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Multi-temporal remote sensing data to monitor terrestrial ecosystem responses to climate variations in Ghana

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ABSTRACT

Operational monitoring of vegetation and its response to climate change involves the use of vegetation indices (VIs) in relation to relevant climatic data. This study analyses the temporal variations of vegetation indices in response to climatic data (temperature and precipitation) to better understand the phenological changes in the Wa-West and Tolon districts of Ghana during 1999–2011. This study also examines the inter-annual variation of vegetation indices and lag effects of climate variables (temperature and precipitation) using simple regression and correlation approaches. Results indicate that the mean Normalized Difference Vegetation Index (NDVI) and Normalized Difference Soil Index (NDSI) were significantly correlated with the mean temperature, whereby the value of NDVI increases with a decrease in temperature and value of NDSI increases with an increase in temperature. On examining seasonal variations, our findings indicated that the months of August and September have the highest mean NDVI values. This study confirms that consistently rising temperature and altered precipitation patterns have exerted a strong influence on temporal distributions and productivities of the terrestrial ecosystems of the Tolon and Wa-West districts of Ghana. Furthermore, this research demonstrates how vegetation indices can be used as an indicator to monitor phenological changes in the terrestrial ecosystem.

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KEYWORDS
Terrestrial ecosystem; vegetation indices; climate change; lag effect

1. Introduction

Climate change has significantly affected terrestrial ecosystems and is receiving attention from scientists and governments (Field et al. 2014). Transient climate change will significantly affect a large portion of the population in developing countries, principally people

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living on agricultural subsistence (Morton 2007). The agriculture sector is characterized by complex issues and problems, ranging from the macro-economic policy levels to the micro-economic smallholder farming. The agriculture sector is different from other sectors of the economy due to variability in yield, which depends on various climatic and soil conditions.

Agriculture in Africa is mainly seasonal and faces high levels of uncertainties because of poor infrastructure, isolated rural communities, fluctuating market, trade conditions, climate change, etc. (Stoop and Hart 2005; Rippke et al. 2016; Molekoa et al. 2019; Vaughan et al. 2019). Due to many agricultural uncertainties, farmers have to optimize their farming practices. In addition to being alert in optimizing their operations based on new production and marketing opportunities, farmers also need to consider the timing of different field operations. The crucial strategies required for proper crop management include: early planting; close matching between crops and different land/soil types; frequent use of intercrop combinations often on adjacent and transition land; and fine-tuning of the above systems by selecting local varieties with different growth/maturity cycles (Stoop 2002).

In African countries, sustainable agriculture is the key to food security. However, in the present scenario of climate change, various climate-related disasters (e.g., flooding and drought) result both in critical instability and in agriculture production. While the importance of climate change and its consequences with respect to primary productivity and overall biogeochemical cycles are well known (Myneni et al. 1997; Imhoff et al. 2000; Bonan 2002), more studies are required to fully understand how climate change affects vegetation phenology. Especially for African countries that contribute about 17% of the global carbon budget, these regions have been identified as one of the most vulnerable regions to climate change impacts (Adole et al. 2016). Despite this, a limited number of studies has addressed the phenology and climate trends across Africa, a region which has a diverse range of vegetation types (Favier et al. 2012). In this context, monitoring the terrestrial ecosystems, which include forests and agricultural areas provide useful means to assess the effect of climate on biological productivity (Menzel et al. 2006). At present, most studies believe that average temperature and precipitation have an important role in phenological changes of terrestrial ecosystems (Zhang and Gao 2005).

Remotely sensed vegetation phenological data from satellite images and derived productivity indices have been shown to capture responses to climate variations on short and long time scales (White and Nemani 2006; Hmimina et al. 2013; Avtar, Takeuchi, et al. 2013; Avtar, Suzuki, et al. 2013). They capture seasonality, productivity, and inter-annual variation principally through an earlier start of season (SOS) and later end of season (EOS) (Minh et al. 2019), as well as provide an integrated measurement of ecosystem responses to climatic factors such as temperature, rainfall, and insolation (Jeganathan et al. 2014; Kobayashi et al. 2016; Li et al. 2017). For example, Jeong et al. (2011) and Zhou et al. (2016) have shown that vegetation indices derived from satellite data reveal more realistic estimates of the trends in SOS and EOS. Monitoring vegetation phenology and productivity based on vegetation indices have a tremendous potential for addressing the status and change of ecosystems, as well as associated changes in temperature and rainfall.

A wide dynamic range of vegetation indices (VIs) has been developed for remote quantification of biophysical characteristics of vegetation, seasonality, and inter-annual variations (Gitelson 2004). These VIs are mostly related to the characteristic properties of leaf chlorophyll, leaf area, and canopy biomass (Huete et al. 2010; Schaaf et al. 2011). A variety of spectral wavelengths are applicable to produce a multitude of VI equations.

