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Inter-Annual Vegetation Changes in Response to Climate Variability in Rwanda

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Abstract

Comprehensive studies on how vegetative ecosystems respond to fluctuations in precipitation and temperature patterns are of great necessity for environmental risk assessment and land-use evaluations. The present study examined the annual trends in vegetation greenness in Rwanda from 2000-2015 and assessed the relationship between these dynamics and climate factors by means of MODIS NDVI, air temperature, SOI and precipitation datasets. Mann Kendal trend test has been utilized to determine the direction and the rates of changes, while Spearman's rank correlation method has been used to determine the levels of associability between NDVI changes and climatic variables. The results indicate that approximately 11.9% of the country's vegetation has significantly improved ($p < 0.05$) from slight to significant improvement while 10.4% of the vegetative cover degraded from slight to severe degradation and an estimated 77.6% of the country's vegetation cover has remained relatively stable. Much of improvement has been detected in the lowlands of eastern province whereas much of degradation has been highlighted in the western highlands of the Congo Nile ridge and Kigali city. There was a weak correlation between NDVI anomalies and SOI anomalies ($rs = 0.36$) while near surface air temperature was moderately correlated ($rs = 0.47$) with changes in Mean NDVI. Precipitation was more significantly associated ($r = 0.84$) with changes in vegetation health in low plains of Eastern Province (Nyagatare District in particular) than in the high altitude regions of the Congo Nile ridge. A strong positive correlation with precipitation was found in rain fed croplands; mosaic vegetation; mosaic forest or shrubland, herbaceous vegetation/grass- land savannah and sparse vegetation. Identification of degradation hotspots could significantly help the government and local authorities galvanize efforts and foster results driven policies of environmental protection and regeneration countrywide.

Keywords

MODIS NDVI, Mann Kendall Test, Vegetation Health, Rwanda, Climate

1. Introduction

Over the last century, global surface temperature data have shown an increase of approximately 0.74˚C according to the fourth Assessment report (AR4) of the Intergovernmental Panel on Climate Change (IPCC) [1]. Africa is one of the most vulnerable continents to climate change and climate variability. This situation is aggravated by the interaction of 'multiple stresses', occurring at various levels, and Africa's low adaptive capacity [2]. Interannual rainfall variability is large over most of Africa and, for some regions, multi-decadal variability is also substantial [3]. Increased interannual variability has however been observed in Africa, during the period post 1970; with high rainfall anomalies, more intense and widespread droughts [3].

In most of tropical regions, it has been observed that the most significant drivers of inter-annual variations in climate and ecosystem productivity include El Niño and La Niña Southern Oscillations (ENSO) [4]. Both phenomena have been demonstrated to considerably influence ecological processes and terrestrial ecosystems [5] [6]. For instance, Milena Holmgren *et al.* suggested that ENSO-induced pulses of enhanced plant productivity can cascade upward through the food web invoking unforeseen feedbacks, and can cause open dryland ecosystems to shift to permanent woodlands [7].

The United Nations Economic Commission for Africa, in its 2008 report, defined desertification as a process of land degradation in arid, semi-arid and dry sub-humid areas, resulting from various factors, including climatic variations and human activities. The commission further reiterates that desertification manifests itself through soil erosion, water scarcity, reduced agricultural productivity and loss of vegetation cover and biodiversity [8]. Vegetation plays a primordial role in the interactions between the biosphere and the atmosphere [9] and vegetation phenology, as a sensitive indicator, could reflect the effects of climatic variability on vegetation growth and distribution [10]. Comprehensive studies on how vegetative ecosystems respond to fluctuations in precipitation and temperature patterns are of great necessity, not only for environmental risk assessment and land-use evaluations, but also in modelling ecosystems productivity and carbon exchange [11]. With the advent of new sensors like MODIS (Moderate Resolution Imaging Spectroradiometer), offering unparalleled sets of data to extract key parameters and monitor trends in vegetation, satellite remote sensing has been considered as an ideal technology to assess phenological responses to climate variability in a sense that it permits analyses of large areas with a high temporal frequency [12].

Despite the growing interest of researchers in examining the forcing-response mechanisms between vegetation and climate on the African continent [11] [12] [13] [14] [15], only a handful of investigations have been carried out in the East African region [16] [17]. For instance, John Musau *et al.* [18] found that persistent declining vegetation trends are present from Southern Ethiopia extending through Central Kenya into Central Tanzania.

Notwithstanding their well-known topographical and ecological discrepancies however, little attention has been paid to ascertaining trends in specific geographical entities of the region. The recent attempt to analyze the dynamics of vegetation in Rwanda [12] left many questions unsolved in a sense that it was only confined to one season out of four and only precipitation was considered as a climatic variable. Yet, in other areas, it was proven that temperature plays a most significant role in driving the vegetation photosynthetic activity [11] [19]. Hence, the spatial temporal vegetation responses to climate variability in Rwanda are still ambiguous and cannot be exactly pinpointed at the annual scale. In its extraordinary session of November 10th 2016, the cabinet meeting placed emphasis on tree planting for green spaces extension and sustainability throughout the country. Therefore, indicative studies on areas of high priority are paramount to facilitate in the regeneration campaign.

This research primarily seeks to provide additional inputs to the current scope of knowledge by (1) spatially and qualitatively assessing the seasonal responses of vegetation to inter-annual climatic variability in Rwanda; (2) identifying the likely influences of ENSO events on vegetative activity in Rwanda; (3) and determining both the seasonal and annual trends in vegetation greenness over Rwanda from the year 2000 through 2015.

