Vegetation Greenness Trend in Dry Seasons and Its Responses to Temperature and Precipitation in Mara River Basin, Africa

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Abstract: The Mara River Basin of Africa has a world-famous ecosystem with vast vegetation, which is home to many wild animals. However, the basin is experiencing vegetation degradation and bad climate change, which has caused conflicts between people and wild animals, especially in dry seasons. This paper studied the vegetation greenness (VG), vegetation greenness trends (VGT), and their responses to climate change in dry seasons in the Mara River Basin, Africa. Firstly, based on Google Earth Engine (GEE) platform and Sentinel-2 images, the vegetation distribution map of the Mara River Basin was drawn. Then dry seasons MODIS NDVI data (January to February and June to September) were used to analyze the VGT. Finally, a random forest regression algorithm was used to evaluate the response of VG and VGT to temperature and precipitation derived from ERA5 from 2000 to 2019 at a resolution of 250 m. The results showed that the VGT was fluctuating in dry seasons, and the spatial differentiation was obvious. The greenness increasing trends both upstream and downstream were significantly larger than that of in the midstream. The responses of VG to precipitation were almost twice larger than temperature, and the responses of VGT to temperature were about 1.5 times larger than precipitation. The climate change trend of rising temperature and falling precipitation will lead to the degradation of vegetation and the reduction of crop production. There will be a vegetation degradation crisis in dry seasons in the Mara River Basin in the future. Identifying the spatiotemporal changes of VGT in dry seasons will be helpful to understand the response of VG and VGT to climate change and could also provide technical support to cope with climate-change-related issues for the basin.

Keywords: Mara River Basin; dry seasons; vegetation greenness; random forest regression; spatiotemporal differentiation

1. Introduction

The dynamic of vegetation greenness (VG) is important for understanding the effect of climate change and human encroachment on land surfaces [1]. In general, vegetation greenness can be explained as the growth of surface green vegetation. The East African region is classified as semi-arid land that is sensitive to human intrusion on vegetation and climate variation [2]. This region is one of the most important land ecosystems specified by the codominance of grasses, forests, and shrubs, and it covers 20% of the world’s land [3]. However, vegetation is almost brown in the late dry seasons [4]. It was found that the deforestation rate increased from 0.22% (1900) to 0.39% (2000) in the East African region [5]. In recent years, frequent drought disasters have caused a continuous decline in vegetation greenness from Central Kenya to Central Tanzania during the El-Nino period [6]. Therefore,
it is important to monitor vegetation greenness change to mitigate the natural disaster in the East African region.

Remote sensing is the most widely used tool for monitoring vegetation change, desertification, and agriculture activity on a global scale [7]. In recent decades, various satellite products at different temporal, spatial, and spectral resolutions have provided accurate datasets for the earth’s surface [8]. The high-spatial-resolution satellite imagery, such as LANDSAT (30 m) and Sentinel-2 (10 m), provides timely and accurate monitoring of vegetation classes [9]. Sentinel-2 optical image especially gives an additional advantage in monitoring vegetation changes due to their red edge bands [10]. Moreover, the short-wave infrared and optical bands in the satellite sensor have the capability to construct a band-ratio such as the normalized difference vegetation index (NDVI) [11]. However, due to their short observation period, the Landsat and Sentinel-2A sensors cannot be used for near-real-time monitoring and long-term changes in VG [12]. The Moderate Resolution Imaging Spectroradiometer (MODIS) sensor has 36 spectral bands, including two vegetation indices (NDVI and EVI) for comparison of global vegetation change [13]. In addition, the MODIS NDVI product allows for the monitoring of vegetation dynamics for a long period of time, at a high spatial (250 m) and temporal (16-day composite) resolution [14].

The normalized difference vegetation index (NDVI) has been proved to be the best indicator of vegetation greenness [15,16]. Most of the previous studies used MODIS NDVI products for long-term VG monitoring at a both the regional and global scale. Hmimina et al. [17] investigated the usefulness of MODIS NDVI data for monitoring the seasonal changes of VG in the African savanna, including terrestrial biomes and deciduous and evergreen forests. This study found that the 16-day composite of MODIS NDVI allows for accurate estimation of greenness in the spring season. Potter [18] analyzed the recovery rates of VG by using MODIS NDVI in Alaska’s severely burned wetland ecosystem. Fang et al. [19] reported vegetation dynamics by using the Breaks for Additive Seasonal and Trend (BFAST) method and MODIS NDVI product in Quebec, Canada, from 2000 to 2011. Wang et al. [20] monitored VG change by using MODIS NDVI data at three river source regions in China. Similarly, Gillespie et al. [21] investigated the spatial and temporal pattern of vegetation changes in Southern California by using MODIS NDVI data from 2000 to 2016. In recent years, Touhami et al. [22] evaluated the MODIS NDVI time series to monitor the vegetation dynamic over the Mediterranean forest region in Northeast Tunisia in response to the climatic variable. Therefore, this study considers MODIS NDVI products to monitor VG over the Mara River Basin in East Africa.