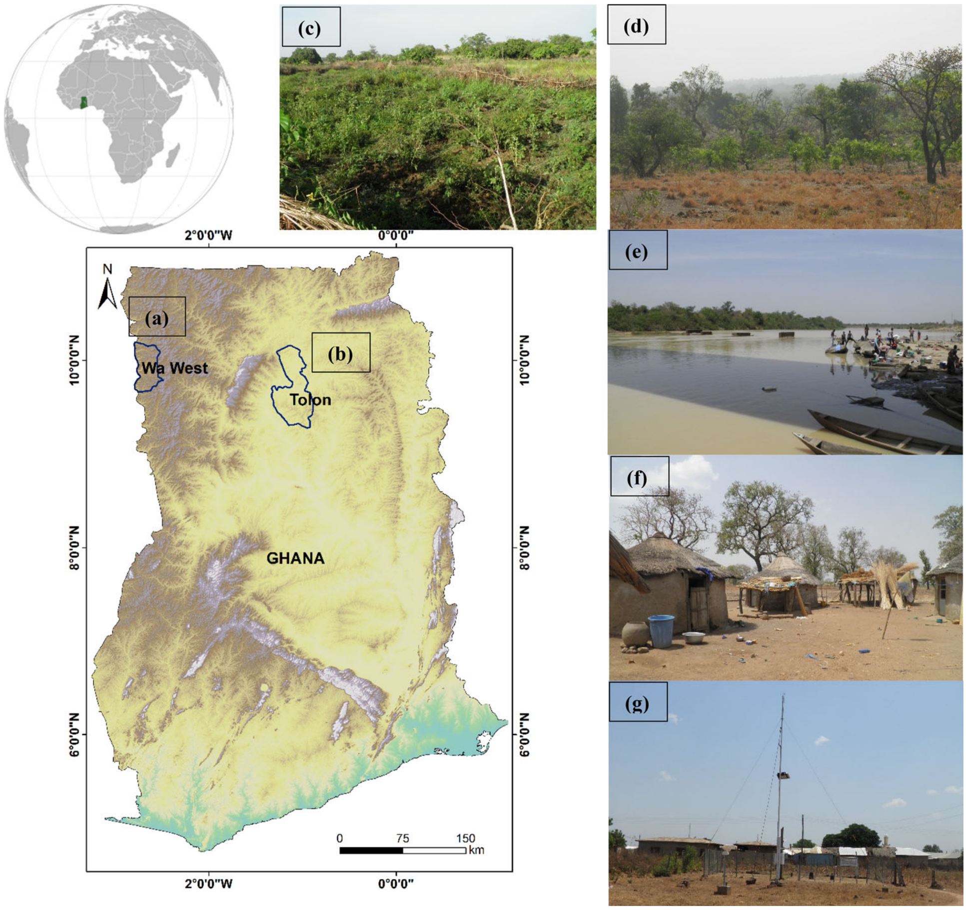

Figure 1. Map shows the location of the study area. Clockwise: (a) Wa-West district and (b) Tolon district of Ghana and field photographs, (c) agriculture area, (d) savanna forest, (e) the Black Volta river, (f) residential area, and (g) meteorological station.

However, the red and near Infra-red (NIR) portions of the electro-magnetic spectrum are the most employed wavelength regions. Among the different VIs, Normalized Difference Vegetation Index (NDVI) proposed by Rouse Jr et al. (1974), soil-adjusted vegetation index (SAVI) established by Huete (1988), and enhanced vegetation index (EVI) are some of the most useful indicators of vegetation phenology (Liu and Huete 1995; Xue and Su 2017). However, only a limited number of satellites (e.g., AVHRR) have provided the source of satellite vegetation index (VI) for phenological mapping. However, with the release of satellite data products from the Moderate-Resolution Imaging Spectrometer (MODIS) instrument, the Système Pour l'Observation de la Terre (SPOT) 4 and 5 satellites and the Landsat series (4 - 8) with improved spatial resolution and revisit cycle have enabled considerable improvement in phenological research. Most of the large-scale vegetation monitoring is based on time-series analysis of NDVI (Beck et al. 2006) and SAVI (Huang et al. 2013).

Changes in climate forcing are recognized to modify vegetation phenology of the earth through changes in temperature, precipitation, evapotranspiration, land use, soil conditions, and CO_2 concentration. Each of these factors may have different impacts on vegetation growth. Previous studies showed that temperature and precipitation are the main

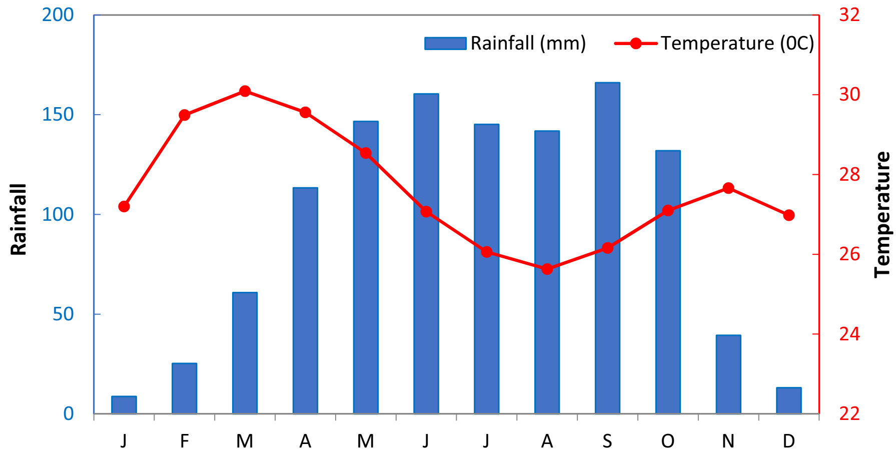

Figure 2. Mean monthly temperature and rainfall pattern of Ghana during 1991-2016.

indicators used to explain changes in vegetation phenology (Ji and Peters 2004; Chuai et al. 2013). Various vegetation indices have been used to study climatic effects on changes in vegetation phenology (Meng et al. 2011; Zhang et al. 2011). The results from these studies varied because of the differences in topographic and vegetation conditions. Zhang et al. (2011) reported that NDVI variations were significantly correlated with temperature and precipitation.

Ghana, having a vast forest territory with a rich diversity in species and ecosystems that covers 34% of the total area of the country (Hall and Swaine 2013), contributes an integral part to Africa's carbon budget. Climate-induced changes in the SOS and EOS, and consequently the length of the growing season, are critical factors contributing to the observed carbon cycle dynamics. Therefore, it is important to accurately understand the spatial patterns of the phenological changes and their driving forces. This study is intended to identify the process to evaluate the effects of climate change on the terrestrial ecosystem of Ghana. We aim to analyse the relative effects of changes in (1) temporal variation of Landsat and SPOT-based vegetation indices, as well as changes in precipitation and temperature in the Tolon and Wa-West districts of Ghana; (2) to compare correlations between NDVI with temperature and precipitation; and (3) to discuss the different trends in seasonal NDVI, NDSI, and the lag effect of climatic variables.