2. Materials and Methods

2.1. Study Area

Rwanda is a landlocked country located in East-central Africa, occupying a superficies of 26,338 square Km on the eastern shoulder of Kivu-Tanganyika rift, lying between 1˚41' and 2˚51" south latitude and 28˚53" and 30˚53" east longitude [20]. The country has four climatic seasons in which long rainy (late February-late May) and short rainy seasons (end September-early December) alternate with long dry (June–September) and short dry (mid-December–mid-February) seasons [12]. The land mass consists of a diversified range of vegetation species; where in the southern parts, mixed broadleaved, need leleaved and mosaic croplands concatenate with mosaic vegetation (grasslands/bushlands/forests). In the western province, along the Congo Nile ridge, the broadleaved, ever green or semi-deciduous forests are dominant, with the deciduous forests towards the southwestern part of Rwanda, especially the Nyungwe forest. In the northern parts, the rainfed croplands are predominant in cohabitation with several patches of deciduous forest and woodland while, in the eastern province, herbaceous vegetation/grassland savannah is the main type of vegetation. Figure 1 shows Rwanda and its geographical position on the African continent.

2.2. Datasets

The Normalized Difference Vegetation Index (NDVI) has proven to be a useful index in depicting the continental-scale distribution and phenological seasonal changes of vegetation [21] [22]. In tropical Africa, NDVI integrated over the growing seasons has been found to be highly correlated with the ground-observed total dry biomass production of natural vegetation [15]. It is thus the most commonly used remote sensing dataset for vegetation and land degradation monitoring [23]. This study has used the NDVI dataset MOD13Q1A2 from 2000 to 2015, acquired from the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard NASA's Terra satellite calibrated at 250 m resolution and can be accessed online at http://ladsweb.nascom.nasa.gov/data/html. This dataset is believed to offer better performance due to onboard calibration and improved pixel geo-referencing. Rainfall estimates have been obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS _version 2). CHIRPS incorporates 0.05˚ resolution satellite imagery with in-situ station data to create gridded rainfall time series for trend analysis and seasonal drought monitoring worldwide [24]. In this study, we have used CHIRPS version 2.0 dataset; available online at ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/global_monthly/tifs/. Temperature data from 2000-2012 have been downloaded from the World Bank's meteorological data sharing service portal and have been used to determine the temperature tendencies and to estimate the correlation between them and vegetation. Temperature is a key parameter in the physics of land-surface processes on regional and global scales, combining the results of all surface-atmosphere interactions and energy fluxes between the atmosphere and the ground, and has been utilized in vegetation monitoring studies by various authors [25] [26] [27]. In addition, a vegetation Land Cover map was acquired from the Database of Global Change Parameters of the Chinese Academy of Sciences (http://blog.sina.com.cn/s/blog_670ee7720101c0ng.html) in order to assess the annual trends per vegetation type. Indicative of the El Niño/La Nina phenomena, the Southern Oscillation Index data have been obtained from the Japan Meteorological Agency (JMA) (http://ds.data.jma.go.jp/tcc/tcc/products/ elnino/ index/). Table 1 summarizes the datasets used in this study.

2.3. Methodology

2.3.1. Data Processing

The Modis Re-projection Tool (MRT) has been utilized to extract the targeted index from the whole assemble of indices contained in the original HDF-EOS data files while concurrently transforming the data from the original projection to an earth surface based projection (World Geodetic System, UTM 36S) and mosaicking the subsequent raster datasets [28] to allow for a Region-of-Interest

