

Spatial Determinants of Forest Landscape Degradation in the Kilimanjaro World Heritage Site, Tanzania

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Received: 29 June 2022; Revised: 25 August 2022; Accepted: 20 September 2022; Published online: 3 October 2022

Abstract: Forest degradation occurs in natural World Heritage Sites (WHS) in the Global South despite the implementation of various strategic policies and the World Heritage Convention (WHC) on forest protections of the sites and this poses challenges to improve natural heritage sustainability. The current study aims to investigate spatial determinants of forest degradation in the Kilimanjaro WHS, Tanzania, to support strategic policies for forest landscape protection and natural heritage sustainability. Using remotely sensed, Digital Elevation Model, and tourism location data, we performed the supervised classification of satellite images, Digital Elevation, Euclidean distance, and linear regression modeling to identify spatial determinants of forest degradation. Our key findings indicated that while spatial determinants vary with different locations, human (tourism) activities e.g., developments of campsites, picnics, tourist routes, the historical site, and attraction areas are associated with forest degradation in the southern parts of the site. In addition to human activities, natural factors such as low levels of elevation and degrees of slope are associated with forest degradation at the site. However, in the northwest and southwest of the site, high degrees of slope are associated with the degradation. Our findings showed that while bare land surface encroached the primary forest with about 2.88%, moorland vegetation encroached the primary forest with about 16.95%, indicating a large degradation of the primary forest with about 19.83% for the past four decades. The information provided in this study is crucial to support site managers and decision-makers in strategic policies and WHC implementations on forest protection for natural heritage sustainability.

Keywords: Forest degradation, montane primary forest, spatial determinants, natural heritage sustainability, World Heritage Site, Kilimanjaro.

Citation: Enoguanbhor, E. A., Enoguanbhor, E.C., & Albrecht, E. (2022). Spatial Determinants of Forest Landscape Degradation in the Kilimanjaro World Heritage Site, Tanzania. *Central European Journal of Geography and Sustainable Development*, 4(2), 5-23. <https://doi.org/10.47246/CEJGSD.2022.4.2.1>

1. INTRODUCTION

Forest degradation occurs in the Global South [1-3], including natural World Heritage Sites (WHS). For example, in the eastern part of Tanzania, including the Kilimanjaro WHS, forest degradation occurred over the years [4-7], despite various strategic policies and acts [8-10], as well as the World Heritage Convention (WHC) of 1972 [11] that made provisions for forest protection of the sites. Forest degradation in natural WHS was reported across the Global South, including Coast Atlantic Forest Reserves in Brazil, Kinabalu Park in Malaysia, Mount Wuyi in China, Iguazu National Park in Argentina [12], and Sundarbans WHS, India [13]. Such degradation poses challenges to improving heritage sustainability, which is a condition that allows the utilization of the benefits (e.g., tourism destination and income) provided by the natural WHS without compromising the current and future forest ecosystems. Also, the degradation may

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put the heritage sites in danger if strategic measures are not put in place to protect the sites from forest degradation.

Generally, forest degradation is determined by natural and human factors [14-16]. While natural determinants are attributed to physical geographical factors e.g., topographic elevation and slope [16,17], human determinants are attributed to human factors e.g., tourism activities, transportation, agriculture, charcoal production, settlement expansion [18-21,14,22,23,15,24,17] and can be used to explain spatial patterns and determinants of forest landscape degradation. In this context, spatial determinants can, therefore, be regarded as natural and human factors that are associated with or contribute to the explanation of the location of forest landscape degradation.

Spatial determinants of forest landscape degradation vary with space and location [18]. According to Bhattarai, et al. [19] distances to roads and settlements are positively associated with forest degradation in southern Tanzania. While distances to transportation and settlement, as well as topographic elevation (altitude) between 400 and 800m above sea level, are positively associated with forest loss in the Piracicaba River basin of the States of Sao Paulo and Minas Gerais, Brazil [17], distance to settlement is negatively associated with forest landscape degradation in the Democratic Republic of the Congo [18].

Previous studies e.g., Hamunyela, et al. [4]; Kilungu, et al. [5]; Rutten, et al. [6]; Soini [7]; Allan, et al. [12]; Levin, et al. [25] on natural WHS majorly focus on impacts and human driving factors of forest degradation with little or no emphasis on spatial determinants. In the Kilimanjaro WHS, no previous study was conducted on spatial determinants of forest degradation and this makes it difficult to identify such determinants to provide useful information for strategic policy decision-makers on the montane forest landscape protection and natural heritage sustainability. The montane forest is the primary forest with dense vegetation that provides habitats for wild animals in the Kilimanjaro WHS (Figure 4) (5).

The aim of this study, therefore, is to investigate spatial determinants of primary forest degradation in the Kilimanjaro WHS, Tanzania, to support strategic policies for forest landscape protection and natural heritage sustainability. Specifically, we seek to: analyze spatial patterns of land cover types for 1976, 2000, 2012, and 2020; compute the degraded primary forest, and analyze the association between various human/natural features and the degraded primary forest to identify spatial determinants of forest degradation.

2. STUDY AREA

The study area is the Kilimanjaro WHS (Kilimanjaro National Park), located in northeast Tanzania and it covers 1686.72 km² (Figure 1). The site is about 300 km south of the Equator [6]. We chose the Kilimanjaro WHS because of the forest degradation over the years [5-7] and the forest landscape, particularly the montane forest as one of the outstanding universal values of the natural heritage site [11]. The Kilimanjaro National Park was established in 1973 that initially composed of the whole mountain and moorland vegetation above the montane forest and was inscribed as a natural WHS in 1987 under criteria vii, with the mountain as an outstanding universal value, which is one of the largest volcanoes in the world [11,26]. The topographic elevation of the mountain within the site ranges from 1,277 to 5,880 m above sea level at Kibo peak, which is relatively located at the center of the mountain (Figure 1). Other peaks of the mountain include Shira peak (3,952 m above sea level) and Mawenzi peak (5,130 m above sea level) located in the northwest and southeast of the Kibo peak, respectively (Figure 1). In 2005, the site was extended to include the montane forest (the natural or primary forests that serve as buffer zones and habitats for wildlife) due to human pressure on forest degradation, which is also defined as the outstanding universal value and integrity feature of the site [11,26]. As a WHS and a National Park, various strategic actions, including the Forest Act of 2002 [9], National Environmental Policy of 1997 [10], and WHC of 1972 [11] have been implemented to protect the site from forest degradation. Despite the implementation of those strategic actions, forest degradation was reported by Hamunyela, et al. [4]; Kilungu, et al. [5]; Rutten, et al. [6]; Soini [7]. As a WHS and a National Park, Mount Kilimanjaro serves as a tourism destination for national and international tourists as the site receives about 50,000 tourists annually creating tourism pressure and associated problems, including vegetation trampling, water pollution, and soil erosion [26]. Other threats associated with the WHS include yearly wildfires that destroy natural forests that serve as buffer zones and habitats for wildlife, illegal logging of forest trees, and climate change causing the melting of glaciers that may lead to the disappearance of the snow cap [26].