2. Study area

The present study was conducted over two districts of the northern part of Ghana: the Wa-West and Tolon districts located along the southern coast of the African panhandle, bordering the Gulf of Guinea that is situated just a few degrees (4–11°) north of the equator having a tropical climate. The northern part of Ghana is predominantly characterized by savanna, with some cropland and grasslands in the far north and central parts of the region. The southwestern portion of the country consists of partly moist evergreen forest and partly deciduous forest with some urbanization and cropland areas (CIA World Factbook 2012). Figure 1 shows the location of the study sites and field photographs taken during the field visit, as well as the collection of meteorological data. The Wa-West and Tolon districts are situated in the Guinea and Sudan savanna agro-ecological zones (Boafo et al. 2014). The main tree species in the study area are neem (*Azadirachta indica*),

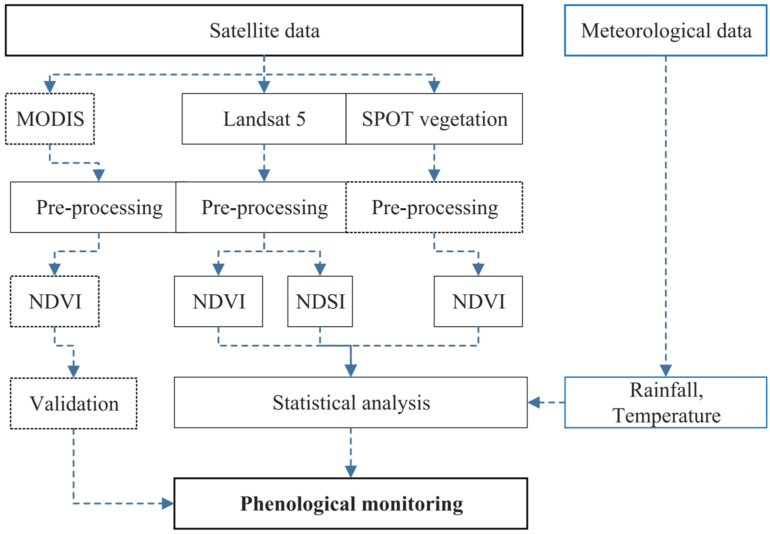

Figure 3. Flowchart of the methodology.

baobab (*Adansonia digitata*), dawadawa (*Parkia biglobosa*), and shea tree (*Vitellaria paradoxa*).

The Wa-West district is considered as a flood-prone area because of overflows from the Black Volta river, whereas the Tolon district is considered as a drought-prone area. The rationale for selecting these two districts originates from their common ecological zones and socio-economic conditions with differences in exposure to the droughts and floods as well as climate change vulnerability (Boafo et al. 2014). Wa-West and Tolon have a flatland topography with less variation in elevation. Figure 2 shows the mean historical monthly temperature and rainfall pattern of Ghana. Rainfall and temperature patterns in the study area are highly variable. Average annual rainfall ranges between 935 and 1327 mm with the rainy season starting from April and reaching its average maximum in the months of August/September. The rainy season is the period of intense farming activities. The temperature in the study area ranges between 25 °C (minimum) to 31 °C (maximum). The highest temperature is normally recorded in March, and the lowest in January, respectively.

3. Material and methods

3.1. Satellite data and processing

Due to the free availability and long archive that enable continuous monitoring of the Earth's changing land surface and climate, we used Landsat-5 and SPOT-vegetation satellite products to analyse the ecosystem variations in the two districts of Ghana. All cloud-free Landsat-5 data from 1984–2011 and SPOT derived vegetation data from 1999 to 2012 were used to monitor seasonal changes in the vegetation. Landsat-5 data with 16 days repeat cycle and 30×30 m spatial resolution were acquired from USGS (https://earthexplorer.usgs.gov/); whereas SPOT-vegetation images with 10 days composite (maximum-value) temporal resolution, 1.15 km $\times$ 1.15 km spatial resolution, and stretched values ranging from 0 to 255 were downloaded by the SPOT-vegetation programme (http://www.vgt.vito.be/. . . . .). SPOT-vegetation based NDVI data were used to

Table 1. Details of the study area and pixels covered by Landsat, SPOT, and MODIS data.

Districts	Total Area (km^2)	Total Landsat-5 pixels (30 m)	Total SPOT-vegetation pixels (1.15 km)	Total MODIS pixels (250 m)
Tolon	2,949.9	3277,688	1,311	90,522
Wa-west	1,410.5	1567,177	626	61,937

complement the Landsat results which are lacking continuity because of their limited temporal coverage.

A total of 32 and 31 scenes of Landsat-5 were available for Wa-West and Tolon, respectively. These Landsat scenes were further preprocessed using standard image preprocessing techniques including image enhancement, subsetting, and histogram matching to augment the quality of the image. Due to the limited temporal coverage of Landsat images, SPOT-vegetation derived NDVI was used. MODIS 16-day composite NDVI products were also used for validating the results. The prime motive to use MODIS data for validation schema is that they possess enough cloud-free images for the entire study area for each year because of their daily temporal coverage. MODIS 250 m 16-day composite images between 2000 and 2018 were used for validating the result. MODIS data for Ghana were downloaded from AppEARS System (https://lpdaacsvc.cr.usgs.gov/appeears. . . . .). In order to select the growing season period, we chose the 90% quantile of NDVI for each year. Using r-program, we computed the linear regression of each pixel in the images between 2000 and 2018. Figure 3 shows the flow chart of the methodology adopted in this study. Table 1 shows the study area information and total number of pixels covered by Landsat, SPOT, and MODIS images in the Tolon and Wa-West districts.

3.2. Meteorological data

Daily average rainfall and temperature data of Ghana were obtained from the Ghana Meteorological Agency for the period of 1984–2011. Rainfall and temperature data for the Wa-West and Tolon districts were selected from the available datasets. There was no meteorological station in Tolon, so we selected data from the closest meteorological station in Tamale district. The location of the Wa-west and Tamale meteorological stations are Lat/Long: 10°03′07″N 00°15′12″W and Lat/Long: 09°24′02″N 00°50′21″W, respectively. Selected data has been used to monitor the changes in the vegetation indices with respect to the changes in climate variables.