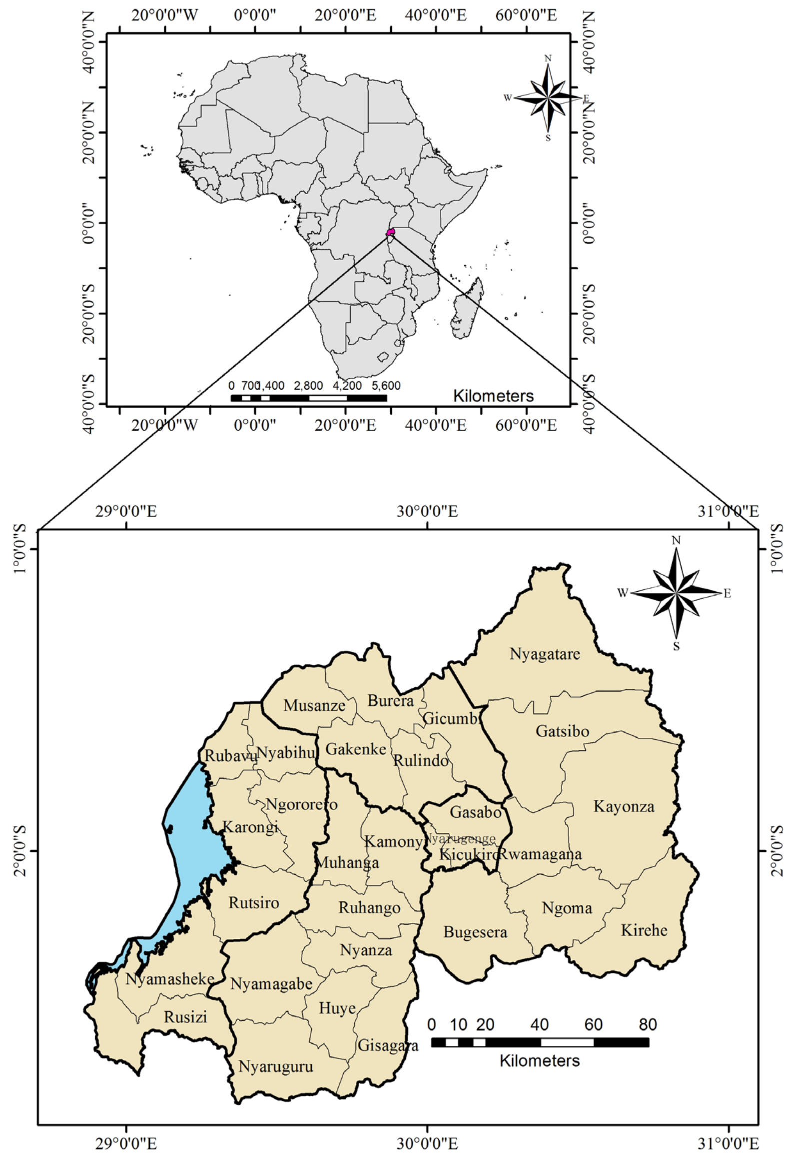

Figure 1. Location of Rwanda and its administrative subdivisions.

Table 1. Descriptive summary of the data used in this study

	Resolution				
dataset	spatial	temporal	provider	period	source
Modis NDVI	250 m	16 days	NASA	2000-2015	http://ladsweb.nascom[a]
Rainfall	0.05˚	monthly	CHIRPS	2000-2015	ftp://ftp.chg.ucsb.edu[b]
Temperature	-	monthly	World Bank	2000-2012	http://sdwebx.worldbank[c]
SOI	-	monthly	JMA	2000-2015	http://ds.data.jma.go.jp[d]
Vegetation map	250 m	-	CAS	2005	http://blog.sina.com.cn[e]

[a]http://ladsweb.nascom.nasa.gov/data/html.
[b]ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/global_monthly/tifs/
[c]http://sdwebx.worldbank.org/climateportal/index.cfm?page=downscaled_data_download&menu=historical
[d]http://ds.data.jma.go.jp/tcc/tcc/products/elnino/index/
[e]http://blog.sina.com.cn/s/blog_670ee7720101c0ng.html

focused analysis. Although MODIS NDVI, due to increased resolution, has reportedly had improved performance in comparison with the index retrieved from the Advanced Very High Resolution Radiometer, researches have shown that this dataset is still vulnerable to cloud contamination, aerosol concentrations, the residual atmospheric and the bidirectional effects [29]. **Figure 2** Therefore, a smoothing technique based on the Savitzky Golay filter has been applied to the dataset before analysis to eliminate contamination from the aforementioned factors that may tend to suppress NDVI values [30]. A recent study carried out by Geng *et al.* demonstrated that Savitzky Golay filtering method outweighs the other filtering methods in terms of performance [31].

2.3.2. Data Analyses

Mann-Kendall trend test is a nonparametric test used to identify a trend in a series, even if there is a seasonal component in the series. This test is the result of the development of the nonparametric trend test first proposed by Mann (1945), before being further developed by Kendall in 1975 and improved by Hirsch and colleagues in 1982 and 1984, allowing the test to take seasonality characteristics into account [32]. A number of studies have previously used the Mann Kendall test to analyze the trends in hydro-meteorological variables [33] [34] [35] as well as in studies involving vegetation dynamics [36] [37] [38]. The Mann-Kendall S Statistic is computed as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign\left(T_j - T_i\right) \tag{1}$$

$$sign\left(T_j - T_i\right) = \begin{cases} 1 & \text{if } T_j - T_i > 0 \\ 0 & \text{if } T_j - T_i = 0 \\ -1 & \text{if } T_j - T_i < 0 \end{cases} \tag{2}$$

where, T_j and T_i are the annual values in years j and i, $j > i$, respectively [39].

Correlation was analyzed by applying the Spearman's rank correlation test. Spearman defined r_s as follows:

$$r_s = 1 - \frac{6\left(\sum d^2\right)}{n\left(n^2 - 1\right)} \tag{3}$$

where $d = x_i - y_i$; n is the number of ranked pairs of ranking and x_i and y_i are ranks [40].

3. Results

3.1. Analysis of Seasonal Vs Annual Changes in NDVI

NDVI is the most commonly used remote sensing index as a proxy to assess changes in vegetation health [23]. Despite the constantly evolving number of vegetation indices, NDVI remains an indispensable reference index for vegetation and land degradation monitoring. Therefore, based on NDVI, we present, in **Figure 3**, the spatial distribution of seasonal changes in Rwanda's vegetation from 2000 through 2015. Water bodies have been masked to preclude any possible interference throughout the spatial and statistical analyses contained herein.

From Figure 3, it can be observed that during the short rainy and long dry seasons, vegetation vigor and health considerably improved in many parts of the country. Regions where NDVI trends could go as high as 0.05 $year^{-1}$ have been categorized as substantially improving, while regions where NDVI trends could go as low as -0.06 $year^{-1}$ have been denoted as substantially degrading. Much of interest, however, has been focused on the overall trend, calculated over the annual scale as shown in Figure 4. The annual trend reflects the annual changes in vegetation health as a response to interrelated environmental forces occurring throughout the year.