The greenness of grass and shrub was more sensitive to climate change than forests [5]. Generally, the NDVI had a linear relationship with average annual precipitation. However, the response of NDVI to precipitation was more significant than temperature [1]. The increase in precipitation can promote a vegetation greenness trend (VGT), while the increase in temperature will inhibit the VGT of a region [6]. Nicholson et al. [2] showed that NDVI variability is closely related to climate factors. Therefore, it is important to monitor climate factors on VG. For African Savannas, most of the previous studies proved that the VG presented a decreasing trend in dry seasons, using NDVI, which is retrieved from various satellite sensors, such as Advanced Very High Resolution Radiometer (AVHRR), the Global Inventory Monitoring Modeling System (GIMMS), and MODIS [1,5,23]. The Maasai Nara National Park in East Africa especially showed decreasing rainfall and a rising temperature in the dry seasons, thus causing the forests and shrubs to show a preceding greening trend, and the grass showed a browning trend [24,25]. In general, climate change significantly impacted VG in the Mara River Basin [26], and vegetation degradation seriously threatened the survival of livestock and wildlife in the Mara River Basin [27]. However, there is still little known about the VGT in dry seasons and its responses to climate change in the Mara River Basin. Currently, most studies consider only the temporal differentiation and responses of VG to environmental factors and ignore the spatial differences. In addition, most studies focus only on the Maasai/Serengeti ecosystem, whereas few studies consider the whole basin. In addition, most studies choose a large area to establish the relationship
between VG and climatic variables (precipitation and temperature). However, no studies have shown the VG on a basin scale. Therefore, this paper considers the Mara River Basin for analyzing the responses of VG to climate change.

Based on the spatial vegetation distribution maps of the Mara River Basin drawn on the GEE platform, this paper uses the MODIS NDVI product and climate data for dry seasons in the Mara River Basin from 2000 to 2019. Our study analyzed the relationship between VG and climate change. The main objectives of this study were (i) to estimate the spatial and temporal distribution of VG by using the random forest (RF) regression algorithm in the Mara River Basin; (ii) to investigate the trend of VG and climatic variables (precipitation and temperature), using the Sen+Mann–Kendall test of the studied region; and (iii) to provide a clear view of the spatial distribution of VG, VGT, and their responses to climate change on a basin scale. In addition, this paper provides a theoretical basis for scientific assessment and reference to formulate ecological protection policies in the Mara River Basin.

2. The Study Area and Data

2.1. The Study Area

The Mara River (Figure 1) is the transboundary between Tanzania and Kenya in East Africa (Location: 33°88’ E to 35°90’ E and 0°28’ S to 1°97’ S). The basin contributed 65% of its area in Kenya and 35% in Tanzania. The river originates at the Mau Forest Escarpment and merges at the rural Musuma in Tanzania to Lake Victoria, passing group ranches, Maasai-Mara National Reserve, and Serengeti National Park. The Mara River is the only perennial river in the region that plays an important role in the ecohydrology of the basin [28]. The upstream of the Mau Forest Escarpment is a protected complex forest, and the rest of the areas in the upstream are almost farmland. The midstream mainly consists of grass and ranches, including two international wildlife reserves, which are the main wildlife tourist attractions in the basin. The downstream includes the Mara wetland and Mara mine. Moreover, it is the main source of production and living materials for residents and wild animals [29].

Figure 1. Location Map of the Mara River Basin.
The precipitation in the basin is bimodal with two rainy and dry seasons. The long dry season is from June to September, and the short dry season is from January to February. The average temperature is 18–23 °C, and the annual total precipitation is 200–500 mm in the dry season [30]. The dry season is the time for the great migration of wild animals [31], and also the time for the largest water requirement for agricultural irrigation upstream [32]. The more frequent and severe drought disasters in the dry seasons [24] have caused rapidly increasing water demand for agricultural irrigation [32]. The ecological environment in this region is fragile, which has led to a terrible impact on the basin’s ecosystem.