3.3. Vegetation indices

To monitor the phenological behaviour of the terrestrial ecosystem, various indices employing multiple wavelength bands obtained from satellite images have been developed (Table 2). We used NDVI and NDSI in this study owing to the following reason. While NDVI emphasized the vegetation properties, NDSI highlights the soil properties (Rogers and Kearney 2004). Thus, these two indices together highlight the difference between the strongest and weakest spectral response of an object. NDVI is a normalized ratio of red (R) and near-infrared (NIR) reflectance and correlates with photosynthetic activity (Rouse Jr et al. 1974). It has been widely used to monitor the spectral reflectance properties of vegetation (Delbart et al. 2005; Avtar et al. 2011; Alatorre et al. 2016). Following the same rationale as the NDVI, the NDSI employs the near-infrared band and short-wave infrared (SWIR) band instead of using the red band (Rogers and Kearney 2004). Equations (1)

Table 2. Vegetation indices used in this study (yellow color) along with other common satellite derived indices.

Type of index	Index	Formula	References
Vegetation	NDVI	(NIR – Red) /(NIR + Red)	Rouse Jr et al. (1974)
Soil	NDSI	(SWIR-NIR) / (SWIR + NIR)	Rogers and Kearney (2004), Takeuchi and Yasuoka (2005)
Soil and built-up	BUb	NDBIb – NDVIb where b indicates binary image and NDBI = (SWIR-NIR) / (SWIR + NIR)	Zha et al. (2003)
Snow	NDSI	(blue – SWIR) / (blue + SWIR)	Delbart et al. (2005)
Water	NDWI	NIR – SWIR / NIR + SWIR	Delbart et al. (2005), Xiao et al. (2009)
Vegetation	GVMI (Global Vegetation Moisture Index)	(NIR + 0.1) – (SWIR +0.2) / (NIR + 0.1) + (SWIR +0.2)	(Ceccato et al. 2002)
Vegetation	EVI (Enhanced Vegetation Index)	2.5 * ((NIR– Red/ (NIR + 6 * Red – 7.5 * Blue + 1)).	Kaufman et al. (1998)
Vegetation	SAVI (Soil Adjusted Vegetation Index)	(1 + L) (NIR – Red) /(NIR + Red + L) *where L is soil adjustment factor*	Huete (1988)

and (2) show the formula for calculation of NDVI and NDSI.

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{Red})/(\mathrm{NIR} + \mathrm{Red}) \tag{1}$$

$$\mathrm{NDSI} = (\mathrm{SWIR} - \mathrm{NIR})/(\mathrm{SWIR} + \mathrm{NIR}) \tag{2}$$

SWIR is the reflectance at the shortwave infra-red band, NIR is the reflectance at the near infra-red band, and Red is the reflectance at the red band. The response of NDVI and NDSI to temperature and precipitation was analysed with the help of SPSS software.

4. Results and discussion

4.1. Temporal changes in NDVI, NDSI, temperature, and precipitation for Wa-West and tolon

Figure 4a illustrates the temporal pattern of Landsat-based NDVI and NDSI with respect to temperature during 1984–2011 in the Wa-West district of Ghana. The NDVI and NDSI indices indicate that their value did not change significantly until 2006. However, since 2006, the NDSI values show a weak increasing trend and the NDVI values show a very weak decreasing trend. These trends indicate a changing pattern in the growing season in the mid-2000s. It is also noted that the mean temperature during the same period has increased. However, the increasing trend was not significantly similar to the NDSI index. Figure 4a also illustrates that the NDVI and NDSI fluctuations correspond well with the temperature fluctuations. For instance, the growing season's values for NDVI during September 1990, July 2001, and September 2002 were relatively high. On the other hand, the corresponding temperature for the same period is relatively very low. These fluctuations in NDVI and temperature are consistent with the findings of Chuai et al. (2013) who analysed growing season NDVI and temperature during 1998–2007 in inner Mongolia, China. In the case of NDSI, the temperature and NDSI indices increase and decrease in tandem. The high value of NDSI shows that the surface is exposed to solar

