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RESEARCH ARTICLE

Vegetation dynamics in response to human and climatic factors in the Tanzanian Coast

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Abstract This study of vegetation dynamics in the coastal region of Tanzania provides a fundamental basis to better understand the nature of the factors that underlie observed changes. The Tanzanian coast, rich in biodiversity, is economically and environmentally important although the understanding of the nature and causes of vegetation change is very limited. This paper presents an investigation of the relationship between vegetation dynamics in response to climate variations and human activities using Moderate Resolution Imaging Spectroradiometer (MODIS), Normalized Difference Vegetation Index (NDVI), meteorological, and Globeland30 Landsat data sets. Spatio-temporal trends and the relationship of NDVI to selected meteorological variables were statistically analyzed for the period 2000–2018 using the Mann-Kendall test and Pearson correlation respectively. The results reveal a significant positive trend in temperature ($\beta > 0$, $Z = 2.87$) and a non-significant trend in precipitation ($|Z| < 1.96$). A positive relationship between NDVI and precipitation is observed. Coastal Tanzania has therefore experienced increased temperatures and variable moisture conditions which threaten natural vegetation and ecosystems at large. Classified land cover maps obtained from GlobeLand30 were analyzed to identify the nature and scale of human impact on the land. The analysis of land use and land cover in the region reveals an increase in cultivated land, shrubland, grassland, built-up land and bare land, while forests, wetland and water all decreased between 2000 and 2020. The decrease in forest vegetation is attributable to the fact that most livelihoods in the region are dependent on agriculture and harvesting of forest products (firewood, timber, charcoal). The findings of this study highlight the need for appropriate land-use planning and sustainable utilization of forest resources.

Keywords remote sensing, NDVI, climate variations, spatio-temporal changes, LULCC, coastal Tanzania

1 Introduction

Globally, spatio-temporal changes in vegetation are influenced by a range of natural and anthropogenic factors (Zhao et al., 2018). The effects of human disturbances such as climate change have resulted in land degradation that adversely impacts vegetation cover and its productivity (Lambin and Geist, 2006). As a result of land degradation, the provision of ecosystem services such as land-surface energy exchange, carbon balance, climate stability, water regulation, and soil preservation are threatened (Sutton et al., 2016; Pacheco et al., 2018). Vegetation, as a component of the ecosystem, influences the environment in a diverse range of aspects, it is hence frequently used as an indicator in the assessment of socio-ecological conditions and climate change (see for example, Huang et al., 2016; Daham et al., 2018).

Remotely sensed data have been widely used in the monitoring of ecosystem dynamics because of their synoptic coverage, accuracy, reliability, and cost-effectiveness and has benefitted from continuous developments in technology and improvements in resolution (Dubayah et al., 2020). In assessing vegetation dynamics,

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the satellite sensor data-based NDVI has been extensively applied in biophysical studies. It has demonstrated its simplicity and efficiency in studying the vegetation dynamics at both local and global scales, and, in combination with other sensors has even been used to predict future changes (Reddy and Prasad, 2018). Numerous recent studies have employed MODIS satellite data to study large-scale vegetation changes due to its higher spatial-temporal resolution. Additionally, MODIS data have exhibited consistency in spatio-temporal change detection by delivering more precise vegetation details (Fensholt and Proud, 2012). In the assessment of the wider range of human activities, Landsat data are useful due to its higher spatial resolution in obtaining specific details and computation of various land use and land cover types.

Many studies in Africa have applied remotely sensed data to the assessment of vegetation dynamics in relation to climate change and human impact. Such studies have been conducted in different countries including southern Africa (Richard and Poccard, 1998), Nigeria (Igbawua et al., 2016), Tanzania (Detsch et al., 2016), Zimbabwe (Matsa and Muringaniza, 2011; Mberego et al., 2013), Uganda (Abonyo et al., 2007), and Kenya (Kirui et al., 2013). The use of remotely satellite data is also crucial in the often-inaccessible areas along the coastal zone. Coasts are more vulnerable environments due to its high population growth and diverse economic activities (Danladi et al., 2017). In Tanzania, the majority of the population live in the coast and about 80 to 90% of them depend directly on the adjacent resources to sustain their livelihoods (Kebede and Nicholls, 2012; Nordic Development Fund, 2014). The increase in population has resulted in extensive pressure on coastal resources. Unsustainable utilization of the resources, for example, through forest clearing and shifting cultivation, has potential impact on ecological functioning, and ultimately further increasing the vulnerability of affected populations. Several researchers have reported on the impacts of human activities on the Tanzanian coast (Mligo, 2011; Kimaro and Lulandala, 2013; Idukunda et al., 2020). However, comprehensive assessments that consider both human and natural (climatic) forces are limited and detailed scientific information is therefore necessary to enhance understanding of relative effects of such factors.

This study uses NDVI MOD13Q1, Meteorological (MOD11A2 and CHIRPS) and Globeland30 land-use data sets to examine the vegetation dynamics in coastal Tanzania. Specifically, the study intended to: 1) analyze the trend between temperature and precipitation variables; 2) assess the response of vegetation (NDVI) to temperature and precipitation changes; and 3) determine the status and extent of LULCC in the study area. It is anticipated that the information from this study will be fundamental to planners, policymakers, and other environmental stakeholders. The ultimate goal is to achieve sustainable coastal management, and optimal utilization of coastal resources for poverty reduction, climate change adaptation, and sustainable development.