2.2. Data

The data used in this paper include Sentinel-2 images and MODIS NDVI, temperature, and precipitation data. The time series of Sentinel-2 images were from June 2015 to June 2020 and were obtained from the Google Earth Engine (GEE) platform (https://earthengine.google.com/, accessed on 30 July 2021). This paper used Sentinel-2 images to draw vegetation distribution map referring to some relevant references [33,34]. The VG (NDVI) data were derived from MODIS sensor (MOD13Q1) from Aeronautics and Space Administration (NASA) (https://modis.gsfc.nasa.gov/, accessed on 10 August 2021). The time series of the MODIS NDVI data were from January to February and June to September during 2000–2019. The temperature and precipitation data were obtained from ERA5-Land monthly averaged data from 1950 to present from the European Centre for Medium-Range Weather Forecasts (https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5, accessed on 20 August 2021), during January/February, and June–September from 2000 to 2019. The temperature and precipitation data were resampled to a 250 m resolution to match with the spatial resolution of MODIS NDVI products.

3. Methods

The overall workflow of our study was structured with three sections (Figure 2). First, this study used the random forest (RF) algorithm to classify Sentinel-2 images into four main vegetation types (forest, crop, shrub, and grass) and obtained the vegetation distribution map in GEE platform. Second, the RF regression algorithm was used for MODIS NDVI, temperature, and precipitation data to analyze the response of VG to climate change. Then Thiel–Sen/Mann–Kendall trend-testing was used for the VG, temperature and precipitation. Finally, the RF regression algorithm was used again to investigate the response of VGT to temperature and precipitation.

![Figure 2. Flowchart of the methodology.](image-url)
3.1. Random Forest Algorithm

The random forest algorithm is an algorithm based on the classification tree, combining bagging, random subspace, and decision tree methods [35,36]. The algorithm integrates the bootstrap aggregation method to generate subsets; that is, \( M (M = 1, 2, 3, \ldots, n) \) training sample sets with the same size as the original sample sets are randomly selected from the original sample set through bootstrap aggregation, and multiple decision trees are constructed accordingly. When splitting each node of the decision trees, the random subspace method is introduced to evenly and randomly extract a feature subset from all \( K \) features, and then an optimal splitting feature from the subset is selected. Finally, the mean value of multiple decision trees is taken as the final result. The RF algorithm has been widely used in classification and regression [37,38]. When the dependent variable is a classified variable, the algorithm is a classification algorithm. When the dependent variable is a continuous variable, the algorithm is a regression algorithm. The random forest algorithm can be briefly expressed as follows:

\[
\hat{f} = \frac{1}{B} \sum_{b=1}^{B} f_b(x)
\]

where \( \hat{f} \) represents the final results, \( B \) is the number of the trees, \( f_b \) is the classification or regression function, and \( x \) represents the training sample values.

The RF algorithm improves the accuracy of results using bootstrap to alleviate high variance and weak the correlation between decision trees. It is easily operated by only adjusting the number of trees in the forest and debugging the number of features of each node is needed to generate a reasonable model quickly and efficiently. Compared with other machine learning algorithms, the RF algorithm can incorporate nonlinear relationships and explain complex relationships between variables [39]. Therefore, this study used RF algorithms to draw a vegetation distribution map and to analyze the responses of VG and VGT to climate change in dry seasons of the Mara River Basin.

3.2. Vegetation Distribution Mapping Based on GEE Platform

The RF algorithm was used to create a vegetation distribution map from Sentinel-2 images on the GEE platform. The classification process was as follows.

Savanna is dominated by grass, forests, and shrubs, so the vegetation was planned to be classified into four types (forest, crop, shrub, and grass), according to the references [33,34] and the consideration for saving classification time and observability. Then we extracted ROIs for each vegetation type. Considering the above ROIs should be evenly distributed in the whole basin and proportional to the area of each vegetation, 20,000 ROIs were finally extracted: forest (2240), crop (3620), grass (10,500), and shrub (3640), respectively, on the GEE platform as the training samples for the supervised classification. After exporting Sentinel-2 images into the GEE platform, the QA60 band was used to remove the clouds from the study area, and we calculated the 5-day cycle of NDVI. The Max Value Compound (MVC) method [40] was used to synthesize the maximum monthly NDVI to generate 12 months of monthly NDVI for every year. To further eliminate clouds and smooth the filtering, we used the time series harmonic analysis method (HANTS) to reconstruct the monthly NDVI [41]. Before the supervised classification, the importance of monthly NDVI was evaluated by RF regression, and only the months with the importance greater than 50% (January, February, June, July, August, and November) were selected as the characteristic months [42]. The 20,000 samples were randomly split into two groups during classification by the RF algorithm: 70% for training and 30% for validation. Then the yearly vegetation distribution maps from 2015 to 2019 were drawn. Based on the vegetation distribution maps from 2015 to 2019, the final vegetation distribution map of the Mara River Basin was created from the dominant vegetation type of each grid.
3.3. Thiel–Sen/Mann–Kendall Trend-Testing Approach