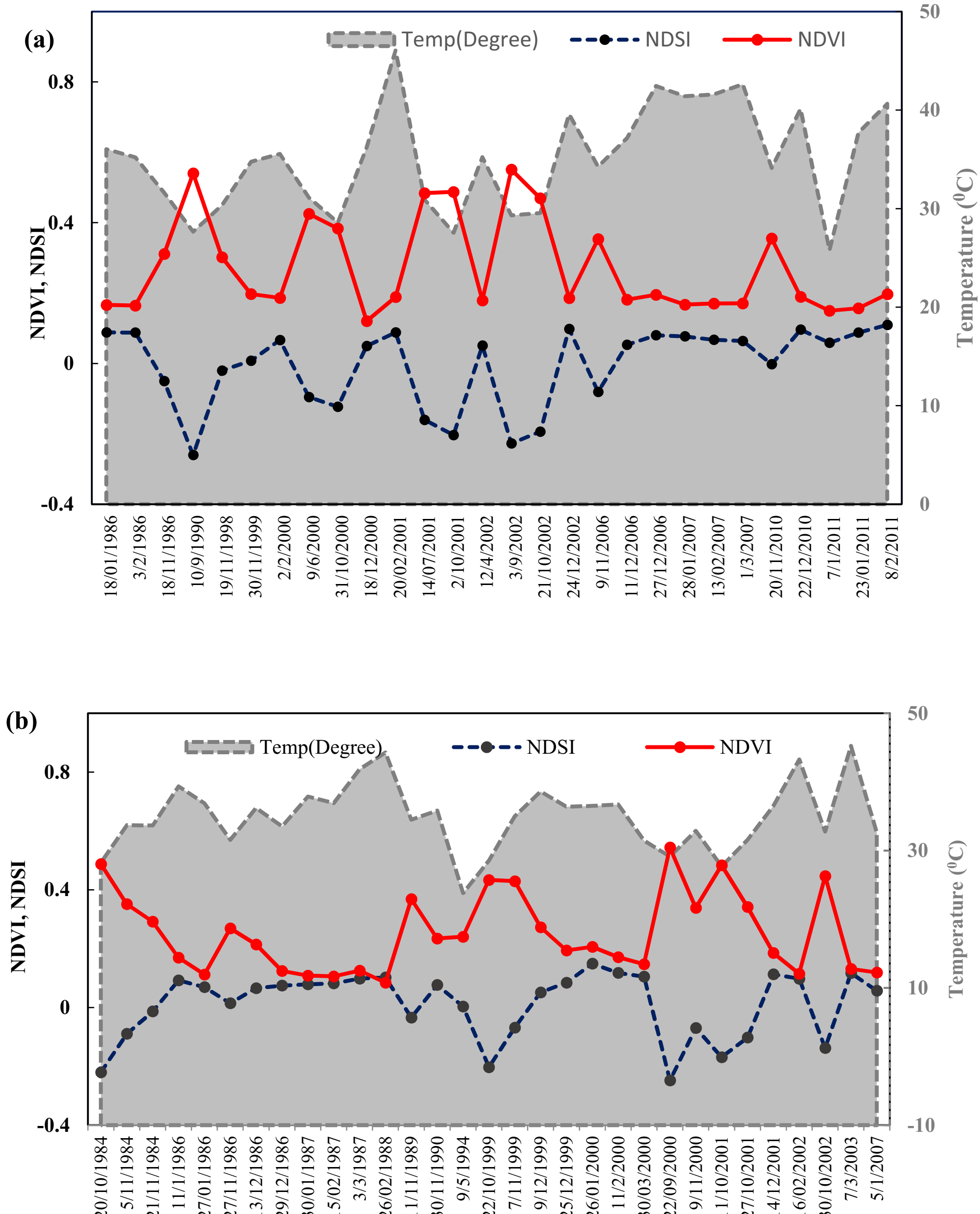

Figure 4. Temporal variation of Landsat based NDVI and NDSI vs. ground temperature (a) Wa-west (b) Tolon district of Ghana.

illumination and has less vegetative cover. The NDSI value increases in dry season, which is evident in Figure 4a.

Figure 4b illustrates the changes in NDVI and NDSI with respect to temperature during 1984–2007 in Tolon, Ghana. Unlike the Wa-West district, the NDVI and NDSI do not show any increasing or decreasing trend over the years 1984–2007 in the Tolon district. However, the fluctuations noted in temperature, NDVI, and NDSI are similar in pattern to the Wa-West and other studies (Chuai et al. 2013). Results show that NDVI and

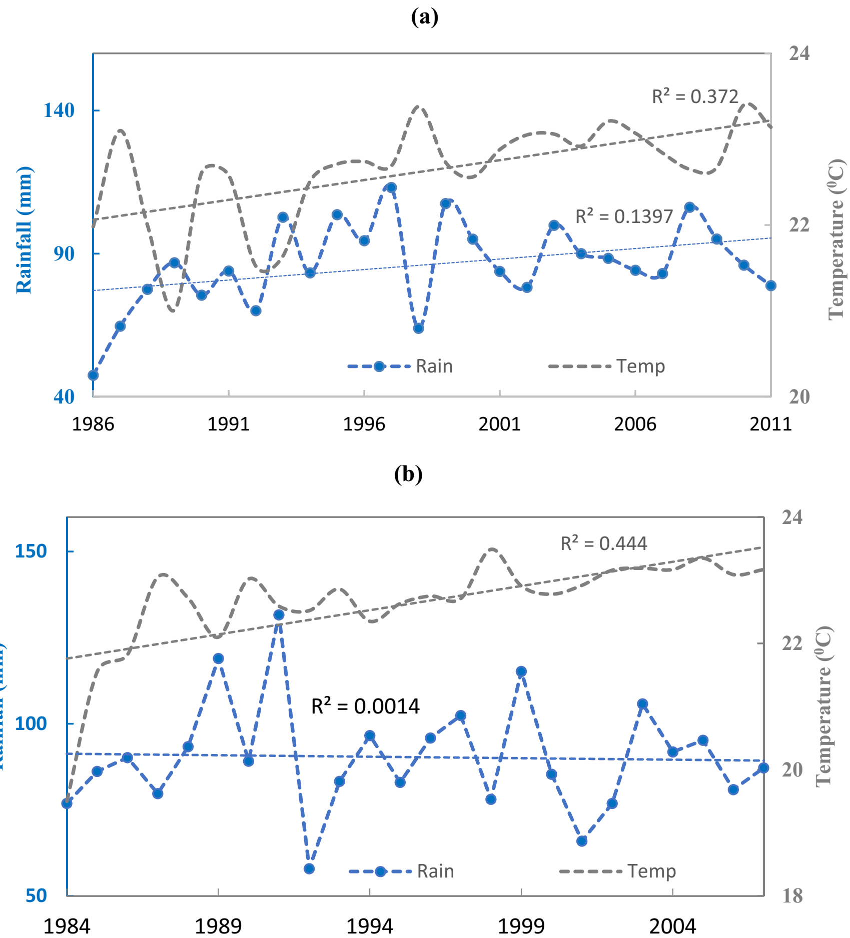

Figure 5. Annual changes in precipitation and temperature in the (a) Wa-West and (b) Tolon districts of Ghana.

NDSI have the potential to detect changes in vegetation phenology and soil water content, thus showing the sensitivity of optical sensors in observing land surface conditions.

Figure 5 shows the pattern of annual changes in precipitation and temperature in the Wa-West (Figure 5a) and Tolon (Figure 5b) districts of Ghana. We noticed that the precipitation in Wa-West does not show any decreasing trend with the increasing temperature (Figure 5a). During the last 25 years, the regional precipitation and temperature in Wa-West increased slightly. Minimum values of precipitation were observed for the year 1986 and extreme wet years arising from heavy precipitations were also observed during the study period. Although the temperature of Tolon shows an increasing trend over the period, the precipitation does not change substantially (Figure 5b). This result is not consistent with other global and regional analyses of precipitation (Ichii et al. 2002; Chuai et al. 2013). In the context of the study area, Owusu et al. (2008) also analyzsd the spatio-temporal variability in annual rainfall in Ghana from 1951 to 2000. Their results indicated the general reductions seen in the precipitation trends over the northern part of Ghana.