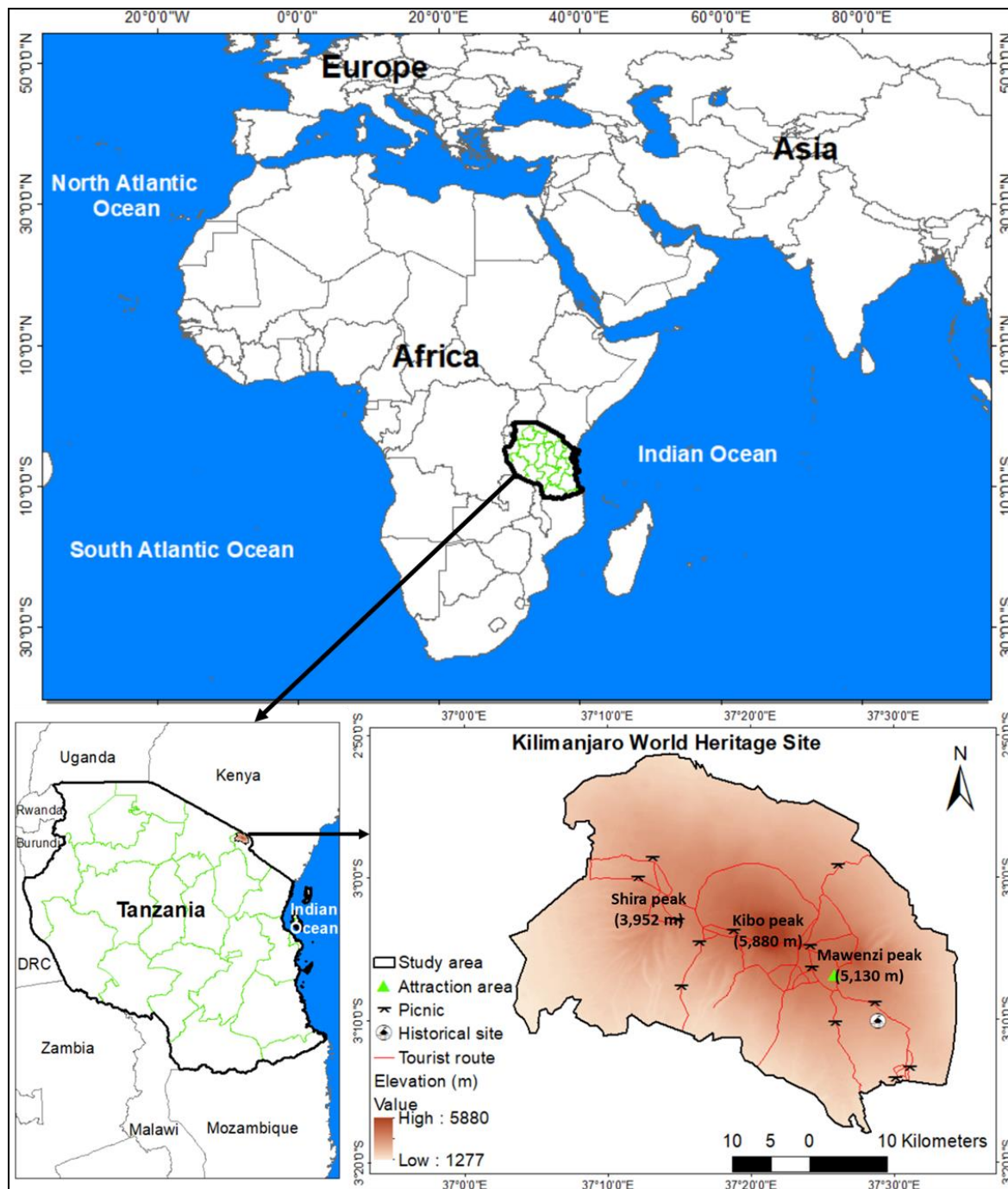


Figure 1. Maps showing the location of the Kilimanjaro World Heritage Site.

Source: Produced by authors

3. METHODS AND DATA

3.1. Data collection

We collected satellite images captured by Landsat 2 Multispectral Scanner System (MSS) in 1976 and Landsat 7 Enhanced Thematic Mapper Plus (ETM+) in 2000, 2012, and 2020 from the United States Geological Survey (USGS) [27]. The reason for collecting this set of data is due to the openly accessible platform and the coverage of the study area. Also, the set of data has been calibrated atmospherically with free cloud cover [27]. Additionally, all images were captured during precipitation seasons with heavy rainfall and snow on the Kilimanjaro Mountain and environs, which is from November to May, except that of 1976 and 2000, which were captured in January and February, respectively with little precipitations on the Kilimanjaro Mountain and environs [28]. However, in January and February with little precipitations, all

types of vegetation, especially tree canopies may retain the same or similar level of green growth (chlorophyll contents) as in other months (e.g., December and March) with heavy rainfall. Furthermore, Landsat data have been deployed successfully in mapping forests to support the management of forest protections in various protected areas across the Global [29-31]. While the Landsat 2 data used for the current study is 60 m spatial resolution, that of Landsat 7 is 30 m. Table 1 summarizes the characteristics of all satellite images. An additional set of data used for the current study are tourist routes, campsites, picnics, the historical site, and the attraction area and were collected from ArcGIS online [32]. Furthermore, we collected the Digital Elevation Model (DEM) of 90 m spatial resolution from the Shuttle Radar Topography Mission (SRTM) [33].

Table 1. Summary of the remotely sensed data description.

Landsat series	Sensor	Spatial resolution	No: of bands	Date of acquisition	Sources
Landsat 2	MSS	60 m	7	21/01/1976	USGS
Landsat 7	ETM+	30 m	9	21/02/2000	USGS
Landsat 7	ETM+	30 m	9	09/03/2012	USGS
Landsat 7	ETM+	30 m	9	28/12/2020	USGS

Source: Prepared by authors.