Thiel–Sen/Mann–Kendall trend-testing [43] was used to investigate the trends of VG, temperature, and precipitation. This approach uses the Sen trend degree S-value to reduce the interference of images’ noise and to judge whether the images show increased or decreased trends. The S-value is calculated by Formula (2):

\[ S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}(x_j - x_i) \]  \hspace{1cm} (2)

\[ \text{sgn}(x_j - x_i) = \begin{cases} +1, & x_j - x_i > 0 \\ 0, & x_j - x_i = 0 \\ -1, & x_j - x_i < 0 \end{cases} \]  \hspace{1cm} (3)

For vegetation, a positive value of S-value indicated a greening trend, and a negative S-value indicated a browning trend. For temperature and precipitation, a positive S-value presented an increasing trend for climate factors, while a negative S-value presented a decreasing trend.

Then this approach uses Mann–Kendall Z-value to test the significance of the long-term sequence trend, which can better detect areas with minor changes and judge the change trends more accurately. The length of time series in this paper is 20 (n ≥ 10); the S-value approximately obeys the standard normal distribution, and then the Z-value can be used for trend testing.

\[ Z = \begin{cases} \frac{S - 1}{\sqrt{\text{VAR}(S)}}, & S > 0 \\ 0, & S = 0 \\ \frac{S + 1}{\sqrt{\text{VAR}(S)}}, & S < 0 \end{cases} \]  \hspace{1cm} (4)

\[ \text{VAR}(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{m} t_i(t_i - 1)(2t_i + 5)}{18} \]  \hspace{1cm} (5)

where \( n \) is the number of time series, \( m \) is the number of ties (repeated data groups) in the time series, \( t_i \) is the extent of any given tie (numbers of repeated data in group \( i \)), and the bilateral trend test is performed for Z-value.

When taking significance level \( \alpha \) as 0.05, the significant change trend \(|Z\text{-value}|\) is 1.96. When the \(|Z\text{-value}|\) is more than 1.96, this means that the VG or climate factors changed rapidly, and when the \(|Z\text{-value}|\) is less than 1.96, this means that there was no rapid change.

3.4. The Relationship between VG and Climate Factors

To analyze the responses of VG and VGT to temperature and precipitation, this study first converted all the rasters to ASCIIs in ArcGIS, including dry seasons’ MODIS NDVI, temperature and precipitation, and NDVI trend during 2000–2019. Then a RF regression model was built for MODIS NDVI and climate factors to analyze the response of VG to temperature and precipitation. The \textit{importance} function in the \textit{Random Forest} R package was used to investigate the contribution of temperature and precipitation to the VG. The importance of the responses was quantified by how much the model accuracy decreases (%IncMSE) when the variable was excluded. Finally, after all the ASCIIs were reconverted into rasters in ArcGIS, the importance of the four vegetation types (forest, crop, grass, and shrub) was extracted, respectively, and the mean importance was used as the response. The same work was performed to analyze of VGT to temperature and precipitation by using NDVI trend, temperature, and precipitation data. We used the coefficient of determination (\( R^2 \)) and root means square error (RMSE) to evaluate the model-fitting results.
4. Results
4.1. Vegetation Distribution Mapping of Mara River Basin