2 Materials and methods

2.1 Description of the study area

This study was conducted on the coastal region of Tanzania situated between latitudes 5°20′S–10°20′S and longitudes 38°00′E–40°20′E. The study area is defined here as the five coastal regions of the country, *viz*. Tanga, Pwani, Dar es Salaam, Lindi, and Mtwara (Fig. 1) and occupies some 142095 km^2, representing approximately 15% of the land area of Tanzania. Report from the 2012 census data showed that about 25% of the entire country's population (44.93 million) resides within the coastal region.

The dominant climatic condition throughout these coastal regions is hot and humid tropical. The atmospheric humidity of the coastal climate is high, which often goes up to 100% maximum and 65% to 70% minimum. In most

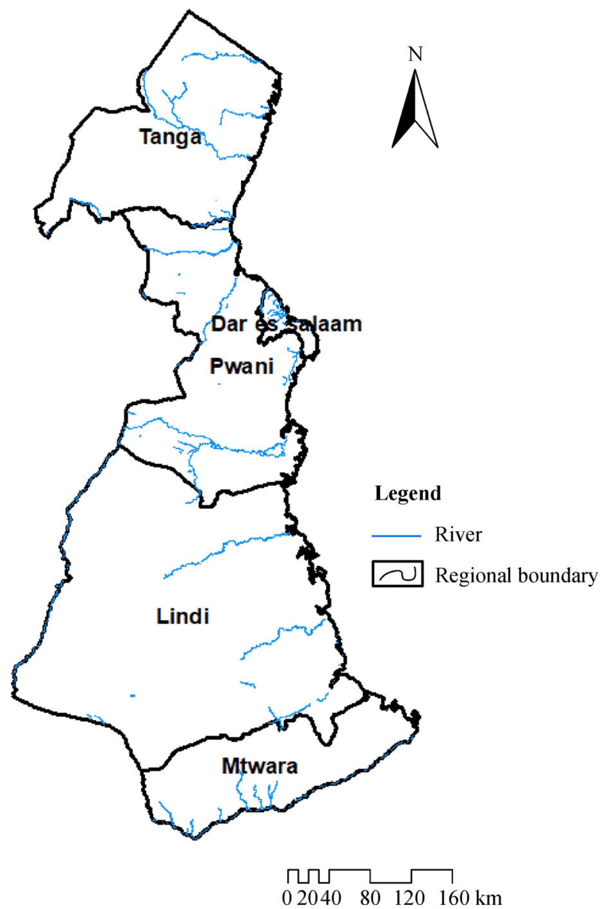

Fig. 1 Map of Tanzania showing location of the study area.

cases, there is no big variation of temperature at the coastal regions due to the influence of the Indian Ocean. The average annual temperature ranges between 20°C to 30°C. The rainfall has two seasons: the short rainy season (Vuli) and the long rainy season (Masika), and seasons vary depending on the spatial location. The northern coast (Tanga, Pwani and Dar es Salaam) experiences two rainy seasons i.e., long rains (March–May) and short rains (October–December), while the southern coast (Lindi and Mtwara) experiences rain only between November–April. Mean annual rainfall ranges from 800 to 1400 mm.

The coastal zone of Tanzania is well-endowed with good tourist attraction sites and a wide diversity of biotopes and species. These ecosystems (natural resources) include among others: coral reefs, saltmarshes, mangroves, coastal forests, seagrass beds, sandy beaches, dunes, estuaries, rocky shores and muddy tidal flats. The muddy flats are found in the intertidal zone, whereas the sublittoral zone comprises of extensive seagrass beds and coral reefs. Coral reefs are situated along shallow, tropical coastlines. They are mostly favored in the clean, clear, and warm water environment. Moreover, they are more common along the Tanzanian coastline, and well-developed barrier reefs occur along most of the ocean-facing eastern coastline of the islands. Furthermore, mangrove ecosystems play a key ecological role in the coastal environment. They are located along sheltered coastlines of brackish water (where wave interactions are minimum) in estuaries, lagoons, bays, tidal creeks, and inlets. The brackish water is formed where seawater mixes with fresh water from rivers such as Pangani, Wami, Ruvu, Rufiji, Matandu, Mbemkuru, Lukuledi, and Ruvuma. This environment (estuary) is very productive for nourishment of mangroves and seagrass beds. Seagrass beds are very common in sand-muddy tidal flats, coastal lagoons, and sandy areas around the bases of shallow fringing and patch reefs. They are widely scattered between high intertidal and shallow subtidal areas.