Areas of severe degradation extend along the Congo Nile ridge in the western province whereas areas of improvement are mostly found in the eastern savannahs and the northern Bubereka highlands. Additionally, a colossal amount of

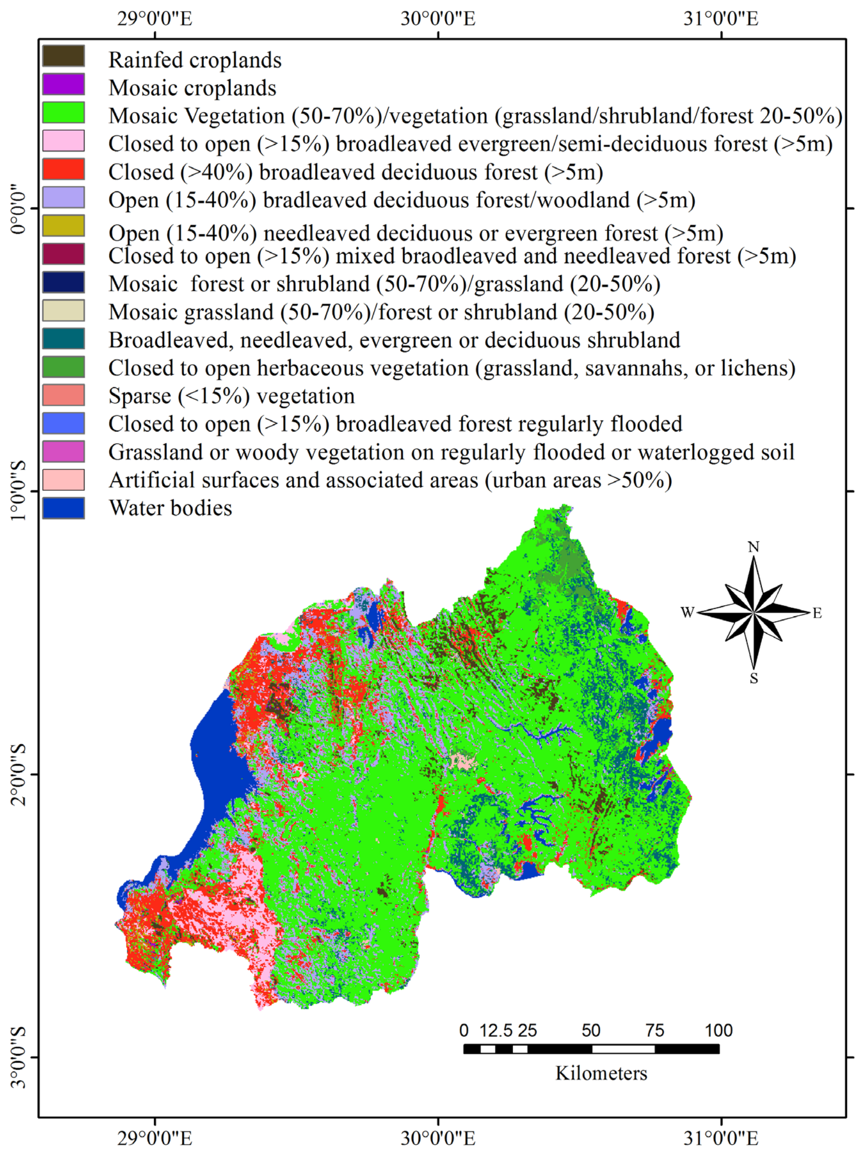

Figure 2. Spatial Distribution of different vegetation biomes on the Rwandan territory.

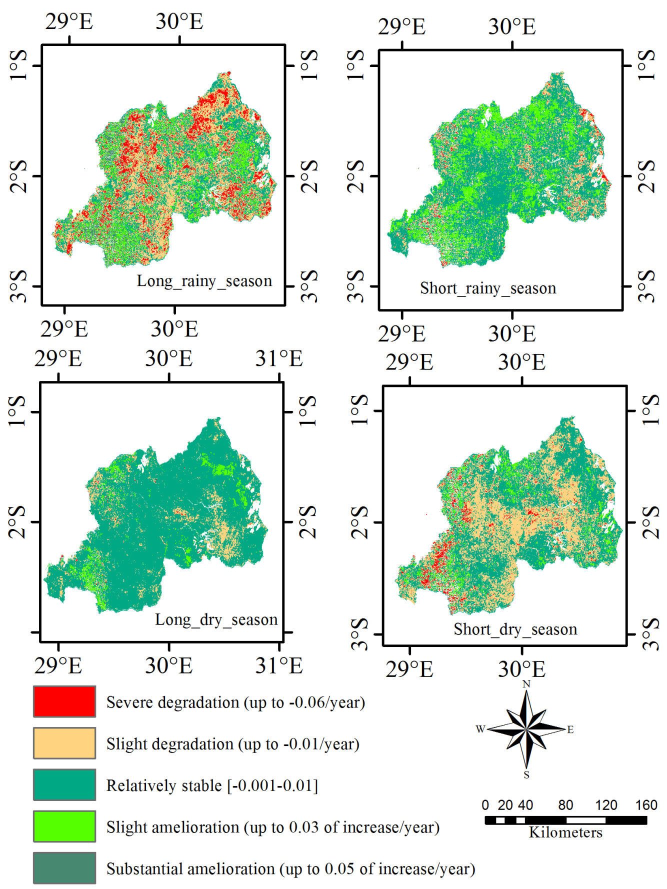

Figure 3. Seasonal changes in vegetation NDVI from 2000-2015.