From the aforementioned analysis, it can be seen that temperature can have significant effects on NDVI and NDSI as compared to precipitation in Wa-west and Tolon. The correlation between temperature and Landsat based NDVI and NDSI for both the Wa-West

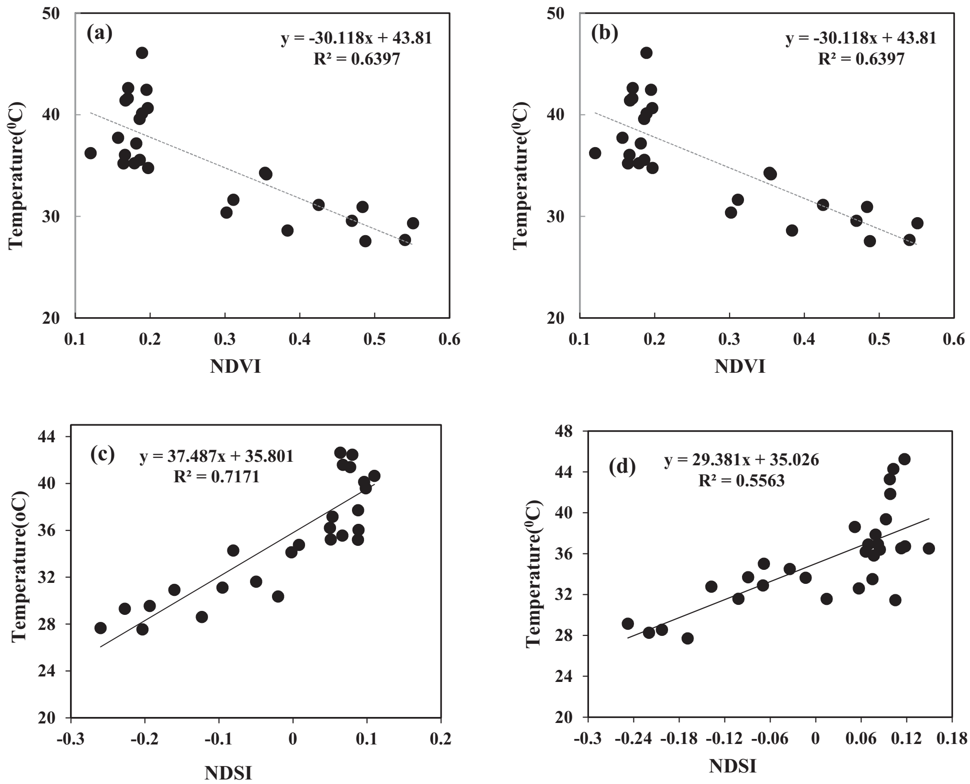

Figure 6. Temporal variation of Landsat based NDVI (a, b) and NDSI (c, d) vs. ground temperature; (a), (c) Wa-West; (b), (d) Tolon.

and Tolon districts are shown in Figure 6a and 6b. A negative correlation between temperature and NDVI was observed for both Wa-West ($r^2 = 0.64$, $p < 0.01$) and Tolon ($r^2 = 0.52$, $p < 0.01$). This indicates that the increasing temperature causes a decline in vegetation growth in northern Ghana. It is obvious that the higher temperature accelerates evaporation and leads to water scarcity thereby suppressing vegetation growth. The significance of the correlation is comparatively higher in Wa-West than in the Tolon district. Figure 6c and 6d display a significantly positive correlation between temperature and Landsat-based NDSI in the Wa-West ($r^2 = 0.71$, $p < 0.01$) and Tolon ($r^2 = 0.56$, $p < 0.01$) districts of Ghana. The Wa-West district has comparatively higher significance than the Tolon district. The differences in significance between Wa-West and Tolon can be explained by their different growth environments and a difference in their degree of anthropogenic disturbances rather than species variation. The dominant vegetation type in Wa-West and Tolon is guinea savanna woodland type. It consists of grasses and tree species such as *Butylosternum paradoxum* (Shea tree), *Parkia biglolosa* (Dawadawa), *Adansonia digitata* (baobab), *Anarcadium occidentale* (cashew), Acacia, Ebony, Neem, and Mango.

4.2. Seasonal NDVI and rainfall pattern

The effect of precipitation on NDVI may differ according to its growth phase (Piao et al. 2006; Chuai et al. 2013). Therefore, we analysed SPOT VGT-DN based monthly mean

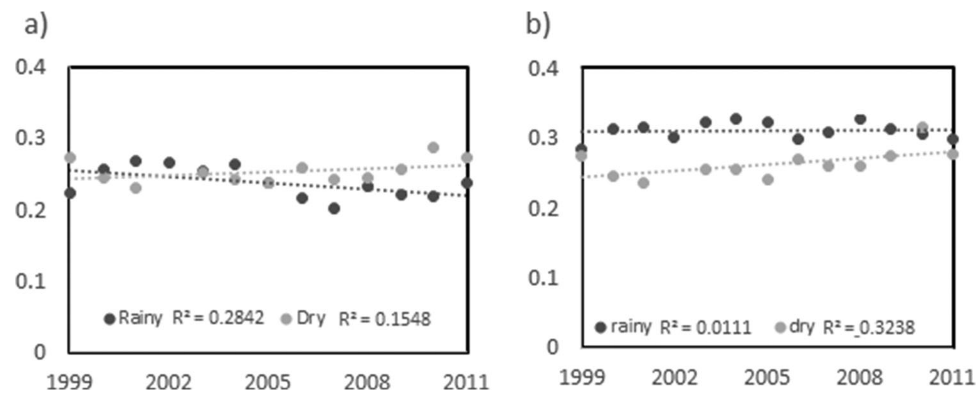

Figure 7. Seasonal NDVI trends (a) Wa-West and (b) Tolon.

