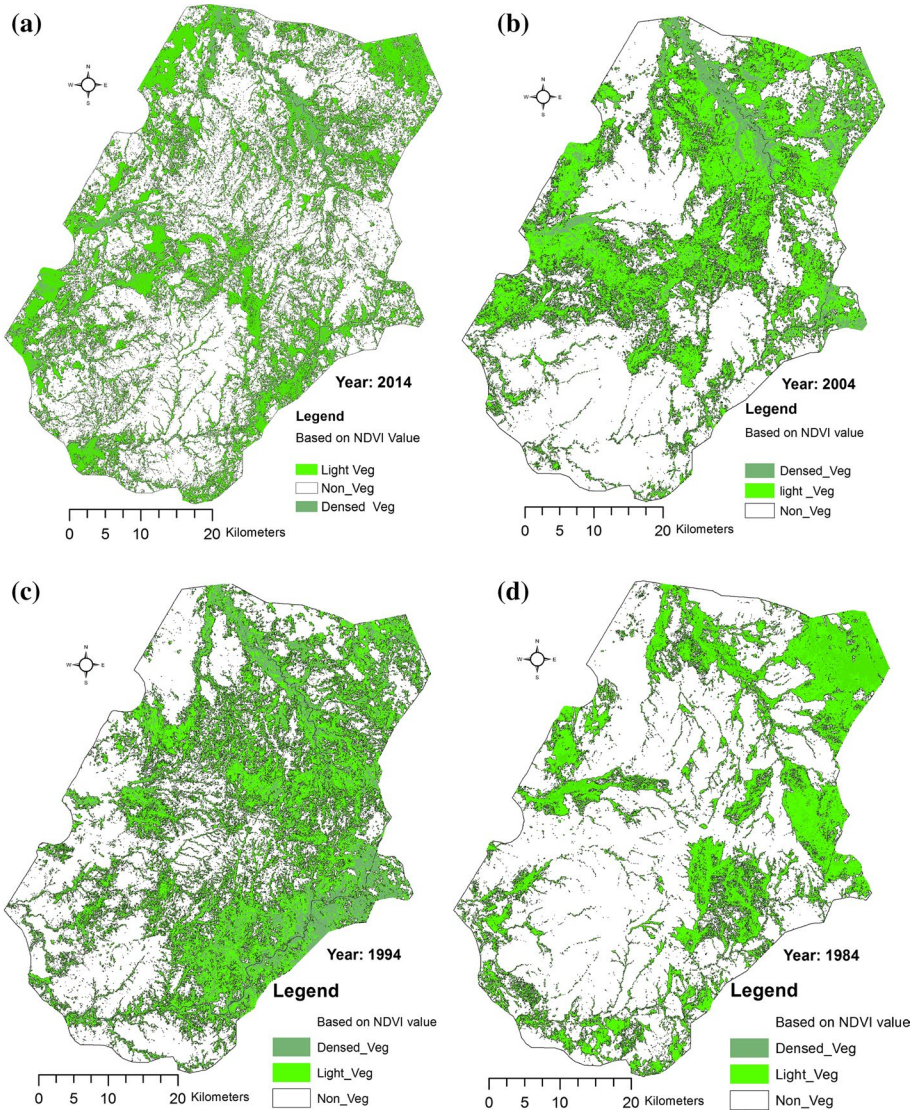
About 23 different satellites data which were acquired in different years (mostly consecutive) were analyzed. Of this, only four periods with 10-year interval results were put in the form of map to show spatial and temporal dynamics of woodland vegetation (Fig. 4a–c).

### 3.2 Discussion

Multiple and simple regression analysis result indicated that RF and RH had strong relationship with NDVI. Of this, RF was contributing higher role while RH was limited. It implies that RF was a significant factor for vegetation growth and cover. But, Temp was insignificant factor to NDVI as such. This result was consistent with the research conducted elsewhere

Table 1 Correlation between dependent with independent variable

Correlations matrix	NDVI	RF	RH	Temp
NDVI	1.00			
RF	0.655**	1.00		
RH	0.505*	0.094	1.00	
Temp	0.085	-0.235	-0.77	1.00