2.2 Data

2.2.1 NDVI

This study used the MOD13Q1 NDVI (Terra Vegetation Indices 16-day Global 250 m) data set from 2000 to 2018 archived in the Google Earth Engine (GEE) online platform. The starting period for the data set was selected based on the MOD13Q1 NDVI data availability (available at Google Earth website). The final year for data collection was based on recent data availability during PhD study for the first author. The assessment of large-scale vegetation dynamics was evaluated from the inter-annual time-series MODIS NDVI data during 2000–2018, through developing code in the GEE editor (available at Google Earth website). The platform provides cloud-based data storage across a wide range of time periods (extending over more than four decades) for geospatial analysis at a planetary scale (Patel et al., 2015) and has proved very significant in the analysis of environmental problems including drought, deforestation, climate change, and other environmental changes. The GEE comprises a multi-petabyte analytical catalog of data together with various computational services accessed and controlled via the Javascript Application Programming Interface (API) and Web-based Interactive Development Environment (IDE) (Gorelick et al., 2017). This tool is unique, efficient and fast as it provides a data set that is already corrected, calibrated and pre-processed according to the needs of this study. The MOD13Q1 has 250m spatial resolution and 16 days of temporal resolution. The NDVI values range between –1 and +1, with values less than 0.5 incorporating non-vegetation to sparse vegetation, and values above 0.5 for sparse to dense vegetation. The NDVI uses visible red (RED) and near-infrared (NIR) radiances of the spectral reflectance bands to measure the photosynthetic activity and health status of the vegetation, as shown in Eq. (1):

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}}. \tag{1}$$

2.2.2 Meteorological data

The study also made use of the meteorological data sets consisting of precipitation and land surface temperature obtained from the GEE platform. Remotely-sensed precipitation was calculated using the recently available CHIRPS (Climate Hazard Group Infrared Precipitation with Station) data sets for the period 2000 to 2018. The data set offers global coverage, delivers daily precipitation values at 0.05° spatial resolution, and has been applied successfully to climate change studies in other regions of East Africa (Funk et al., 2013; López-Carr et al., 2014; Shukla et al., 2014). The annual temperature data were retrieved from the MOD11A2 (Terra Land Surface Temperature and Emissivity 8-Day Global 1km) data set, which has an average of 8-days per-pixel, a spatial resolution of 1km in a 1200 km×1200 km grid; the LST_Day_1 km band, was used to evaluate the temperature trend from 2000 to 2018. The temperature value in Kelvin was then converted into degrees Celsius using Eq. (2):

$$t = a \times \mathrm{pixel} + b, \tag{2}$$

where t represents the real LST value (°C), a is the scale factor with a value of 0.02, pixel is the Digital Number (DN) value, and b is the offset with a value of -273.15.

2.2.3 GlobeLand30 land use data

The land use/cover patterns within the study area were assessed based on LULCC maps for the years 2000 and 2020 using the open-access GlobeLand30 landsat product (doi:10.11769/GlobeLand30.2000.db;doi:10.11769/GlobeLand30.2010.db). The global data set contains ten major land cover classes, although only eight (cultivated land, built-up land, forest, shrubland, grassland, wetland, bare land, and water) were applied in this study (Table 1).

2.3 Method

2.3.1 Landsat data preprocessing

Data tiles S37_0, S37_5 and S37_10 from Globeland30 cover the study area. The study used land cover data of 2000, 2010, and 2020, generated from Landsat TM and ETM + by selecting the best quality available images. The images were acquired from USGS at Level 1T, in which radiometric and geometric corrections were already applied (Chen et al., 2017). These images were stacked to generate multi-layer composite images so as to reduce computation and analysis time. Atmospheric correction was then performed on the images to remove inconsistencies caused by atmospheric constituents (dust, water vapor, CO_2, and O_3). Subsequently, the images were geographically projected onto the Universal Transverse Mercator (UTM) coordinate system, Datum WGS 1984, zone 37S. Thereafter, the corrected and projected data for the three data sets were clipped to the study boundary using the 'extract by mask' algorithm of the spatial analysis tool in GEE. Image processing was conducted using ENVI 5.1, ERDAS 2014 and ArcGIS 10.3 software.

2.3.2 Statistical analysis

Two analytical approaches were adopted in determining NDVI dynamics in relation to climatic variables. Trend and correlation analyses were carried out to determine NDVI dynamics in SPSS software. The inter-annual directional trend analysis for the NDVI and meteorological data sets were calculated from the monotonic Mann-Kendall (M-K) trend test (Zhang et al., 2018). Subsequently, the magnitude of trend was demonstrated using Sen's slope (β) and evaluated using a non-parametric robust trend analysis technique introduced by Theil (1950) and developed by Sen (1968). Generally, the Sen slope values range from –1 to + 1, where positive or negative values means the trend is increasing or decreasing respectively. The method assumes the trend is significant at $|Z| > 1.96$ at 95% confidence level ($\alpha < 0.05$). The parameters Z and β are defined and computed as follows (Cao et al., 2014):

$$Z = \left\{ \begin{matrix} \dfrac{s-1}{\sqrt{\mathrm{Var}(S)}} \\ 0 \\ \dfrac{s+1}{\sqrt{\mathrm{Var}(S)}} \end{matrix} \right\} \quad \text{if} \begin{cases} S > 0 \\ S = 0, \\ S < 0 \end{cases} \tag{3}$$

$$S = \sum_{j=1}^{n-1} \sum_{i=j+1}^{n} \mathrm{sgn}(x_j - x_i), \tag{4}$$

$$\mathrm{sgn}(x_j - x_i) = \begin{cases} -1 \text{ for } (x_j - x_i) < 0 \\ 0 \text{ for } (x_j - x_i) = 0 \\ 1 \text{ for } (x_j - x_i) > 0 \end{cases}, \tag{5}$$

$$\mathrm{Var}(S) = \frac{n(n-1)(2n+5)}{18}, \tag{6}$$

$$\beta = \mathrm{Median}\left(\frac{x_j - x_i}{j - i}\right),\ i < j, \tag{7}$$

where n is the total time duration (19 years), x_i and x_j represent the value of NDVI, temperature or precipitation at times i and j, and sgn is the symbol of sign function.