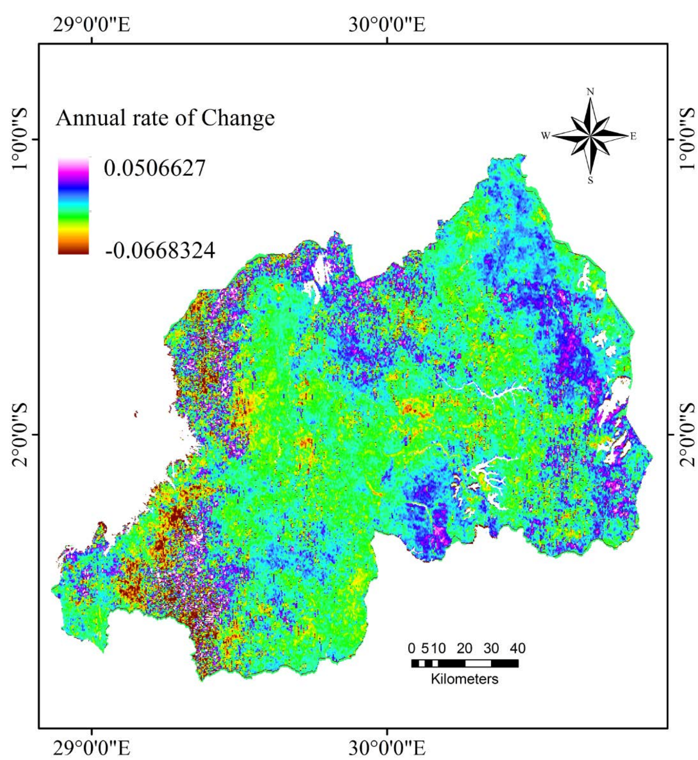

Figure 4. Annual rate of changes in vegetation NDVI from 2000-2015.

patches in regeneration (up to 0.05 increase yr^{-1}) is located along the Western portions of the Nyamagabe district while acute degradation in the surrounding areas along the gates of Rusizi and Nyamasheke districts stunts the extension of regeneration. These results are congruent with the findings of Kayiranga *et al.* [41] who, while monitoring forest cover changes in the Nyungwe-Kibira corridor, reiterated that patches in Nyung we National Park and its buffer zone were vastly degraded due to anthropogenic activities. Signs of slight degradation apparent in the central plateau and in Kigali city should also be underscored. The statistical analysis of area proportions in terms of amelioration/degradation is presented in **Table 2**:

It can be noted that almost 12% of the vegetation area improved either substantially (up to +0.05 yr^{-1}) or slightly (with an annual increase ranging from 0.008 to 0.02), while 10.4% degraded throughout the study period. Evaluated on the annual scale, a vast majority of pixels (77.6%) were characterized by a relative stability in a sense that no signs of degradation or improvement were detected.

3.2. Inter-Annual Changes in Seasonal Air Temperature; Mean NDVI, ENSO Anomaly and NDVI Anomaly

While there have been no significant changes detected in air temperature within the 12 years considered, a seemingly upward trend has been found in the short dry season and the long rainy season while a diminishing trend was observed within the remaining two seasons. **Figure 5** represents fluctuations in mean air temperature and Mean NDVI, mean NDVI anomaly and Southern Oscillation Index.

The difference between the monthly average NDVI and the longitudinal average of the same month calculated over the entire study period has been assumed to represent an NDVI anomaly. Negative NDVI anomalies have been detected in the years 2000, 2004 and 2006 in all the seasons. The long rainy season and the long dry season have had the highest record of negative NDVI anomalies, occurring in 9 and 8 years respectively. The years 2005 and 2014 were also marked by a negative NDVI anomaly in all the seasons, except for the first dry season. In 2007 and 2010, positive anomalies were observed in all seasons.

Southern Oscillation Index (SOI) is one measure of the large-scale fluctuations in air pressure occurring between the western and eastern tropical Pacific

Table 2. Synthetic analysis of the status and the magnitude of inter-annual vegetation changes from 2000-2015.

S_{NDVI}	Change description	Area percentage (%)	
≥ 0.02	Strong improvement	0.18135403	11.93
0.008 - 0.02	Slight improvement	11.75619128	
−0.0005 - 0.008	Relative stability	77.6491624	77.64
−0.02 - (−0.0005)	Slight degradation	9.887622707	10.41
< −0.02	Severe degradation	0.525639584	