3.2. Data analysis

To analyze spatial patterns of land cover types for 1976, 2000, 2012, and 2020, we used ArcGIS 10.8.1 to perform supervised classification of satellite images using a maximum likelihood algorithm [34-37]. The supervised classification uses training samples of the known pixels to assign pixels to different classes and the maximum likelihood algorithm uses the highest probability to assign pixels to such classes [34,38-40]. While generating training samples, we computed the Normalize Difference Vegetation Index (NDVI) [41-43] expressed as:

$$NDVI = \frac{NIR - R}{NIR + R},$$

where NIR and R are the near-infrared band and red band, respectively that are used for the spectral reflectance measurements acquired in the near-infrared and visible (red) regions [43]. For Landsat 7 ETM+, band 4 is the near-infrared band with 0.772 - 0.898 μm and band 3 is the red band with 0.631 - 0.692 μm . For Landsat 2 MSS, band 6 is the near-infrared band with 0.7 - 0.8 μm and band 5 is the red band with 0.6 - 0.7 μm . While the healthy vegetation (e.g., primary forest) is reflected more in the near-infrared region due to high chlorophyll contents of the vegetation, unhealthy vegetation (e.g., moorland vegetation) and bare land surface are reflected more in the visible region due to low chlorophyll contents for moorland vegetation and lack of chlorophyll for bare land surfaces, including snow. The NDVI was grouped into three categories and based on their pixels' values for each category, 0.5 and above, 0.2 to 0.4, and 0.1 and below pixels' values were used to guide the selection of pixels' values on the composite multispectral images for healthy vegetation, unhealthy vegetation, and bare land surface, respectively. The selected pixels' values on the composite multispectral images were used to create training samples for the supervised classification, where the maximum likelihood algorithm was deployed [34-37]. We classified the land cover types into primary forest, moorland vegetation, and bare land surface as described in Table 2.

Table 2. Categories of land cover classes.

Land cover classes	Description of land cover
Primary forest	Healthy vegetation with montane and tropical rain forests
Moorland vegetation	Secondary forest, unhealthy vegetation, grasslands, shrubs, and cultivated fields
Bare land surface	Open space with alpine desert, volcanic soil, snow, wetlands, streams/rivers, rocks, and charcoal kilns

Source: Prepared by authors.

We performed accuracy assessments of the classified land cover types using simple random sampling [44] to generate 300 points and the composite images as based data for the assessments. We assessed the user accuracy (UA), producer accuracy (PA), and overall accuracy (OA) for land cover types, following Enoguanbhor, et al. [40]. The accuracy assessments are presented in Table 3.

Table 3. Accuracy assessments of land cover maps.

Land cover types	2020			2012		
	UA	PA	OA	UA	PA	OA
Primary forest	93.88%	88.46%		87.13%	86.27%	
Moorland vegetation	87.25%	89.00%	89.67%	86.87%	87.76%	86.33%
Bare land surface	88.00%	91.67%		85.00%	85.00%	
Land cover types	2000			1976		
	UA	PA	OA	UA	PA	OA
Primary forest	91.75%	85.58%		80.77%	84.00%	
Moorland vegetation	89.00%	89.00%	88.67%	84.62%	82.88%	82.67%
Bare land surface	85.44%	91.67%		81.48%	75.86%	

Source: Prepared by authors.

To compute the forest landscape degradation of the primary forest, we performed the transition change detection between 1976 and 2020 land cover types. We applied the pixel-based method and crosscheck or validated using the polygon-based method. Regarding the pixel-based method, which is the analysis based on the raster land cover maps, we first resampled the 60 m spatial resolution of the 1976 land cover map to 30 m to obtain and maintain the same pixels' sizes for both land cover maps. We applied the Land Change Modeler, an ArcGIS extension Toolbox from TerrSet (Geospatial Monitoring and Modeling Systems) to implement the transition change detection using the Multi-Layer Perceptron (MLP) Neural Network algorithm. The MLP Neural Network algorithm computes the weights of multiple input layers e.g., the 1976 and 2020 land cover maps to produce a single output layer e.g., the transitioned change detection map with the attribute information based on the number of pixels transitioned from different land cover types to others using a non-linear activation function (e.g., sigmoid) [39]. Regarding the polygon-based method to crosscheck the pixel-based method, we converted raster maps of both land cover types to vector maps and used Geoprocessing Tools, including Intersect and Union to run the transition change detection. The validation showed that both methods produced the same results with little difference. Finally, we extracted the transition from primary forest to moorland vegetation and bare land surface and used cartographic GIS overlays [45] to visualize and calculate the area of the degraded primary forest.

To analyze the association between various human/natural features and the degraded primary forest to identify spatial determinants of forest landscape degradation, we digitized locations of human features, including tourist routes, campsites, picnics, the historical site, and the attraction area. Also, we performed DEM analysis to generate parameters for the degrees of slope and levels of elevation. Additionally, we performed the Euclidean distance modeling on the digitized and extracted (degraded primary forest) maps to generate other parameters. We used all parameters to build simple and multiple linear regression models [46]. The simple and multiple linear regression modeling can be expressed as:

$$Y = \beta_0 + \beta_1 X_1 + \varepsilon$$

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_k X_k + \varepsilon ,$$

where Y is the dependent variable (degraded primary forest), X is the independent variable (human and natural features), β_0 and β_1 are intercept and coefficient, respectively and ε represents the random error terms. The independent variables were selected based on the availability of data on both human and natural features. To ensure the reduction of bias in the model, we used the Variance Inflation Factor (VIF) to calculate the multicollinearity problem and eliminated variables with 10 and above VIF values to make sure all independent variables have independent effects on the dependent variable [38,46,39,47]. After the analysis of the entire site, the site was divided into four areas, northwest, northeast, southwest, and southeast. The same analysis was performed for each of the four areas to understand the spatial determinants at the local scale and for comparative purposes between the four areas of the site.