The correlation analysis was used to reveal the strength of a relationship between two variables. In this study, Pearson's correlation coefficient values were employed to indicate the strength of the relationship between NDVI and the climatic variables (Cui et al., 2018) using anomalies for each pixel from 2000 to 2018.

Table 1 Land use land cover classes used in the classification

Land use class	Description
Cultivated land	Land use for agriculture including paddy fields, irrigated and dry farmland, vegetation and fruit gardens, etc.
Grassland	Land covered by grasses mainly used for grazing
Forest	Natural and secondary forest covered with trees, including woodlands, dense and open forests
Shrubland	Land that is dominated by shrubs and bushes
Wetland	Land consisting of standing water bodies and wetland plants such as mangroves and salt marshes
Water	Land covered by water bodies such as rivers, lakes and ponds
Built-up land	Land that is modified by human activities including residential, industrial, transportation and other infrastructures
Bare land	Land which is typically not covered by any vegetation, i.e., bare soil, sandy beaches

$$r_{xy} = \frac{\sum_{i=1}^{n}\left[\left(x_i - \overline{X}\right)\left(y_i - \overline{Y}\right)\right]}{\sqrt{\sum_{i=1}^{n}\left[\left(x_i - \overline{X}\right)^2 \sum_{i=1}^{n}\left(y_i - \overline{Y}\right)^2\right]}}, \quad (8)$$

where: r_{xy} represents the correlation coefficient between x and y, ranging from -1 to $+1$, x_i and y_i are the values of NDVI and temperature/precipitation in the specific (i) year, $\overline{X}$ and $\overline{Y}$ are the mean values of NDVI and temperature/precipitation throughout all years, and n is the total time span from 2000 to 2018 (19 years). In addition, two-tailed p-values were used to determine the statistical significance of the correlation analysis whereby the relationship is said to be statistically significant when $p < 0.05$.

3 Results

3.1 Trends in climate variables

Temperature and precipitation are typically considered to be the most important climatic factors influencing vegetation and can either enhance or constrain greenness. The mean maximum temperature of 31.2°C occurred in 2017 and minimum of 27.4°C in 2002, with a mean value of 29.3°C (Fig. 2(a)). The Mann-Kendall temperature trend analysis estimated values of $Z = 2.87$ and $\beta = 0.152$. This threshold $|Z|$ value is > 1.96, thus rejecting the null hypothesis and implying that the trend in temperature over the period is both positive and statistically significant. Given that increased temperatures are associated with higher evapotranspiration, it is expected that this would impact soil water availability and, in turn, reduce vegetation greenness. Maximum annual precipitation occurred in 2006 (1344 mm) and minimum (650 mm) in 2003, with a mean of 997 mm (Fig. 2(b)). The precipitation trend analysis produces values of $Z = 1.68$ which, being below 1.96, means that the null hypothesis is accepted and that the trend, while positive, is not statistically significant. It is known that precipitation fluctuations in the coastal Tanzania are driven by El-Niño/Southern Oscillation (ENSO) variations which expose the region to major climatic hazards such as droughts, floods and ENSO warm events (Kijazi and Reason, 2005; Park et al., 2020). The influence of ENSO may therefore obscure any directional precipitation trend but, in general, the rainfall situation intensifies moisture stress on vegetation which in-turn will threaten the ecosystems and socio-economic development of the country over time.

3.2 Relationship between NDVI and the climatic variables

The nature of the response of NDVI to the temperature and precipitation dynamics was examined using Pearson correlation analysis. Vegetation growth, as measured by NDVI, exhibits a positive relationship with precipitation