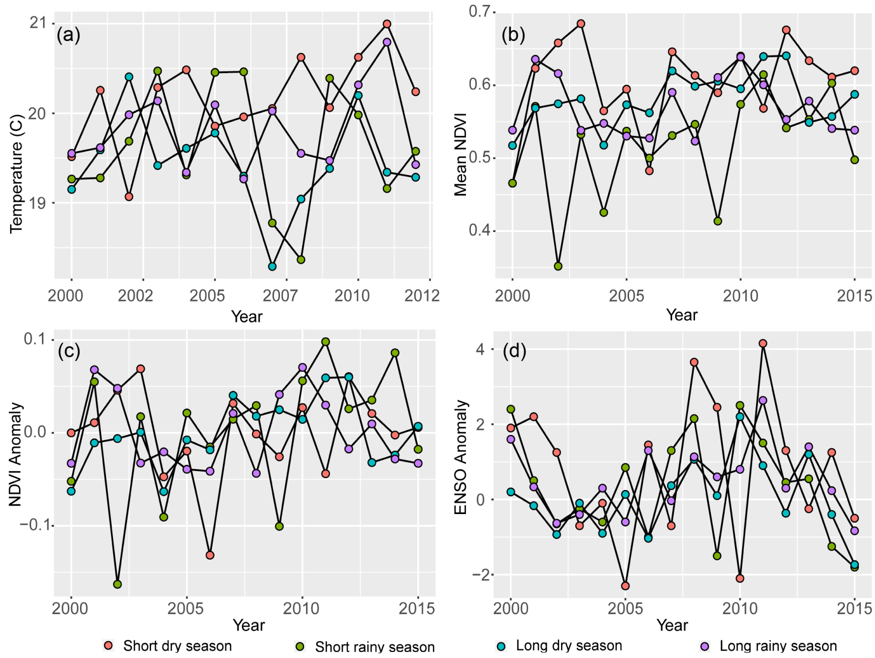

Figure 5. Interannual variations in air temperature (a); Mean NDVI (b); NDVI anomaly (c) and Southern Oscillation Index (d)

during El Niño and La Niña episodes. In **Figure 5**, negative SOI anomalies correspond to El Niño episodes whilst positive SOI anomalies correspond to La Niña episodes [4] [42]. As shown in **Figure 6**, the Mean NDVI was moderately correlated with air temperature while a weak correlation between NDVI anomalies and SOI anomalies was reported.

While Southern Oscillation anomalies may drive changes in annual precipitation and temperature, the detected weak correlation between mean NDVI anomalies and SOI anomalies suggests that there may be a weak direct relationship between vegetation health and SO in Rwanda. According to **Figure 6**, temperature was moderately correlated ($rs = 0.47$) with changes in vegetation activity, indicating that NDVI was directly responsive to other climatic factors such as precipitation and temperature variations rather than the immediate changes in SO events.

3.3. Inter-Annual Rainfall Dynamics and Their Relationship with Vegetation NDVI

Figure 7 illustrates the spatial inter-annual variations of precipitation, as well as the spatial distribution of the correlation coefficient between precipitation and NDVI dynamics in Rwanda.

A Southwest-Eastward deflection in annual precipitation pattern has been noted in Rwanda. From 2000-2015, annual rainfall amounts have been tumbling in the western and southern parts of the country (up to -0.3 mm·year^{-1} in the far west) while gradually rising in the eastern parts of the country (up to $\approx +0.9$ mm·year^{-1} in Nyagatare district). This is in agreement with the findings of Ndayisaba *et al.* [12], who found that there was an apparently split pattern (gra-

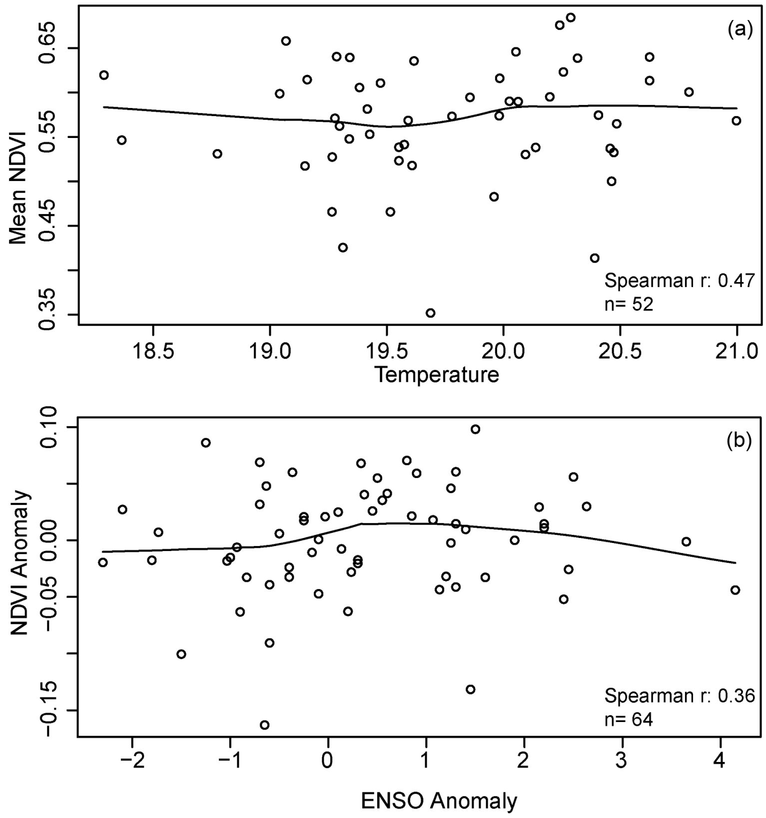

Figure 6: Spearman's correlation coefficient.