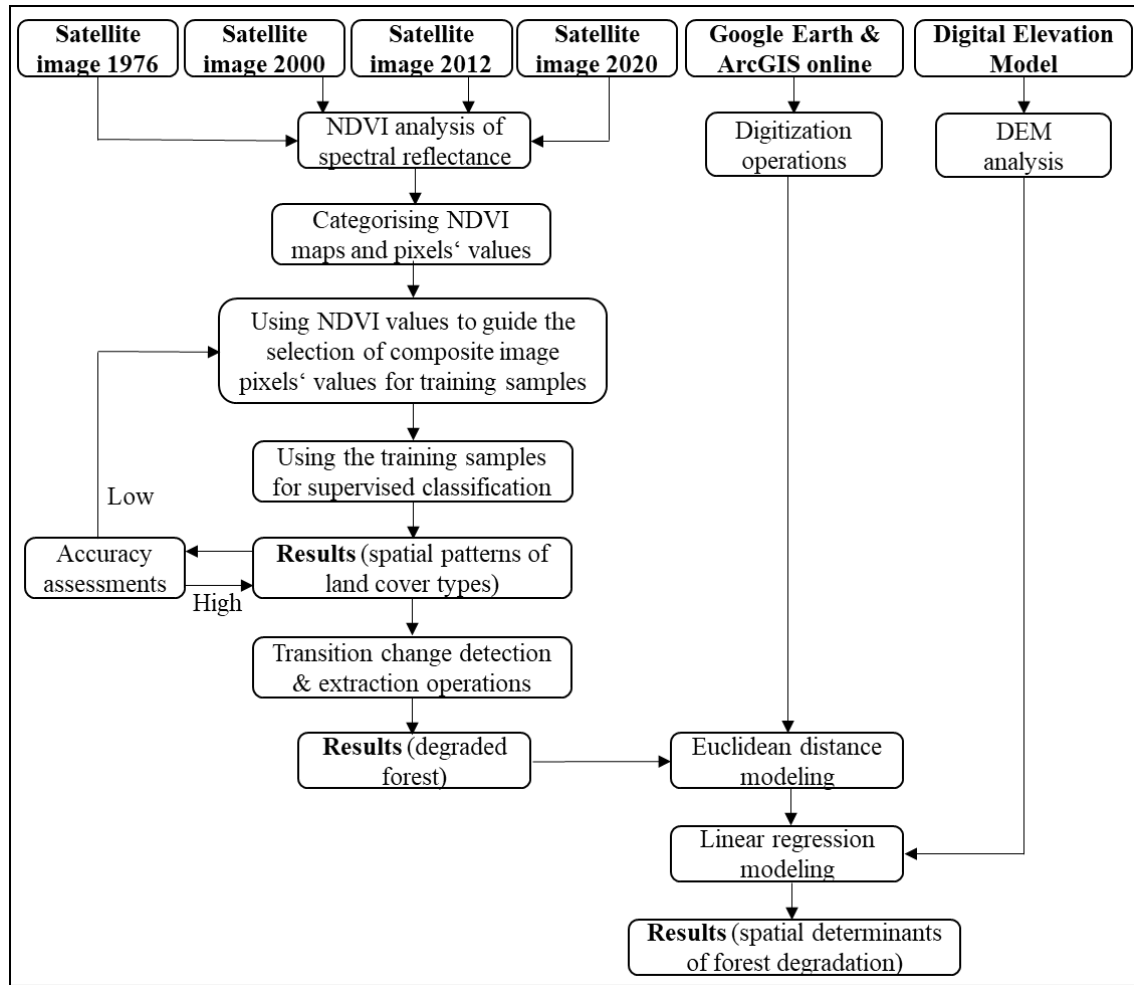


Figure 2. Materials and methods for spatial determinants of forest landscape degradation.

Source: Developed by authors.

4. RESULTS

4.1. Spatial patterns of land cover types

We analyzed the spatial patterns of land cover types for 1976, 2000, 2012, and 2020 in the Kilimanjaro WHS. Our results (Table 4 and Figure 3) showed that the primary forest are spatially distributed in the lower parts of the mountain and decreased from 1,290.64 km² (76.52%) in 1976 to 833.49 km² (49.42%) in 2020. Contrarily, the moorland vegetation is spatially distributed from the middle to upper parts of the mountain and increased from 360.08 km² (21.35%) to 453.04 km² (26.86%) in 2020. The bare land surface is mostly distributed at the mountain top, covering about 35.91 km² (2.13%) in 1976, 431.14 km² (25.56%) in 2000, 401.30 km² (23.79%) in 2012, and 400.12 km² (23.73%) in 2020. The observation in Figure 4 shows that while the bare land surface encroached on the moorland vegetation, the moorland vegetation encroached on the primary forest in the past four decades.

Table 4. Calculated areas of land cover types in km²

Land cover classes	1976	2000	2012	2020
	Area km ²	Area km ²	Area km ²	Area km ²
Bare land surface	35.91	431.14	401.30	402.12
Moorland vegetation	478.08	393.99	437.10	441.04
Primary forest	1172.64	861.45	848.20	843.49
Total	1,686.63	1,686.58	1,686.62	1,686.65

Source: Prepared by authors.

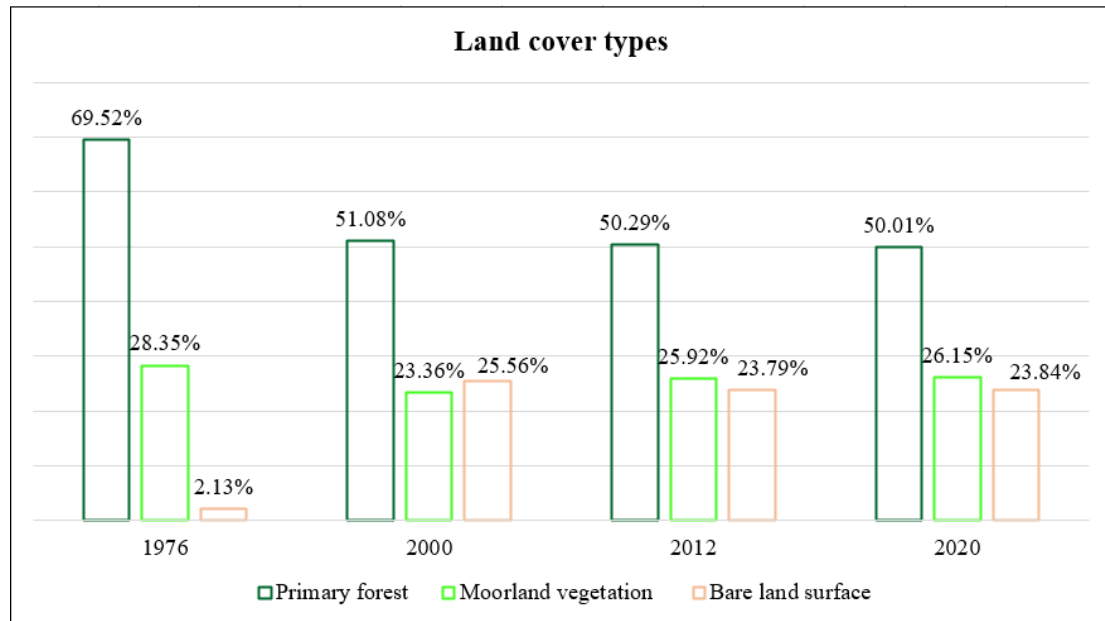


Figure 3. Calculated area of land cover types in percentage.
Source: Produced by authors.