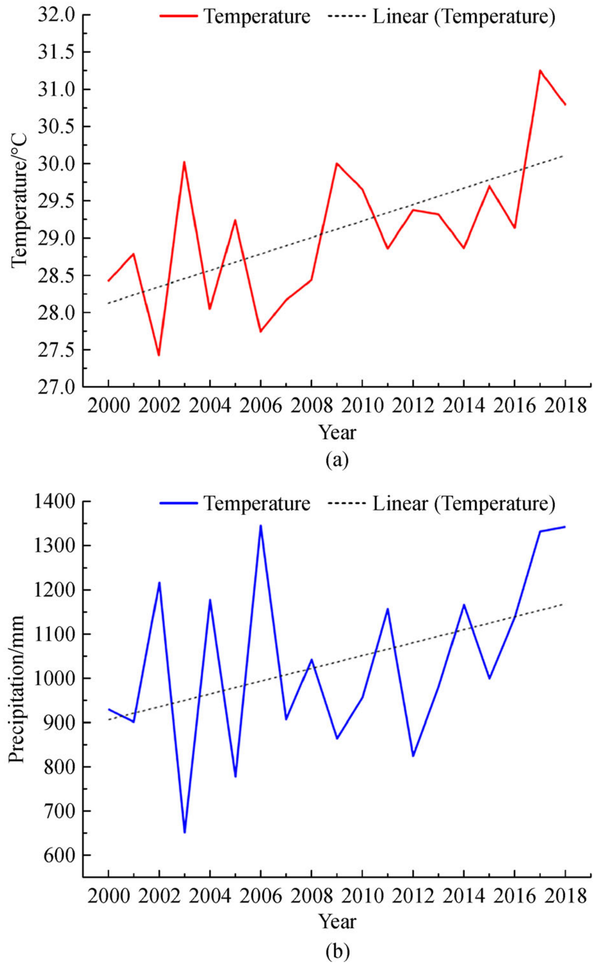

Fig. 2 Inter-annual climatic variations for (a) Temperature; (b) precipitation in Tanzania coast from 2000 to 2018.

but is negatively correlated with temperature (Figs. 3(a)–3(d)) which is consistent with the fact that soil moisture availability strongly influences vegetation growth and productivity (Wang et al., 2003a; Sun et al., 2015; Liu et al., 2016). Results confirmed that precipitation and temperature are the prominent controlling factors and have a strong influence on NDVI time-series. Lag effects are evident in the time series. For example, it is perhaps surprising that, in Tanga and Mtwara, NDVI increased regardless of lower annual precipitation values between 2006 and 2007 (Figs. 3(b) and 3(c)). However, higher rainfall values in the previous two years (2005–2006) appear to have been able to support vegetation growth through the drier years. Moreover, the NDVI varied seasonally, with the wet season depicting higher NDVI than dry season (Supplementary Fig. S1), corresponding to higher rainfall (Supplementary Fig. S2).

Mean annual precipitation is variable over the time period studied, with some years receiving amounts of rainfall considerably below the average and experiencing drought, most notably in 2003. Chang'a et al. (2010) and