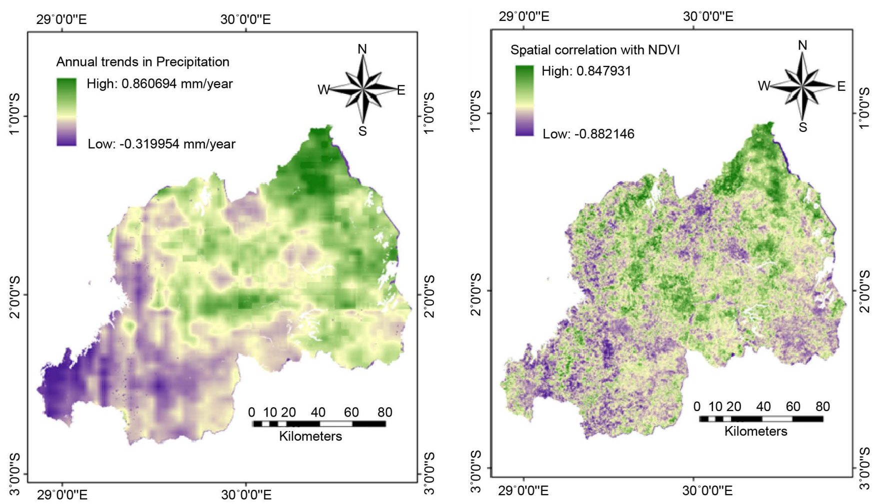

Figure 7. Annual trends in precipitation (left) and the Spatial correlation between precipitation changes and NDVI dynamics (right).

dual decrease in the west vs. gradual increase in the east) in precipitation dynamics over Rwanda during the first growing season [12].

As it can be observed in Figure 7 (right), precipitation was much more associated with vegetation health in low plains of Eastern Province (Nyagatare district in particular) than in the high altitude regions of the Congo Nile ridge. A strong positive correlation was found in rain fed croplands; mosaic vegetation;

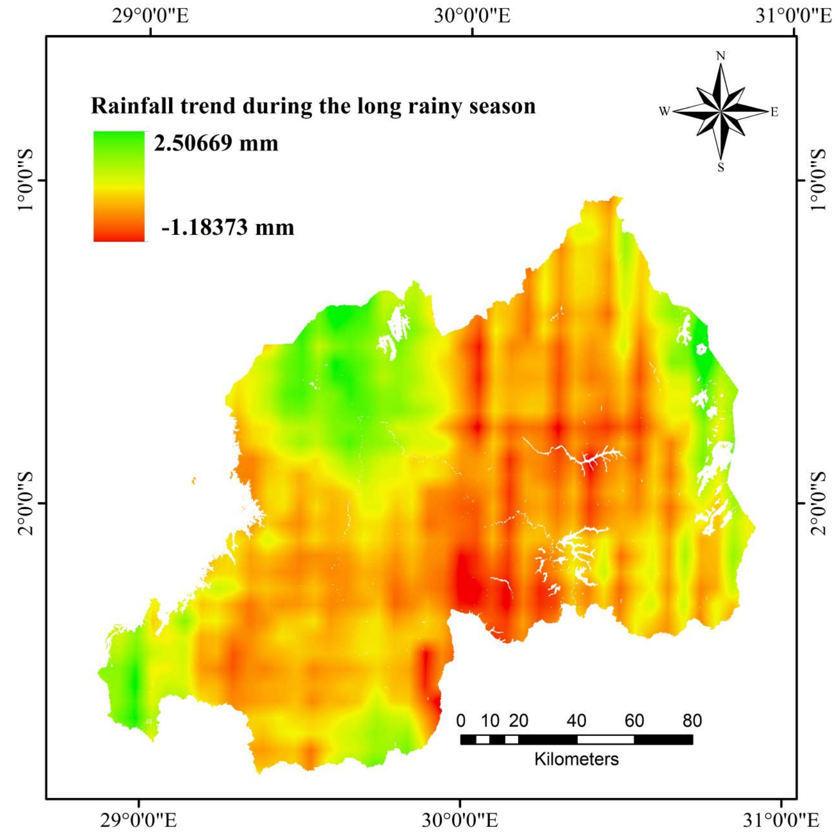

Figure 8. Spatial distribution of Rainfall dynamics during the Long Rainy Season from 2000-2015.

mosaic forest or shrubland, herbaceous vegetation/grassland savannah and sparse vegetation.

4. Discussion

4.1. Spatial Temporal Changes in Vegetation on Annual and Seasonal Basis

Changes in vegetation health and vigor have been evaluated by means of remote sensing, using NDVI as a reflective indicator. Vegetation phenology in the short rainy season (season 1) has generally been characterized by positive trends of increase and the maximum rate was +0.0523878 annually, while some sporadic spots of degradation have been observed on a small extent. These results agree with the previous findings obtained when a similar analysis was solely conducted over the first growing season, arguing that 81.3% of vegetation in the first growing season had improved either slightly or substantially [12]. Also, Bikash Basnet *et al.* [43] argued that reforestation efforts in the region such as national tree planting week (implemented by Government of Rwanda) since 2001 and other environmental awareness campaigns may have contributed to the slowdown of the overall trend in deforestation [43], eventually increasing the robustness of vegetation. For instance, this study has highlighted the overwhelming number of pixels in regeneration over the Nyamagabe district, which is reputed to be among top five districts protected against soil erosion in Rwanda according to the report issued by the National Institute of Statics of Rwanda.

During the short dry season (season 2); there are visibly bigger spatial extents of inter-annual vegetation canopy degradation along the central plateau and the crest Congo Nile from 2000 to 2015. Maximum degradation rate could go as high as -0.06 year^{-1} while the improvement rate could go as high as 0.05 year^{-1}. In the long rainy season (season 3), lots of degradation hotspots have been detected. A large number of pixels distributed throughout the country (**Figure 3**) incurred considerable diminutions in NDVI values; implying that the photosynthetic activity has been regressing during this season. Obviously, the malfunctioning of vegetation during the long rainy season can be attributed to inter-annual variations in rainfall. From **Figure 8**, it is shown that precipitation has been declining during this season in most parts of the country.