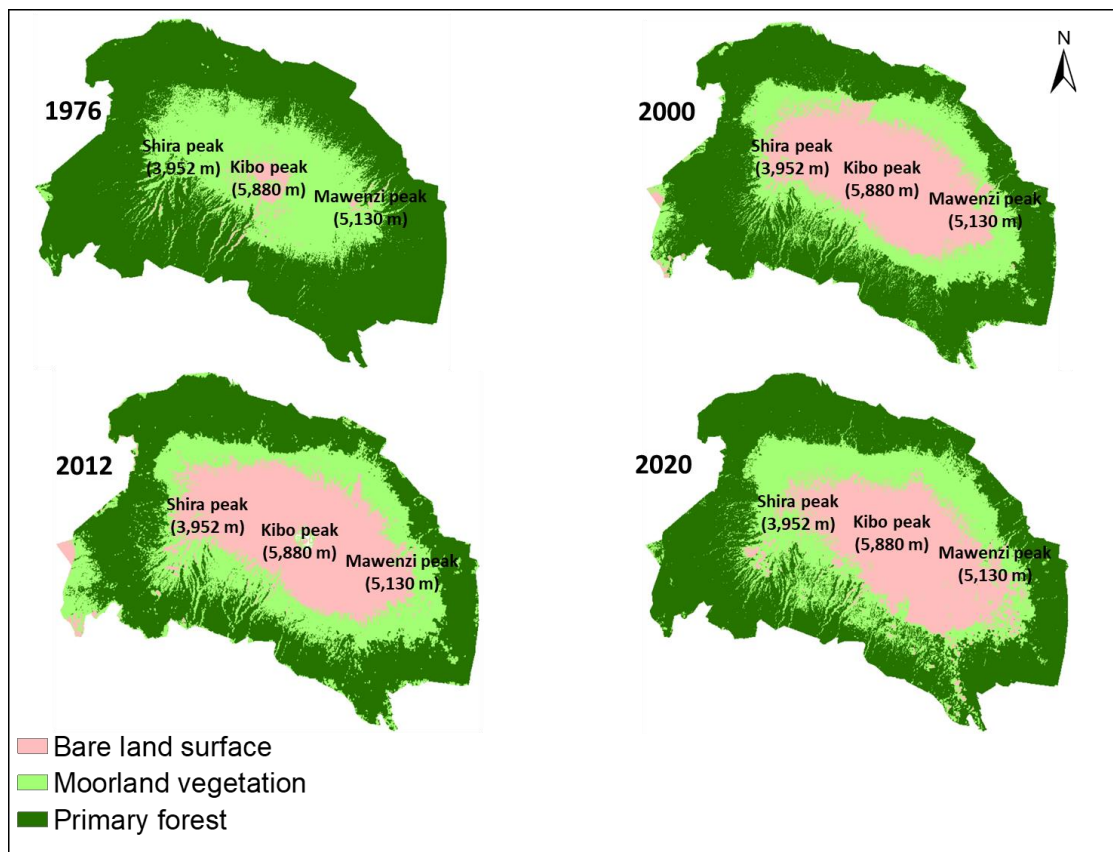


Figure 4. Spatial patterns of land cover types.
Source: Produced by authors.

4.2. Degraded primary forest

We computed the degraded primary forest through a transition mapping process. The transition mapping showed the highest transition that occurred between the primary forest and other land cover types is the moorland vegetation (Figure 5a). While about 16.95% of the primary forest transitioned into

the moorland vegetation, 2.88% transitioned into the bare land surface. Our result in Figure 5b shows that the primary forest that was degraded from 1976 to 2020 is about 19.83% of the total area.

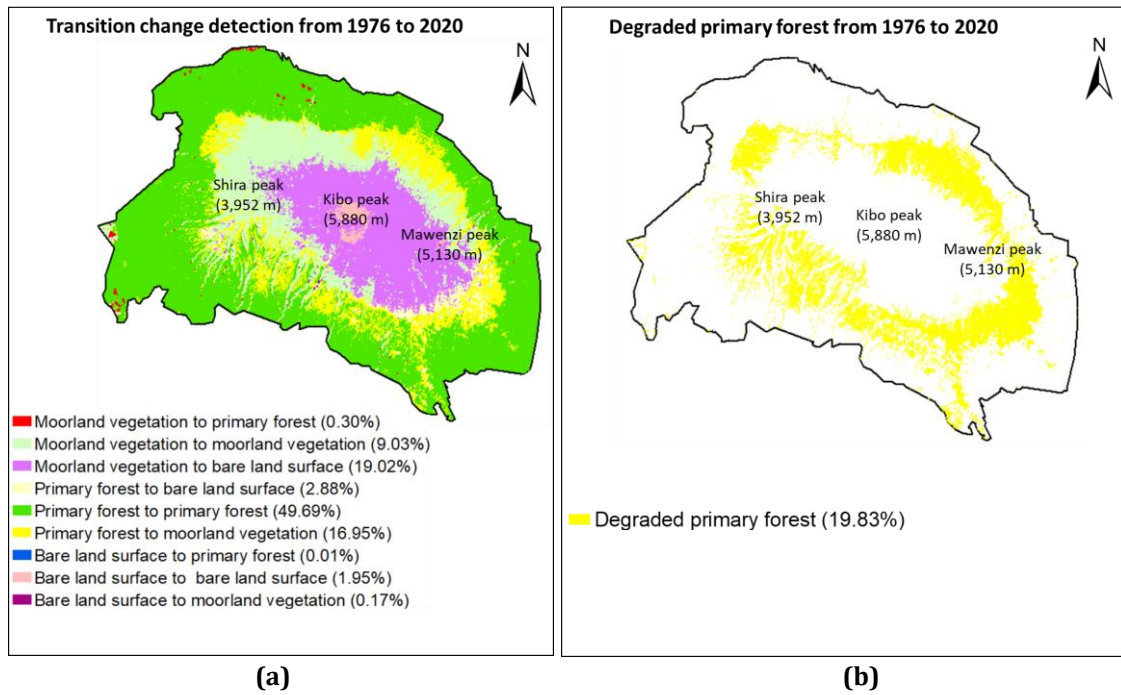


Figure 5. Spatial patterns of (a) land cover transitions and (b) the degraded primary forest.

Source: Produced by authors.