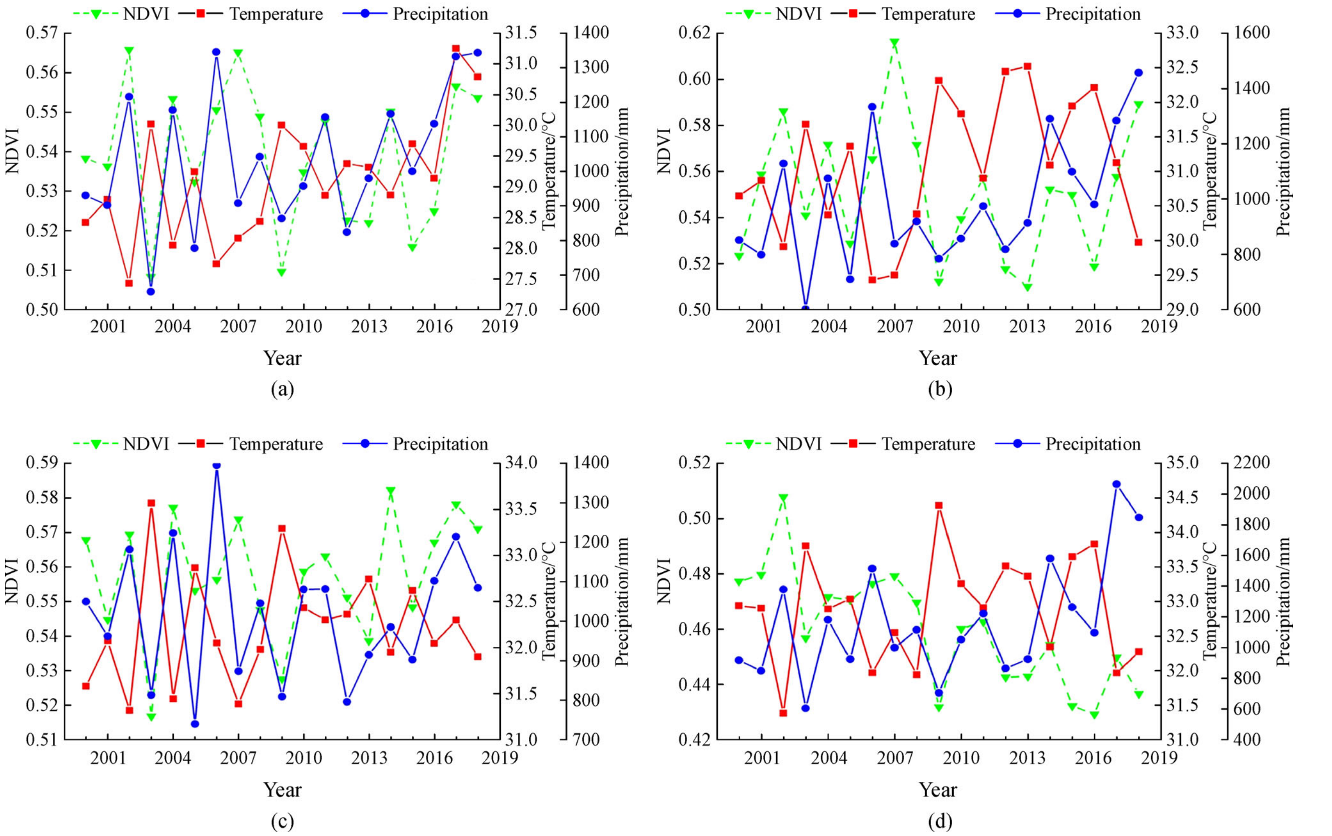

Fig. 3 Inter-annual variations and relationship between NDVI and climatic variables (a) Tanzania coastal regions; (b) Tanga; (c) Mtwara; (d) Dar es Salaam for 2000–2018.

Hassan et al. (2014) also noted the drought in coastal Tanzania around this time. Dar es Salaam (Fig. 3(d)), while exhibiting a general increasing trend in precipitation over the time period, reveals a decreasing NDVI trend. Dar es Salaam has been subject to rapid urbanisation (Ricci, 2012) in the recent past so that vegetation change is mostly attributable to human activities rather than climate.

3.3 Patterns of land use and land cover from 2000 to 2020

Human activities are considered as very important or even dominant factors in global environmental change. While anthropogenic changes are sometimes beneficial, in most cases, human impacts on ecosystems are negative (Abonyo et al., 2007; Eludoyin et al., 2011; Hosonuma et al., 2012). Based on results depicted in Fig. 4, it is evident that the coastal area of Tanzania has undergone considerable changes in the patterns of land use cover between 2000 and 2020. The consistent increase between the interval period (2000–2010) and (2010–2020) were observed in cultivated land, built-up land and bare land, whereas the area occupied by forests, and water was reduced during the same period (Table 2). The areas containing 'no data' were excluded in the land use column of Table 2 to avoid confusion during the land cover change detection analysis. This affects the overall area coverage and seems to differ in each year of analysis as observed in the Table 2. The increase and decrease between land covers is as well illustrated in the Table 3 and Table 4 below, which shows what land covers attribute to either the increase or decrease of the other land cover.

4 Discussion

4.1 Consequences of LULCC

The natural vegetation in the study area has been affected by various human activities over the period 2000 to 2020 as revealed in Table 2. Although forest occupied more than half of the total area, there has been loss of cover in these vegetation types of more than one million hectares (7.87%) between 2000 and 2010. The area was still undergoing minor changes within the next 10-years (2010–2020), where there is a decrease of 1.89%. The decline was mainly due to forest exploitation for resources such as fuelwood, charcoal, timber, and herbs which are sold in urban areas to generate income (Saha and Sundriyal, 2012). Additionally, forest is also cleared frequently for agriculture and settlement in order to sustain increasing

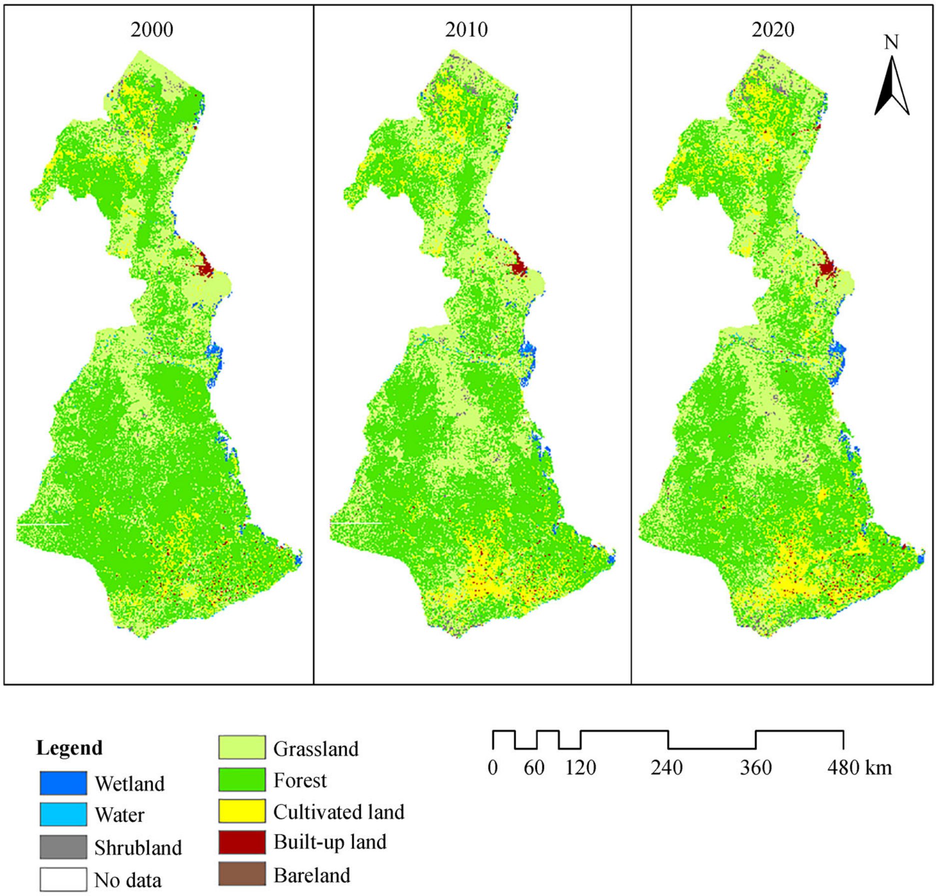

Fig. 4 Land use and land cover change maps in the Tanzania coast for 2000, 2010, and 2020.