The random forest algorithm was used to classify the vegetation into four types (forest, shrub, grass, and crop), and then we used producer’s accuracies, user’s accuracies, Kappa coefficients, and overall accuracies to evaluate the classification results of each year. The producer’s accuracies from 2015 to 2019 for forest were 0.98%, 0.95%, 0.96%, 0.98%, and 0.90%; for crop, they were 0.95%, 0.88%, 0.90%, 0.96%, and 0.84%; for grass, they were 0.88%, 0.85%, 0.87%, 0.90%, and 0.83%; and for shrub, they were 0.82%, 0.80%, 0.80%, 0.85%, and 0.87%. The user’s accuracies from 2015 to 2019 for forest were 0.90%, 0.86%, 0.89%, 0.95%, and 0.83%; for crop, they were 0.86%, 0.81%, 0.84%, 0.82%, and 0.88%; for grass, they were 0.83%, 0.84%, 0.86%, 0.85%, and 0.85%; and for shrub, they were 0.80%, 0.82%, 0.85%, 0.87%, and 0.80%. The overall accuracies from 2015 to 2019 were 90.00%, 87.25%, 88.75%, 91.25%, and 84.37%, respectively, and the Kappa coefficients were all above 0.8. The vegetation distribution map of the Mara River Basin was drawn by the dominant vegetation type of each grid (Figure 3). The basin’s forest, shrub, grass, and crop areas were 1541.68, 2488.49, 7214.55, and 2505.44 km², respectively. Forests were distributed in upstream and downstream areas, crops were distributed in upstream area, and grass and shrubs were mainly distributed in the midstream area.

![Vegetation distribution map of Mara River Basin.](image)

Figure 3. Vegetation distribution map of Mara River Basin.

4.2. Spatiotemporal Trend of VG in Dry Seasons

The average NDVI in the dry seasons (January/February and June–September) from 2000 to 2019 was 0.53. The maximum NDVI (0.63) was observed in the year 2007. The minimum NDVI (0.39) was observed in the year 2000. The mean NDVI in the dry seasons showed a fluctuating trend (Figure 4). The greenness in the upstream and downstream vegetation was relatively high, and the greenness of the midstream was low (Figure 5b). The greenness of each vegetation type from high to low was forest (0.665), crop (0.629), shrub (0.532), and grass (0.474), respectively. The VG in the reclamation area was higher than 0.6 and lower than 0.8 in Mau Forest Escarpment due to irrigation, sufficient heat, and relatively sufficient rainfall in the lower latitude. The VG was mostly 0.7–0.8 in the Mara wetland, the highest in the basin due to Lake Victoria’s plenty of water supply. However, the VG was lower than 0.5 due to insufficient water supply in the reserves in the midstream area. Generally, the spatial distribution of greenness in the Mara River Basin is closely related to climate conditions. The VG was high in the regions with more precipitation and sufficient heat and low in the regions with less rainfall.
Figure 4. Temporal trend of VG in dry seasons of Mara River Basin.

Figure 5 shows the spatial distribution of VGT in dry seasons in Mara River basin. The VG in the dry seasons showed a greening trend in the Mara River Basin, especially in areas where forests and crops are widely distributed (Figure 5c). Meanwhile, in the midstream, where dominant vegetation types were shrub and grass, the VG often presented a browning trend (Figure 5c). In terms of the significant changes, most of the areas showed a non-significant increase trend. The significant change trend presented concentrated in the upstream and downstream areas, where forests and crops were the dominant vegetation types (Figure 5d). The significant decrease change trend and non-significant decrease change trend were often staggered in the midstream and downstream areas (Figure 5d).

Table 1 shows the proportions of area for vegetation in significantly different change trends. Forest had the most proportion in significant increase change trend of all vegetation types, and grass had the most proportion in significant decline trend. In general, the most vegetation was in non-significant increase change trend (62.17%), and the least vegetation was in significant decline change trend (2.26%).

Figure 5. Cont.
Figure 5. Spatial distribution of VGT in dry seasons in Mara River Basin: (a) NDVI variation in dry seasons; (b) average NDVI in dry seasons; (c) NDVI change trends in dry seasons (S-value); (d) NDVI significant change trends in dry seasons (Z-value).

Table 1. Proportion of area with different VG trends (%).

| Change Trend                | Forest | Crop | Grass | Shrub | Total Area (km²) |
|-----------------------------|--------|------|-------|-------|------------------|
| Significant Decline        | 2.02   | 1.20 | 2.62  | 2.47  | 312.10           |
| Non-significant Decline    | 6.58   | 7.72 | 16.12 | 19.73 | 1950.59          |
| Non-significant Increase    | 37.54  | 46.34| 68.62 | 74.44 | 8547.90          |
| Significant Increase       | 53.87  | 44.74| 12.64 | 3.36  | 2939.57          |
| Total Area (km²)           | 1541.68| 2488.49| 7214.55| 2305.44| 13,750.16        |