4.3. Associations between human/natural features and the degraded primary forest

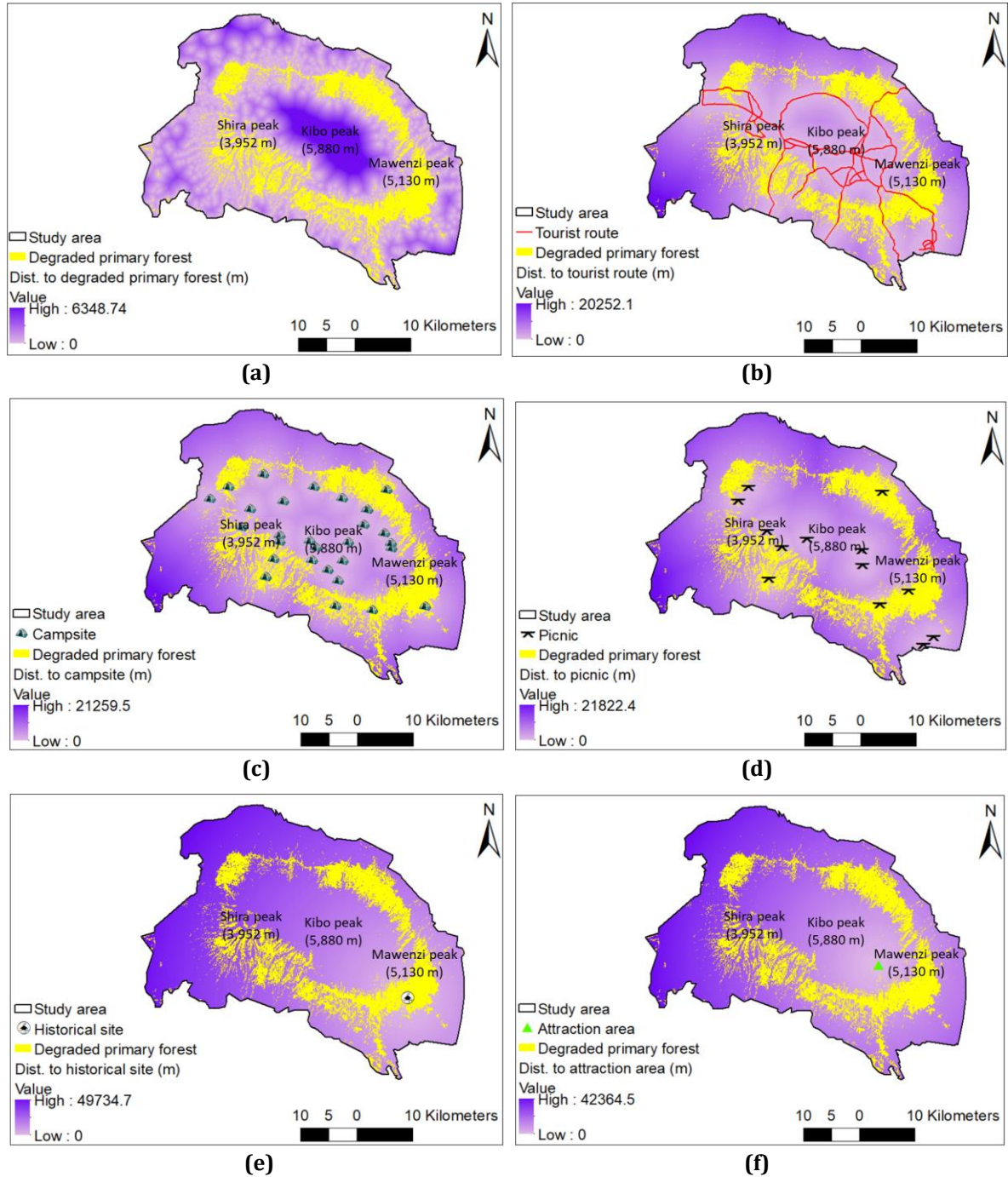
Considering the entire scale of the site, we analyzed the association between various human/natural features and the degraded primary forest to identify spatial determinants of forest degradation in the Kilimanjaro WHS (Table 5 and Figure 6). Our results at the simple linear regression level of the whole site (Table 5) showed that distances to the locations of human activities, including tourist routes, campsites, picnic locations, the historical site, and the attraction area are negatively associated with the degraded primary forest. The level of elevation and the degrees of slope as natural features are positively associated with the degraded primary forest, with slope having the highest coefficient.

Table 5. Spatial determinants of the degraded primary forest of the Kilimanjaro WHS.

Independent variables		Simple linear regression			Multiple linear regression				
		Coef.	P-value	Std. error	Coef.	P-value	Std. error	Initial VIF	Final VIF
1	Dist. to tourist route	-0.010	0.000***	0.003	0.007	0.151	0.005	6.818	5.955
2	Dist. to campsite	-0.010	0.000***	0.003	0.154	0.000***	0.005	6.171	5.339
3	Dist. to picnic	-0.018	0.000***	0.003	-	0.684	0.004	3.765	3.457
4	Dist. to the historical site	-0.001	0.147	0.000	-	-	-	18.106	-
5	Dist. to attraction area	-0.013	0.000***	0.001	-	-	-	22.116	-
6	Level of elevation	0.603	0.001***	0.011	1.109	0.000***	0.013	3.260	1.972
7	Degrees of slope	4.026	0.005***	1.434	-	0.000***	0.012	1.130	1.122
		Residual standard error = 796.1 on 9994 degrees of freedom (multiple linear regression)							
		Multiple R-squared = 0.414, Adjusted R-squared = 0.4139 (multiple linear regression)							
		P-value = 0.000*** (multiple linear regression)							

Source: Prepared by authors.

The results at the multiple linear regression level (Table 5) showed that while the degrees of slope and distance to picnic are negatively associated with the degraded primary forest, distances to tourist routes, campsites, and the level of elevation are positively associated. Distances to the historical site and the attraction area were eliminated from the model due to the problem of multicollinearity in the initial VIF. The final VIF indicated that the final model eliminated the multicollinearity problem and the low standard errors associated with all variables indicated good models' fit.