Table 2 Table showing land use land cover change between 2000 and 2020

Land Use	Year 2000		Year 2010		Year 2020		Change 2000–2010		Change 2010–2020	
	Land/ha	Percent/%	Land/ha	Percent/%	Land/ha	Percent/%	Land/ha	Percent/%	Land/ha	Percent/%
Cultivated land	923375.88	6.35	1356133.50	9.32	1744766.19	12.06	432757.62	2.98	388632.69	2.74
Forest	9063002.97	62.29	7917180.39	54.42	7596891.27	52.53	–1145822.58	–7.87	–320289.12	–1.89
Shrubland	50422.41	0.35	125711.10	0.86	121369.95	0.84	75288.69	0.52	–4341.15	–0.02
Grassland	4240074.78	29.14	4870028.79	33.48	4698764.10	32.49	629954.01	4.33	–171264.69	–0.99
Built-up land	89119.35	0.61	92005.20	0.63	121395.69	0.84	2885.85	0.02	29390.49	0.21
Wetland	126976.86	0.87	124706.70	0.86	127366.56	0.88	–2270.16	–0.02	–252073.26	0.02
Water	54883.17	0.38	52965.09	0.36	40192.20	0.28	–1918.08	–0.01	–12772.89	–0.09
Bareland	1399.59	0.01	8951.22	0.06	11739.15	0.08	7551.63	0.05	2787.93	0.02
Total	14549255.01	100	14547681.99	100	14462485.11	100	–	–	–	–

population demands. Generally, wetlands are among the areas most vulnerable to change considering their high fertility level. It is shown from the Table 3 and Table 4 that only less amount (18.37%) was encroached, and it seems that in this period, communities appear to have been aware of the conversation practices. Given that the destruction of wetland during 2000 to 2010 managed to be restored within the next interval (2010–2020), it can be established that people's awareness has increased probably due to the Mangrove Management Project (MMP) initiatives (Wang et al., 2003b). In case the coastal forests and wetlands undergoes continuing destruction, the ecological value will certainly be threatened. In the absence of alternative, more sustainable livelihoods, utilization of forest products is

Table 3 Land use and cover change detection matrix for years 2000–2010

Land Use/cover		Year 2010							
		Bareland/ha	Built-up/ha	Cultivated/ha	Forest/ha	Grassland/ha	Shrubland/ha	Water/ha	Wetland/ha
Year 2000	Bareland	**517.79**	0.06	2.69	7.86	131.46	25.31	302.17	3.87
	Built-up		**24407.70**	4504.51	1043.26	580.03	1.91	0.27	91.27
	Cultivated	1.28	1021.13	**162886.29**	56354.72	35782.97	501.43	59.66	107.61
	Forest	28.55	789.60	259756.60	**638772.65**	144135.89	5382.81	187.72	313.64
	Grassland	196.13	565.35	104977.66	74894.20	**188192.49**	18088.20	2512.36	1567.12
	Shrubland	35.83		0.10	22.11	548.75	**787.76**	70.44	0.28
	Water	157.65	1.81	200.33	175.74	4628.46	66.06	**6909.19**	254.62
	Wetland	20.66	0.65	70.09	741.43	527.28	30.72	622.84	**10393.70**
	Total	**957.89**	**26786.31**	**532398.26**	**772011.97**	**374527.34**	**24884.20**	**10664.645**	**12732.10**

Table 4 Land use and cover change detection matrix for years 2010–2020

Land Use/cover		Year 2010							
		Bareland/ha	Built-up/ha	Cultivated/ha	Forest/ha	Grassland/ha	Shrubland/ha	Water/ha	Wetland/ha
Year 2010	Bareland	**780.89**	4.08	2.36	5.95	140.11	34.47	1.77	24.58
	Built-up	3.45	**28809.37**	5001.11	37.45	56.79	7.37	0.88	2.04
	Cultivated	5.00	1080.70	**384978.71**	60201.11	36100.10	700.66	37.02	336.83
	Forest	40.74	905.00	207259.33	**574708.65**	3576.06	6007.34	133.54	70.25
	Grassland	207.00	801.00	105012.11	85056.21	**201011.40**	422.37	73.52	1625.70
	Shrubland	47.00	120.63	206.30	927.10	418.62	**30803.71**	34.35	23.82
	Water	168.00	5.15	176.77	96.00	59.83	40.03	**5700.78**	42.65
	Wetland	32.00	89.06	64.00	658.92	38.62	14.22	55.69	**9716.61**
	Total	**1284.08**	**31814.98**	**702700.69**	**721691.39**	**241401.52**	**38030.17**	**6037.55**	**11842.49**

often the only livelihood option for the majority of poor community members in the coastal area (Shackleton et al., 2011; Aheto et al., 2016).