NDVI with respect to monthly mean rainfall for the past 12 years (1999–2011). A retreating trend was noticed in the average NDVI for the rainy season (April–September) and an increasing trend was noticed in the average NDVI for the dry season (October–March) in the Wa-West district (Figure 7a). For the Tolon district, a very weak increasing trend was noticed in the average NDVI for both the rainy and dry seasons (Figure 7b). It was revealed that the annual rate of seasonal NDVI for the dry season increases for both the Wa-West and Tolon districts. This indicates that the NDVI in each cultivation season shows a positive correlation with the precipitation of the preceding season, thus suggesting a temporal lag in vegetation response to precipitation. A similar temporal lag was also noticed by other studies (Ren et al. 2007). We can visualize this temporal lag in Figure 8. Precipitation causes a decrease in temperature, which may also lead to an increase in vegetation growth in the rainy season. Therefore, our results indicate a high NDVI value in the rainy season.

Although considerable precipitation occurred throughout the months of April and May, the NDVI increases only during the month of June (Figure 8). Furthermore, we can see that the monthly NDVI reaches its peak in the month of September even though August receives the highest amount of rainfall. This indicates that the lag time effect is larger during the spring time precipitation (March-April) than during the summer time precipitation. It is possible that after sizable precipitation in the beginning of the growing season, the changes in temperature triggered the increase in NDVI values. Temperature triggered an increase in NDVI, which had been noticed by other studies (Tanja et al. 2003; Piao et al. 2006). Also, vegetation growth is highly sensitive to temperature (Guo et al. 2014). The time lag of vegetation responses to climatic factors is noted for both the Wa-West and Tolon districts at approximately 1 to 2 months. Temporal lags in vegetation responses have been widely observed in different regions ranging from 2 weeks to more than 3 months (Los et al. 2001; Piao et al. 2006; Mao et al. 2012; Chuai et al. 2013; Guo et al. 2014). The 1 to 2 month temporal lag in precipitation as revealed in our study is consistent with the studies of Chuai et al. (2013) and Guo et al. (2014).

4.3. Validation

The results obtained from Landsat and SPOT vegetation indices were validated with MODIS 250 m NDVI data. This is because observations from Landsat data are limited in each year and mostly come from off season (December – January) with several observations in other months. Additionally, the average time-series NDVI values in Figure 4a

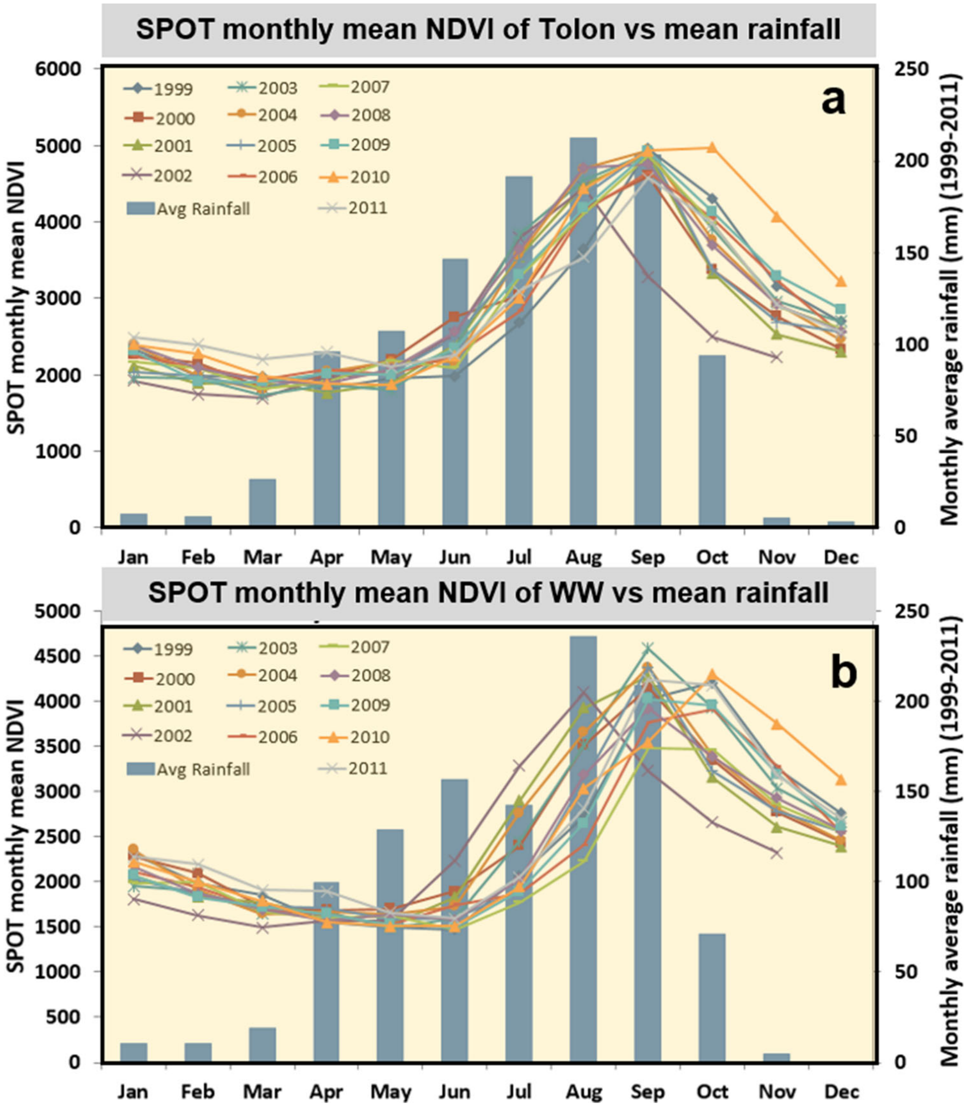

Figure 8. SPOT based monthly mean NDVI vs. mean monthly rainfall for (a) Tolon and (b) Wa-West districts of Ghana.

were about 0.2, which also come from the dry season. Therefore, analysis from these discontinuous datasets may be questioned while exploring the inter-annual changes. Moreover, low NDVI values may be treated as barren soil and be removed in previous vegetation dynamic studies. Therefore, to discuss about the phenology and seasonal variability, we performed the linear regression analysis using the growing season NDVI by selecting a 90% quantile approach from MODIS imagery. The slope of the regression analysis between 2000 and 2018 for Wa-West and Tolon is shown in Figures 9a and 9c. R-squared values obtained from the linear regression analysis for these areas are provided in Figures 9b and 9d. It can be seen from the slope images that the positive slope is dominant for both Tolon and Wa-West. However, R^2 values suggest that the changes are insignificant for both regions. These results are in agreement with the Landsat time-series analysis.