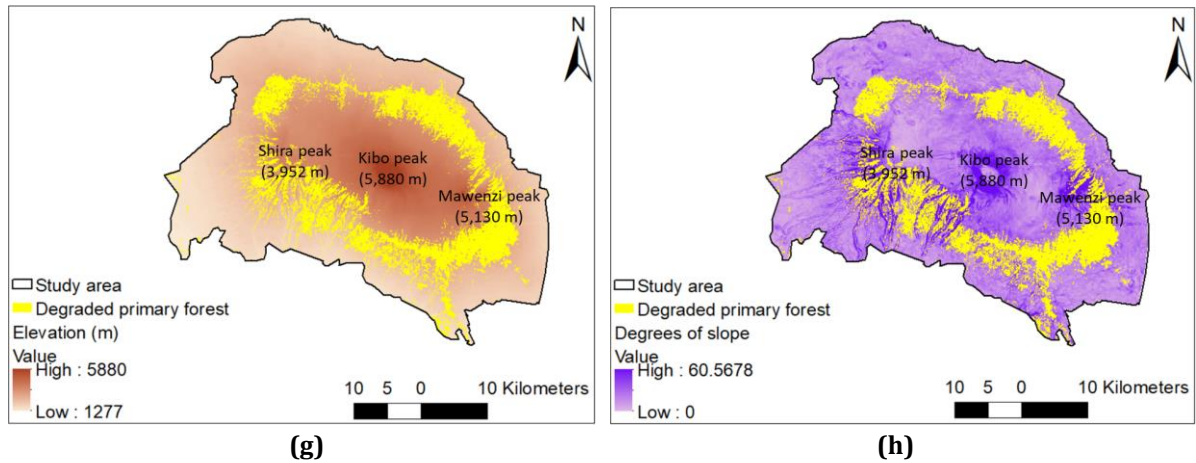


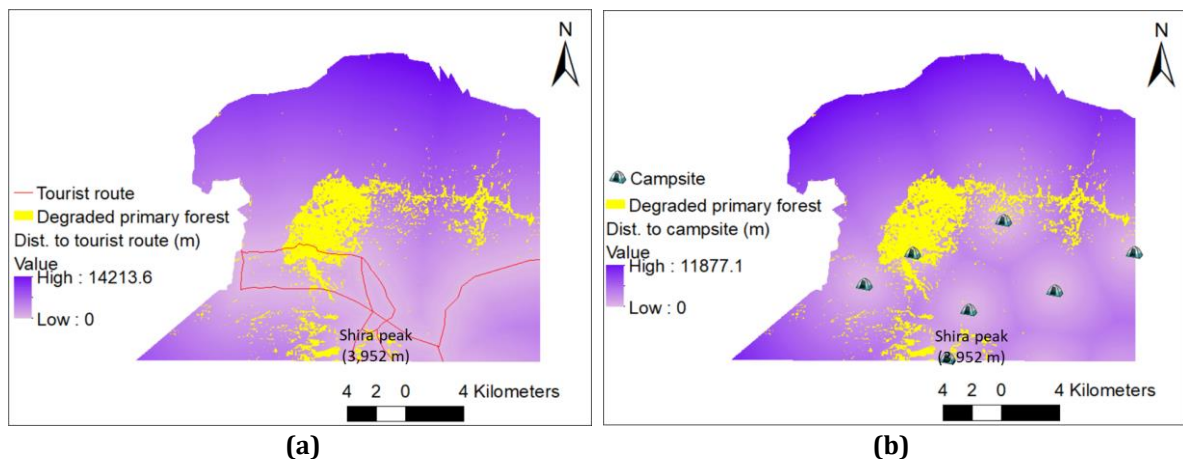
Figure 6. Maps showing Euclidean distances to (a) degraded primary forest, (b) tourist route, (c) campsite, (d) picnic, (e) historical site, and (f) attraction area, (g) level of elevation, and (h) the degrees of slope.
Source: Produced by authors.

Our results at the simple linear regression level of the northwest Kilimanjaro WHS (Table 6) showed that while distances to tourist routes, campsites, and picnic locations are positively associated with the degraded primary forest, that of the historical site and attraction area are negatively associated. The level of elevation and the degrees of slope as natural features are positively and negatively associated respectively. The multiple linear regression level showed that the degrees of slope remains negative and the distance to picnic remains positive. Other variables were excluded from the model due to problems of multicollinearity indicated by VIF values above 10. Low standard errors associated with all variables indicated good models' fit.

Table 6. Spatial determinants of the degraded primary forest in northwest Kilimanjaro NWHS.

Independent variables	Simple linear regression			Multiple linear regression				
	Coef.	P-value	Std. error	Coef.	P-value	Std. error	Initial VIF	Final VIF
1 Dist. to tourist route	0.040	0.000***	0.005	-	-	-	10.603	-
2 Dist. to campsite	0.065	0.000***	0.006	-	-	-	10.256	-
3 Dist. to picnic	0.029	0.000***	0.005	0.026	0.000***	0.005	5.467	1.027
4 Dist. to the historical site	-0.045	0.000***	0.003	-	-	-	1008.795	-
5 Dist. to attraction area	-0.046	0.000***	0.003	-	-	-	1056.567	-
6 Level of elevation	0.407	0.000***	0.027	-	-	-	13.964	-
7 Degrees of slope	-15.844	0.000***	3.374	-13.162	0.000***	3.404	1.202	1.027
Residual standard error = 948.5 on 2564 degrees of freedom (multiple linear regression)								
Multiple R-squared = 0.018, Adjusted R-squared = 0.017 (multiple linear regression)								
P-value = 0.000*** (multiple linear regression)								

Source: Prepared by authors.



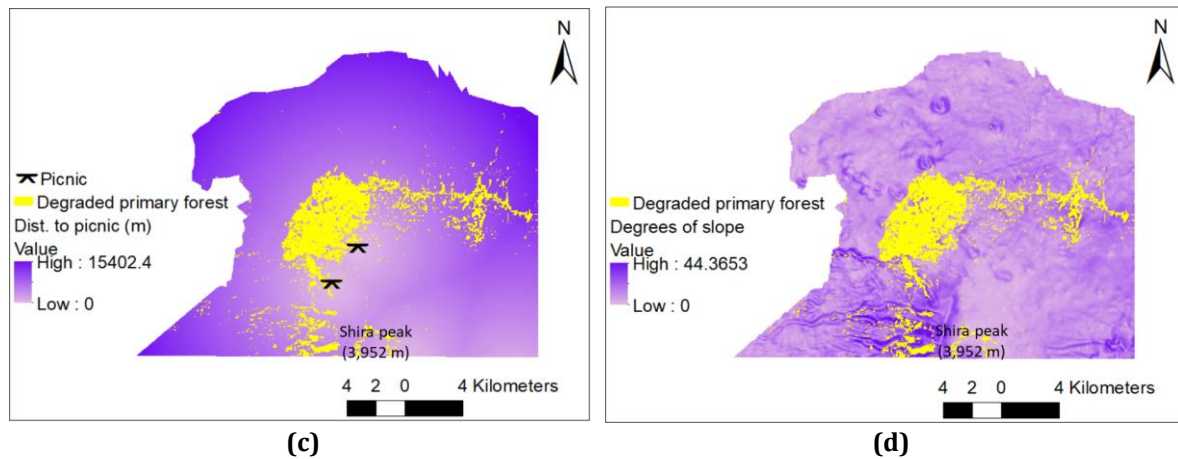


Figure 7. Maps showing relationships between the degraded primary forest and Euclidean distances to (a) tourist routes, (b) campsites, (c) picnics, and (d) degrees of slope in the northwest Kilimanjaro WHS.
Source: Produced by authors.

In the northeast Kilimanjaro WHS, the results (Table 7) showed that while distances to tourist routes and campsites are positively associated with the degraded primary forest, that of the picnic, the historical site, and attraction area are negatively associated. The natural features: level of elevation and the degrees of the slope are positively associated, with slope having the highest coefficient. The multiple linear regression showed that the degrees of slope remains positive and the distance to picnics remains negative. Other variables were excluded from the model due to problems of multicollinearity indicated by VIF values above 10. Low standard errors associated with all variables indicated good models' fit.

Table 7. Spatial determinants of the degraded primary forest in northeast Kilimanjaro NWHS.

Independent variables		Simple linear regression			Multiple linear regression				
		Coef.	P-value	Std. error	Coef.	P-value	Std. error	Initial VIF	Final VIF
1	Dist. to tourist route	0.011	0.362	0.012	-	-	-	15.557	-
2	Dist. to campsite	0.013	0.337	0.013	-	-	-	14.542	-
3	Dist. to picnic	-0.001	0.928	0.001	0.004	0.547	0.007	1.786	1.000
4	Dist. to the historical site	-0.026	0.000***	0.006	-	-	-	88.774	-
5	Dist. to attraction area	-0.061	0.000***	0.006	-	-	-	125.941	-
6	Level of elevation	1.096	0.000***	0.029	-	-	-	11.305	-
7	Degrees of slope	152.800	0.000***	4.730	0.015	0.000***	4.731	2.272	1.000
Residual standard error = 824.1 on 1523 degrees of freedom (multiple linear regression)									
Multiple R-squared = 0.407, Adjusted R-squared = 0.406 (multiple linear regression)									
P-value = 0.000*** (multiple linear regression)									

Source: Prepared by authors.