On the other hand, the areas covered by grassland, agriculture, shrub land, and bare land have increased by 4.33%, 2.98%, 0.52%, and 0.05% respectively during the period 2000 to 2010 (Table 2). Between 2010 and 2020, grassland and shrub land had shown minor degradation of 0.99% and 0.02% respectively. While, bare land and cultivated land were still increasing at the rate more or less similar to the previous years. The marked increase in cultivated land is simply a consequence of the need for food. The type of agriculture carried out by the majority of farmers is shifting cultivation, whereby farmers move in search of fertile land, clear the forest and plant crops. Clearing forests through slash-and-burn practices which are then over-cultivated results in loss of land fertility, thus resulting in further forest clearance and so on (Nwaga et al., 2010). The infertile land abandoned by farmers may regain its fertility over time, but initially it is occupied by shrubs and grasses (Rautiainen et al., 2016). The increase in bare land is the result of cutting down trees for forestry and leaving the land barren.

Built-up land increased during 2000 to 2020 (Table 2) and is attributable to driving factors like population and urbanization as noted by Lambin and Geist (2006). Dar es Salaam is seen to be growing faster (Table 5) than other cities because, as the largest city in Tanzania, it is a focus for business and other socio-economic services, such that there have been high levels of rural-urban migration (Cockx et al., 2019) and currently endures the consequences of high population density due to inadequate planning. Urbanization without adequate planning has had various environmental and socio-economic problems including urban sprawl, poor sanitation (which has detrimental effects on public health), increased surface run-off, and subsequent flooding risk, especially in informal settlements (Jones, 2017; Williams et al., 2019).

4.2 Socio-ecological implications

Recently, the government of Tanzania has proposed transforming into an industrial economy through reliable infrastructure and power-plant development with the aim of achieving middle-income status by 2025 (Sarakikya et al., 2015). Developing a diverse industrial base is intended to serve as the main catalyst to advance the economy, generate sustainable growth and reduce poverty,

Table 5 Tanzania rural and urban coastal regions population census of 1988, 2002, and 2012

Administrative region	Rural/urban coastal regions population/%		
	1988	2002	2012
Tanga	82.4/17.6	81.6/18.4	78.4/21.6
Pwani	85.2/14.8	78.9/21.1	67.2/32.8
Dares Salaam	10.4/89.6	6.1/93.9	0/100
Lindi	85.0/15.0	84.0/16.0	81.3/18.7
Mtwara	85.6/14.4	79.7/20.3	77.1/22.9

Source: NBS and OCGS (2013)

which will facilitate improved development. Coastal areas in particular are deemed to be fundamental economic hotspots globally, especially those associated with major natural gas and oil fields (Masalu, 2000; Choumert-Nkolo, 2018), as is the case in East Africa where there is ongoing infrastructural development including the construction of the East African Crude Oil Pipeline (EACOP), and the DANGOTE Thermal Power Station (Robbins and Perkins, 2012). It is clear that these industries will further increase the emissions of greenhouse gases into the atmosphere as indicated in the IPCC Fifth Assessment Report (IPCC, 2014a). Such changes will likely accentuate the trend in temperature observed in the study, with further intendent impacts on terrestrial ecosystems and constraints to national and regional development strategies. Higher temperatures reduce soil moisture through greater evapotranspiration and thus lead to significant soil water deficit that inhibits vegetation.

The decline in NDVI values arising from increased temperatures shown here for coastal Tanzania is a useful indicator of drought incidence (Sruthi and Aslam, 2015). Increased drought frequency and intensity constrains the plans to develop an industrial economy, since water supply shortages have a negative influence on hydro-electric power supply. Indeed, the severe drought of 2005 contributed to acute power blackouts and food shortages in the country leading to serious economic decline (Kijazi and Reason, 2009). The impact was even more pronounced in 2006, during which direct economic losses of up to 200 million USD in food imports and distribution were incurred (Kijazi and Reason, 2009; Mongi et al., 2010; Sweya et al., 2018). Hassan et al. (2014) and Kashaigili et al. (2014) have identified that, in recent years, the coastal regions of Tanzania have experienced more frequent and pronounced drought conditions than in the past with negative implications for the local communities relying on climate-impacted economic sectors (agriculture, fishing, and tourism) for their livelihoods. This has been particularly notable in crop production; for example, the marked decline in the value of the maize harvest, and a major reduction in coconut production (Lyimo et al., 2013). These reduced crop yields are a threat and may lead to increased poverty and food insecurity (IPCC, 2014b).

5 Conclusions

The coastal zone is greatly affected by climatic variations and human activities. The study used remote sensing data to detect vegetation change in the Tanzanian coastal region with respect to human activities and climatic variations. The results reveal a markedly increasing temperature trend and decreasing vegetation growth caused by increased evapotranspiration and reduction of soil moisture availability. Precipitation plays a major role in supporting vegetation growth in the studied areas. Human activities played key roles in reducing water availability and forest, and ultimately affect vegetation cover negatively. The development of a better governance model that fosters sustainable ecological conservation and ecosystem restoration is critically important in vulnerable coastal regions such as those in Tanzania.

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