4.3. Responses of VG and VGT to Climate Change in Dry Seasons

The average temperature in the dry seasons (January to February and June to September) in the Mara River Basin was 19.4 °C from 2000 to 2019, whereas the highest temperature was recorded in the year 2017 (20.5 °C), and the lowest temperature was recorded in the year 2001 (18.4 °C). The average total precipitation in the dry seasons was 445.8 mm, the maximum precipitation was observed in the year 2007 (660.8 mm), and the minimum was observed in the year 2015 (318.2 mm). Moreover, the temperature and precipitation fluctuated during 2000–2019 (Figure 6). Compared with the VG, the precipitation was highest at the same time in the year 2007. The fluctuation trend of precipitation and VG was more similar compared to the temperature. The VG was smaller when there was a high temperature and less precipitation. On the contrary, the VG had a greater probability to show a high value with low temperature and much precipitation.
Figure 6. Annual average temperature and total precipitation of dry seasons in Mara River Basin.

Figure 7 shows the spatial trend of precipitation and temperature in the dry seasons from 2000 to 2019. A total of 84.16% of the precipitation in the basin showed a declining trend, especially in the downstream area, while only 15.84% of the precipitation showed an increasing trend. The eastern region of the basin had the largest increasing trend. For the significance of the precipitation change trend, 0.29% of the precipitation in the basin showed a significant decline trend, and 83.87% of the precipitation showed a non-significant decrease trend. Only the precipitation in the eastern region showed increase trends, whereas 15.42% of the precipitation in the basin showed a non-significant increase trend, and 0.42% in the basin showed a significant increasing trend. The temperature showed an increasing trend in the whole basin. For the significance of the temperature change trends, 82.88% of the temperature in the basin showed a non-significant increase trend, and 17.12% of the of the temperature in the basin showed a significant increasing trend, which was concentrated in the upstream and midstream areas.

Figure 8 showed the density scatter plots of RF regression for VG and VGT, the R² values were 0.95 and 0.91, respectively; the RMSE values were both 0.023. The fitting degree of the models were high, which verified the feasibility of the RF algorithm in analyzing the responses of VG and VGT to temperature and precipitation in the Mara River Basin.

To clearly understand the spatial responses of VG and VGT to precipitation and temperature, we used the natural breakpoint method to divide the importance into four segments and named the importance from low to high as I, II, III, and IV, respectively (Figure 9). The high importance indicated great responses of VG or VGT to precipitation and temperature.

The VG in the east of the basin had the most responses to precipitation, while the greenness concentrated in the midstream had the least responses to precipitation. The greenness that had the most responses to precipitation scattered around the greenness had the least responses in the downstream. Specifically, crops in the upstream area and some grass in the mid-low stream area had more responses to precipitation. In contrast, the forest in and around the Mara wetland and the shrub in Masai Mara National Park and Serengeti National Park had few responses to precipitation (Figure 9a). The VG in the upstream area had the most responses to temperature, and the greenness in the midstream had the least responses to temperature. Specific to vegetation types, shrub in the midstream had the least responses to temperature changes, while crop had the most responses to temperature changes. The response to temperature in the downstream area was low, expect in the Mara wetland (Figure 9b). The spatial responses of greenness to temperature were similar to
precipitation in the upstream and midstream areas, with both showing a great response. The spatial responses of VG to temperature were opposite to the responses to precipitation in the downstream.

Figure 7. Spatial distribution of temperature and precipitation change trends in dry seasons in Mara River Basin: (a) Precipitation change trend in dry seasons (S-value); (b) precipitation significant change trend in dry seasons (Z-value); (c) temperature change trend in dry seasons (S-value); (d) temperature significant change trend in dry seasons (Z-value).
Responses of VG and VGT to climate factors in Mara River Basin in dry seasons: (a) VG and (b) VGT.

Responses of VG and VGT to climate factors in Mara River Basin in dry seasons: (a) responses of greenness to precipitation in dry seasons; (b) responses of greenness to temperature in dry seasons; (c) responses of greenness trend to precipitation in dry seasons; and (d) responses of greenness trend to temperature in dry seasons.
The spatial responses of VGT to climate were not consistent. The VGT in national parks had great responses to precipitation, while VGT in the upstream area and around the Mara wetland had less responses to precipitation. Specific to vegetation types, crops north of the forest and grass downstream had the least responses to precipitation, while forest and grass in the midstream area had the most responses to precipitation (Figure 9c). The response of VGT to temperature was great from the Mau Forest down to all of the midstream, and crops north of the Mau Forest had the least response to temperature (Figure 9d). The responses of VGT to precipitation were consistent with temperature in the upstream and midstream areas. However, there was a slight difference in the downstream.