Areas in orange-to-red indicate a reduction in rainfall (up to -1.18 mm/year) while areas in medium apple highlight areas with rainfall increases (up to 2.5 mm/year). Referring to the information contained in **Figure 7** (right), areas significantly amenable to changes in rainfall such as the eastern province in Nyagatare and parts of the central plateau have been affected; thus leading to a decline in vegetation activity during this season.

4.2. Correlation between NDVI, Air Temperature and Southern Oscillations

This study has found that NDVI was moderately correlated with air temperature in Rwanda and weakly correlated with Southern Oscillations as shown in **Figure 6**. According to Xiaoyang Zhang et al, vegetation phenology closely follows the spatial and temporal patterns in rainfall seasonality [11]. Our research has found no significant direct relationship between the EN Southern Oscillations and vegetation phenology in Rwanda, corroborating the early findings of Anyamba A. and J. R. Eastman [44] who claimed that they had detected, most particularly over eastern Africa, another form of vegetation phenology inter-annual variation which was not consistent with ENSO anomalies. A number of other studies using standard meteorological data (rainfall and temperature) have shown that ENSO teleconnections over Africa had major centers in Southern Africa [44].

4.3. Investigating on the Correlation between Rainfall and NDVI on the Annual Scale

The results of this study suggest that vegetation phenology is significantly related to rainfall availability in the Eastern province of Rwanda, where the vegetation types are generally grassland savannahs and sparse vegetation. Patterns in vegetation green-up at small scales are partly associated with soil properties and vegetation types. Vegetation (especially herbaceous species) grows rapidly and early on sandy soils since rainfall can quickly infiltrate and is available for plant growth. In contrast, a large amount of rainfall evaporates or runs off from clay soils with low infiltration rates [45]. Negative correlations were established in the forest region of the western Rwanda, along the Congo Nile ridge. While analyzing the global relationships between NDVI and precipitation, Schultz *et al.*, maintain that tropical rainforests tend to have low NDVI precipitation correlations, largely as a result of year-round precipitation rates in excess of a threshold beyond which vegetation is not responsive [46]. The lack of correlation in forest regions is further confirmed by Shinoda M. [15], who suggested that in the equatorial rain forest, the water supply for vegetation is large enough all year round so that vegetation does not respond so markedly to precipitation. On the other hand, in the savanna region, where evaporation exceeds precipitation during the dry season, the vegetation quantities, such as green biomass, tend to respond drastically to the onset of the rainy season [15]. Agreeing to the previous findings of Ndayisaba *et al.*, 2015, vegetation phenology was poorly to negatively correlated with precipitation in highlands of Buberuka and southeastern parts of Rwanda such as Ngoma and Kirehe districts. Floods have been held responsible for major land and ecosystem degradation in the Northern Province [47].

4.4. Uncertainties and Outlooks

Even if there is no alternative to remotely sensed data for global, continental and regional scale monitoring of long term spatial temporal vegetation dynamics, the technique is not flawless. A wide array of phenomena in addition to temperature and precipitation may contribute to the interannual variance of NDVI. Crop scheduling, irrigation, fertilization, deforestation, and reforestation are examples of human impacts on vegetation that may not be directly attributable to climate anomalies [46]. Equally, fires, insect swarms, disease, and changes in topsoil are examples of naturally varying factors that may significantly impact vegetation [46]. Therefore, more research efforts linking satellite remote sensing detected trends to ground observations are greatly encouraged. Characterizing vegetation greenness would be improved by incorporating, at a fine resolution, NDVI, precipitation, air temperature, cloud cover, water availability across world biomes with new tools such as the vegetation sensitivity index [48].

5. Conclusion

The present study examined the influences and the characteristics of inter-annual changes in vegetation health in Rwanda. Changes in annual weather patterns were analyzed by means of precipitation datasets retrieved from CHIRPS and temperature data from the World Bank meteorological estimates. Changes have been elucidated from seasonal to annual standpoint. By analyzing the year-to-year fluctuations of a time series, it has been possible to reveal and quantify variations over the observation period, and the direction of change has been determined through the analysis of the slope value [49]. Trends statistically different from a null trend are assumed to be a measure of degradation of the vegetation cover; trends with non-significant (null) slope values represent stable areas while those with positive or negative slope values are respectively associated with progressive or regressive vegetation activity [50] [51]. It has been found that areas of improvement had improved at a maximum annual rate of approximately 0.05. 11.9% of the country's vegetation has significantly improved ($p < 0.05$) from slight to robust improvement while 10.4% of the vegetative cover degraded from slight to severe degradation. An estimated 77.6% of the vegetative cover has remained relatively stable. From the annual scale point of view, it has been observed that since 2000 to 2015, there's a consistent pattern of amelioration in the eastern province and degradation in the western province, especially along the forests boundaries and the Congo Nile ridge. Precipitation was significantly correlated with NDVI in the eastern province and poorly correlated in the western province. Future researches are encouraged to comprehensively ascertain the drivers of change in vegetation activity in the western province and the district of Ngoma district in the eastern province. Furthermore, flood mitigation policies are paramount to reduce vegetation cover degradation since vegetation canopies located on waterlogged soils and regularly flooded areas of the Western and Northern provinces were characterized by negative trends. Finally, similar studies conducted on a regular basis could significantly help in evaluating the regeneration process and the effectiveness of environmental protection policies throughout the country.

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