**Fig. 4** Ten-year interval NDVI dynamics maps

(Wang 2016) who shows role of precipitation was higher than that of temperature in the process of interaction between NDVI, temperature and precipitation. Based on this, relative humidity may influence vegetation environment partly through modifying microclimate and with other variables. Therefore, NDVI might be considered as key factor to climate variability in the study area. In agreement with our result, NDVI was significantly contributed to climatic factor's variability in semiarid area (Propastin et al. 2005). Both RF and RH were responding to the NDVI positively with different intensity. But, NDVI value had immediate response to RF. This was due to sensitivity nature of woodland vegetation to seasonal change. RF showed increasing trend for the last 30 years corresponding to NDVI values, while RH was not. This indicated us, woodland vegetation cover and growth have strong relationship with RF in the

semiarid area. Such types of woodlands really sensitive and actively respond to RF in terms of growth and greenness (Fig. 2), whereas annual temperature was not. Therefore, RF was found the key factor to woodland's vegetation dynamics in lowland areas, whereas temperature and relative humidity are limited factor which is confirmed with (Hou et al. 2015; Zoungrana et al. 2015). Among other variables, rain fall was exhibited strong positive correlation with NDVI. This is exactly agreed with cumulative precipitation in the growing season having a dominant effect on the vegetation dynamics compared with temperature for all six vegetation types (Xianfeng et al. 2015; Liang et al. 2015). Apart from this, the highest NDVI-RF correlation associated with one month time lag shows rainfall event-induced vegetation growth in subsequent period (Chopra 2006). RH had relatively strong correlation than that of Temp. This indicated that RF and RH are determinants for vegetation cover and growth in semiarid woodland vegetation (Table 1), whereas temperature was not contributed as factor. This result was contradicted with study conducted elsewhere (Hou et al. 2015); at a national scale, the growing season NDVI was significantly and positively correlated with temperature and precipitation, with temperature being the dominant factor, and the impact of precipitation change on NDVI is mainly negative over most of the region. On the other hand, some studies confirmed this result (Habib et al. 2008; Yu et al. 2015).

Landsat remote sensing data analysis results showed that for the last three decades, both vegetation cover and growth were found as increasing trend. It indicated that woodland vegetation cover and growth were changed as per RF changed. This is confirmed that vegetation in the area with the lowest precipitation was more sensitive to the precipitation dynamics than those parts with relatively higher values (Sofue et al. 2017). Spatiotemporal dynamics of vegetation was detected in the study area. Spatial and temporal woodland vegetation dynamics was found as greater. This was due to most likely by the sensitivity nature of woodland vegetation to seasonal change together with induced and wild fire which is very serious problem in the study area. Specifically fire could be a factor for spatial dynamics while sensitive nature of woodland vegetation in the study area with considered the area as national par were contributing to spatial dynamics of vegetation. Only four satellite image NDVI values analysis result maps were put (Fig. 4a–c) with 10-year interval to show spatial and temporal dynamics of woodland vegetation in the area. Thirteen years back, vegetation cover and growth were too low in the study area. Only in the northeast part of the study area had a cover relatively (Fig. 4d). After 10 years, the cover and growth completely changed both spatially and temporally (Fig. 4c). Temporal vegetation dynamics was higher in the study area. Subsequently, central part of the area showed decreasing in terms of cover, whereas the recent map (Fig. 4a) showed increasing trend both growth and cover. In general, the last three decades showed that spatial and temporal dynamics of vegetation in terms of growth and cover were found. Precipitation and relative humidity were found incremental trend, whereas temperature was averagely constant. This was in line with the increase in woodland vegetation cover and growth. It indicated us that RF and RH had played a great role for woodland vegetation dynamics. In the contrary, woodland vegetation dynamic had its impact on climatic factor variability.

## 4 Conclusion and recommendation

Long-term satellite remote sensing data analysis showed that increasing trend with high spatial and temporal dynamics corresponding to precipitation was found in the study area. This was due to sensitivity nature of the woodland vegetation to precipitation and fire. Therefore, spatial and temporal dynamics of woodland vegetation was high which is



overseen by precipitation and relative humidity variability. NDVI values and precipitation had shown strong relationship than that of relative humidity and temperature. Again relative humidity could contribute to vegetation dynamics better than that of temperature. This indicated that precipitation was key factor for NDVI values increment which was vegetation cover and growth. Moreover, woodland vegetation would have an impact on climatic factor variability. Precipitation and relative humidity were found increasing trend with little fluctuation, while temperature was constant trend with a little bit increasing. Therefore, it is possible to conclude that woodland vegetation cover as well as growth had seriously overseen by climate factor variables in the lowland (study area). It is recommended that the effect of fire on the vegetation dynamics in the study area should be considered for further analysis with high spatial resolution.

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