Tables 2 and 3 showed the responses of VG and VGT to climate change, respectively. We considered the importance of temperature and precipitation. The greenness of all vegetation types had more responses to precipitation than to temperature. Crop greenness had the most responses to precipitation, and forest greenness had the least responses to precipitation. Forest greenness had the most responses to temperature, and grass greenness had the least responses to temperature. The Pearson correlation showed that precipitation had a positive impact on VG, while temperature had a negative impact on the greenness of forests and crops and had a positive impact on the greenness of grass and shrubs (Table 2). The crop is rain-fed and more affected by human activities, such as irrigation, so it had less correlation with climate. As a result, the crop greenness will be increased even under the climate change condition, where the temperature is rising and precipitation is falling. The greenness of grass and shrub can decrease if there is no interference from human activities. The VG in the Mara River Basin would decline rapidly because the VG had many more responses to decreasing precipitation than rising temperature.

### Table 2. Response of VG to climate change in dry seasons in Mara River Basin.

| Vegetation | r  | Temperature | Precipitation |
|------------|----|-------------|---------------|
| Forest     | 0.42 | 25.68(−)   | 35.36(+      |
| Crop       | 0.28 | 30.65(−)   | 70.23(+)     |
| Grass      | 0.62 | 18.78(+)   | 60.04(+)     |
| Shrub      | 0.45 | 22.43(+)   | 47.55(+)     |

r is the Pearson’s coefficient between the predicted and observed cover based on the independent validation samples. The signs in the brackets represent the sign of Pearson’s coefficient between the given vegetation and climate factors (n = non-significant).

### Table 3. Responses of VGT to climate change in dry seasons in Mara River Basin.

| Vegetation | r  | Temperature | Precipitation |
|------------|----|-------------|---------------|
| Forest     | 0.36 | 40.10(−)   | 27.46(−)     |
| Crop       | 0.42 | 26.64(−)   | 70.23(+)     |
| Grass      | 0.57 | 44.81(−)   | 34.64(+)     |
| Shrub      | 0.48 | 42.27(−)   | 50.48(n)     |

r is the Pearson’s coefficient between the predicted and observed cover based on the independent validation samples. The signs in the brackets represent the sign of Pearson’s coefficient between the given vegetation and climate factors (n = non-significant).

The responses of VGT to temperature were greater than to precipitation, except for crops. The grass greenness trend had the most responses to temperature, and the crop greenness trend had the least responses to temperature. The shrub greenness trend had the most responses to precipitation, and the crop greenness trend had the least responses to precipitation. The responses were twice as different. The Pearson correlation showed that temperature had negative impacts on all VGTs. Precipitation had a negative impact on forests, it had no significant impact on shrubs, and it had a positive impact on grass and crops (Table 3). The forests in the Mara River Basin are dominated by sparse forests with strong drought resistance; this means that, no matter how much worse the climate gets, forests can maintain green in dry seasons. However, in general, the increasing temperature
and decreasing precipitation were a disadvantage for VGTs. Climate change will lead to vegetation degradation, which will seriously reduce the food sources of wild animals and residents, threaten the production and living of residents, hinder economic development, and ultimately lead to further aggravation of poverty.

5. Discussion

High temperature accelerates the transpiration of vegetation and inhibits the growth of vegetation. As a result, when the temperature was high, the VG was low. Precipitation in the Mara River Basin is controlled by the Indian Ocean El Nino. The precipitation increases in El Nino, and it decreases in La Nina. Under the strong control of La Nina in year 2000, the basin experienced extreme arid conditions all year long; it was the severest drought in nearly a century [44]. The temperature in the year 2000 was also high. Therefore, the VG was lowest in the year 2000. Controlled by the extremely strong El Nino, the precipitation in the dry season increased significantly in year 2007, which was an extremely humid year [45]. Moreover, the temperature was very low, so the VG was highest in year 2007.

The spatial differentiation of VG in the dry seasons of the Mara River Basin was significantly different. The agricultural reclamation in the upstream area in Kenya accounted for the largest proportion of the significant increasing trend, and the grass in the midstream accounted for the largest decline trend. There was an obvious correlation between VG and climate factors [23]. The greenness of grass and shrubs was more sensitive to climate change than forests, as was consistent with the research results of Ghebrezgabher et al. [5]. The responses of VG to precipitation were greater than those to temperature [1]. Increased precipitation will promote greening, and rising temperatures will lead to the greening of grass and shrubs, but the browning of forests and crops.