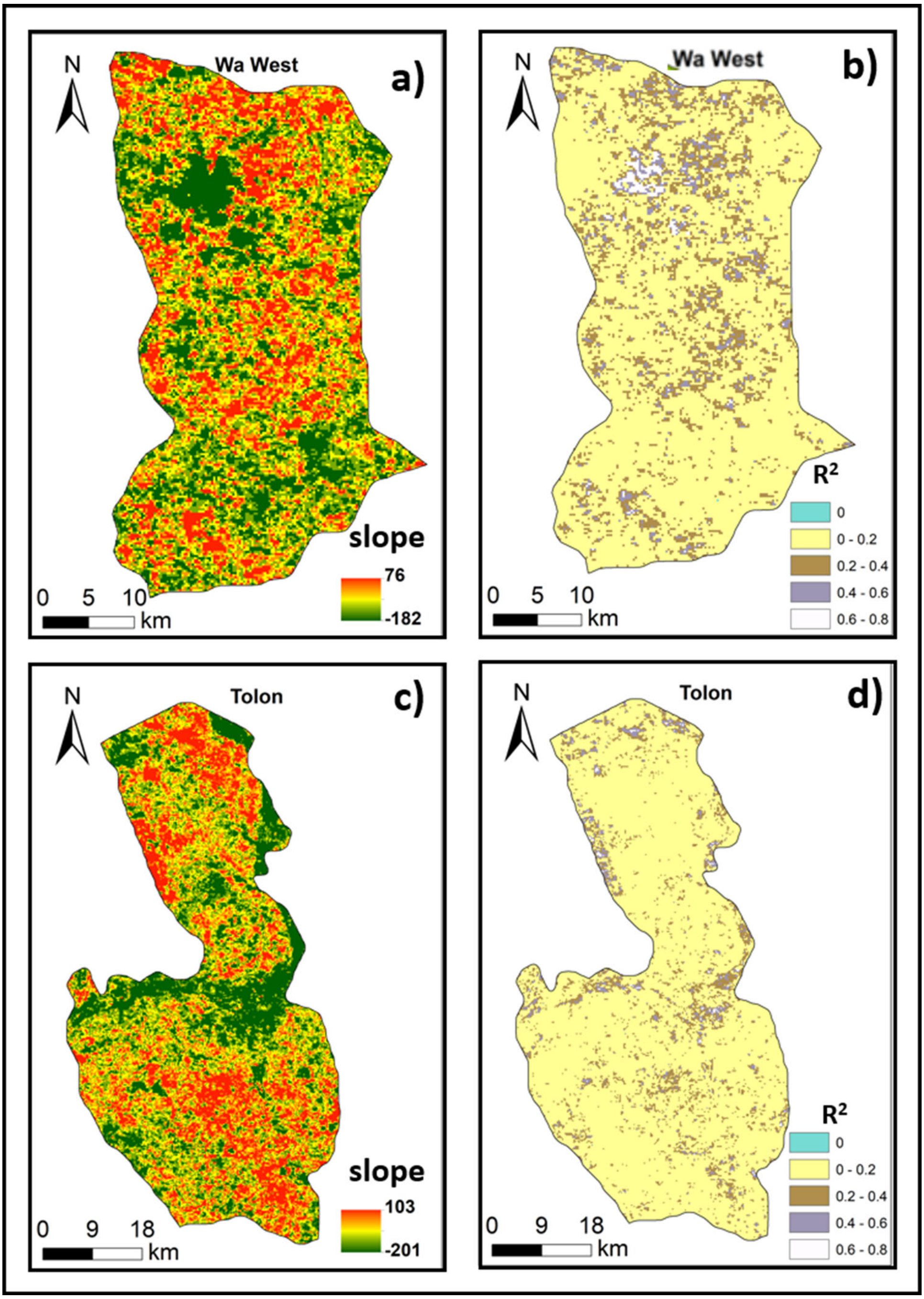

Figure 9. MODIS derived NDVI linear regression analysis for the period 2000- 2018. (a) and (c) slope of the linear regression, (b) and (d) r-squared value.

5. Conclusions

This study focused on phenological changes in the Wa-West and Tolon districts of Ghana and the changing patterns of climatic factors. The results clearly indicated that NDVI and

NDSI maintain a strong relationship with climatic data, i.e., temperature and rainfall. This study investigated vegetation response to climate change by studying the correlation between climatic data and vegetation indices. The purpose was to determine how influential climatic variations are on the NDVI and NDSI. SPOT-based high values of NDVI were observed in the months of August and September during the rainy season. The impact of precipitation on NDVI was positive, whereas the impact of temperature on NDVI was negative. Our results showed that in warm countries like Ghana, temperature plays a significant role in modulating the seasonal cycle of vegetation. An increase in temperature leads to a decrease in NDVI values. About 1 to 2 months' time lag of vegetation response to climatic factors has been noticed in this study.

For future research, we would like to study the different classes of vegetation and their relationship with climatic variables. This will help in identifying the areas for potential environmental restoration by implementing climate change mitigation and adaptation policies. If vegetation parameters with respect to the climate change projections can be simulated, then a new agricultural technique can be developed to supply a constant yield under climate change scenarios. Therefore, climate-smart agriculture practices will be useful for the public and policymakers.

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Disclosure statement

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