The climate change trend of decreasing precipitation and increasing temperature in the dry seasons in the Mara River Basin will lead to significant vegetation browning, a finding that is consistent with the findings of Ogutu et al. [44]. The VG in the upstream area should show a significant browning due to the reduction of precipitation, but the crop greenness increased significantly due to a large amount of irrigation water added to ensure the growth of crops in dry seasons. The shrub and grass were staggered around the forest in Serengeti National Park, due to the manmade drainage channel in the southeast which supplied sufficient water sources to promote vegetation greening [46]. Affected by the reclamation in the upstream area and overgrazing in the midstream area, the runoff and suspended sediment increased greatly in the Mara River [33,47]. As a result, the downstream diverged, and the runoff increased greatly [48], leading to the expansion of the Mara wetland. The rich swamps in the wetlands provided sufficient water and nutrients for vegetation growth, promoting the VG near the Mara wetlands to increase rapidly. In order to support the mining of the Mara Mine, the Tanzanian government destroyed the vegetation and built corresponding infrastructure [49], which led to a significant decrease in VG near the Mara Mine.

The responses of VGT to temperature were more significant than those to precipitation. The increasing temperature will inhibit VGT, and decreasing precipitation will promote the grass greening trend and lead to the forest and crop browning trend, as is consistent with the findings of Li et al. [25]. The VGT had little response to climate due to sufficient irrigation water. The rising temperature in the dry seasons strongly impacted the greenness trend of shrubs and forests in the midstream. The reduction of precipitation led to obvious browning in the Mara wetland. This VGT will threaten the ecological environment and economy [33]. The rain-fed crop relies on the rainfall in the rainy seasons to irrigate, and the growth in the dry seasons requires large-scale irrigation. Due to the rapid population growth in Kenya subbasin, the irrigated area has grown rapidly to ensure food production [50]. For instance, the irrigated area had reached 1000 ha, with a total annual irrigation water volume of 12.25 million m$^3$ in year 2015, and the irrigated area maintains an annual growth rate of 100 ha [29]. The decrease in runoff and the rapid increase in water demand in irrigation caused a water shortage in the midstream and downstream [51]. Degraded grass in the
midstream reduces food sources for wildlife and forces animals in areas where the grass degrades most to travel farther to obtain enough food.

The climate change trend of the Mara River Basin is consistent with that of Africa. It is expected that, by the end of this century, the average temperature in the dry seasons will increase by up to 7 °C, and precipitation will decline [52]. Climate change has already had an enormous impact on the habitats of Africa. Reduced rainfall in the dry season can lead to vegetation degradation and threaten livestock and wildlife survival, even in national parks [53]. Climate change has led to a significant reduction of species [54]. The rising temperature and more severe drought will destroy suitable habitats and increase the risk of species extinction [55,56]. For the Mara River Basin, climate change will increase the probability of droughts and floods [57], which will profoundly negatively impact biodiversity, agriculture, animals, and even human society. Accelerated drying of wildlife habitats has resulted in degraded vegetation and changes in savannah phenology [58,59], which will change the migration routes of wildlife [39] and increase animal diseases such as anthrax and Rift Valley fever [51]. Therefore, corresponding water resources and environmental management policies should be formulated to adapt to climate change and achieve sustainable development of the Mara River Basin.

6. Conclusions

The vegetation greenness of the Mara River Basin in the dry season was fluctuating, especially in the agricultural area in the upstream, from 2000 to 2019. The response of VG to precipitation was much greater than temperature. The increase in precipitation can promote vegetation greening, and the increase in temperature can inhibit greening. The vegetation browning was related to the increasing temperature and the decreasing precipitation, while vegetation greening was related to the increasing precipitation. There were quite differences in the greening trend for different vegetations. The grass browning trend in the midstream was the most obvious due to the decreasing precipitation and the increasing temperature. The decreasing precipitation and increasing temperature in the Mara River Basin will accelerate vegetation degradation and threaten the ecological security of the Masai Mara National Park. Vegetation degradation will make it difficult for animals to obtain food, seriously destroying wild animals’ habitat and safety and causing more frequent ecological disasters. Considering that the decreasing trend of precipitation is much greater than the increasing trend of temperature, VG will experience serious degradation in the dry seasons. Therefore, it is necessary to actively formulate related environmental management policies to address climate change.

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