Table 8. Spatial determinants of the degraded primary forest in southwest Kilimanjaro NWHS.

Independent variables		Simple linear regression			Multiple linear regression				
		Coef.	P-value	Std. error	Coef.	P-value	Std. error	Initial VIF	Final VIF
1	Dist. to tourist route	0.027	0.000***	0.002	-	-	-	27.819	-
2	Dist. to campsite	0.028	0.000***	0.002	-	-	-	35.903	-
3	Dist. to picnic	0.023	0.000***	0.002	-	-	-	13.329	-
4	Dist. to the historical site	0.013	0.000***	0.001	-	-	-	674.671	-
5	Dist. to attraction area	0.012	0.000***	0.001	-	-	-	850.934	-
6	Level of elevation	0.067	0.000***	0.014	-	-	-	12.522	-
7	Degrees of slope	-18.210	0.000***	1.201	-	-	-	1.333	-

Source: Prepared by authors.

In the southwest Kilimanjaro NWHS, the results (Table 8) showed that distances to all the identified human activities are positively associated with the degraded primary forest. The level of elevation and the

degrees of slope as natural features indicated positive and negative associations respectively. The multiple linear regression modeling was not performed due to problems of multicollinearity associated with all independent variables, except the degrees of slope.

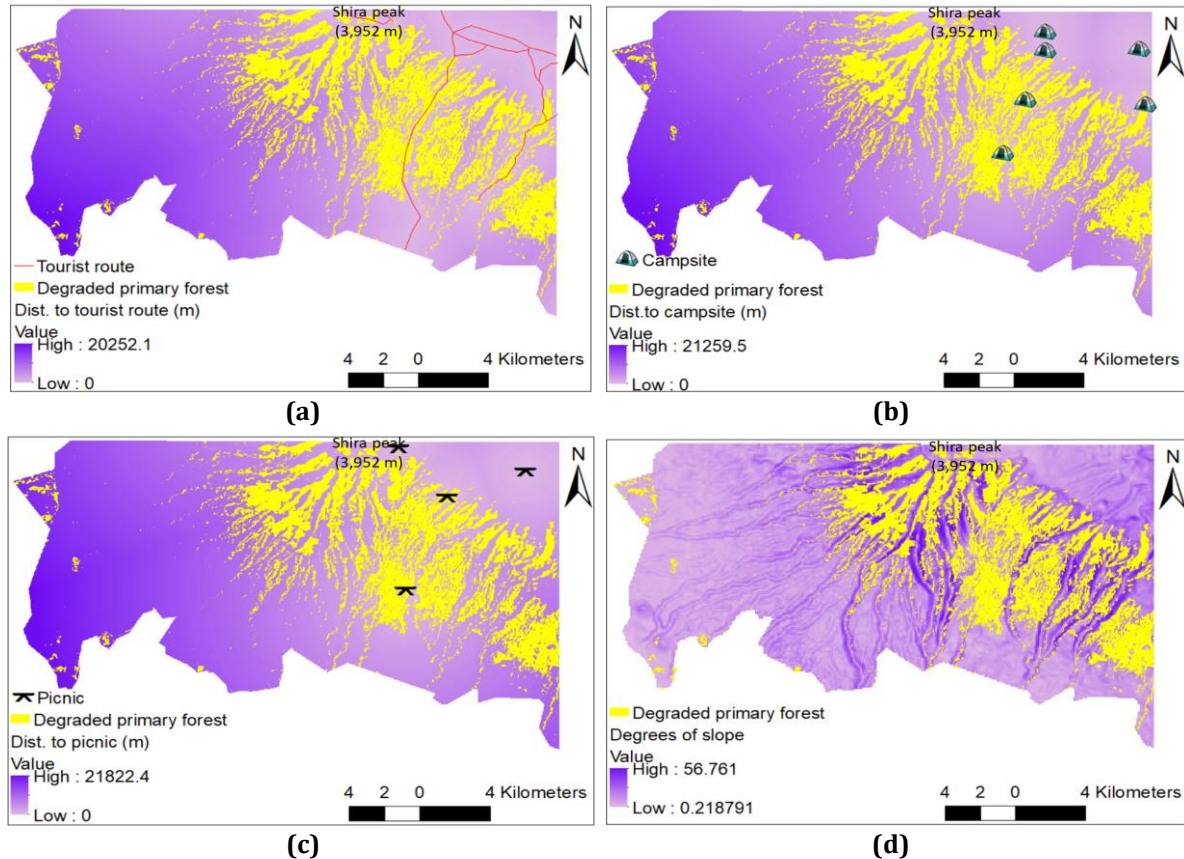


Figure 9. Map showing relationships between the degraded primary forest and (a) tourist routes, (b) campsites, (c) picnics, and (d) the degrees of slope.

Source: Produced by authors.

In the southeast Kilimanjaro WHS, the results (Table 9) showed that while distances to tourist routes, campsites, picnics, and the attraction area are negatively associated with the degraded primary forest, that of historical site is positive. The level of elevation and the degrees of slope as natural features are positively associated, with slope having the highest coefficient. The multiple linear regression showed that distances to picnic and the historical site remain negatively and positively associated respectively. While the initial VIF indicated the absence of multicollinearity problem, low standard errors associated with all variables indicated good models' fit.

Table 9. Spatial determinants of the degraded primary forest in southeast Kilimanjaro NWHS.

Independent variables		Simple linear regression			Multiple linear regression				
		Coef.	P-value	Std. error	Coef.	P-value	Std. error	Initial VIF	Final VIF
1	Dist. to tourist route	-0.156	0.000***	0.009	0.048	0.000***	0.009	2.740	-
2	Dist. to campsite	-0.123	0.000***	0.009	0.066	0.000***	0.007	2.428	-
3	Dist. to picnic	-0.158	0.000***	0.008	-0.187	0.000***	0.009	3.765	-
4	Dist. to the historical site	0.150	0.000***	0.005	0.135	0.000***	0.009	2.718	-
5	Dist. to attraction area	-0.058	0.000***	0.005	0.138	0.000***	0.006	4.042	-
6	Level of elevation	0.826	0.000***	0.018	0.012	0.000***	0.033	6.604	-
7	Degrees of slope	21.969	0.000***	2.973	-0.318	0.000***	0.020	1.486	-
Residual standard error = 705.5 on 3397 degrees of freedom (multiple linear regression)									
Multiple R-squared = 0.6992, Adjusted R-squared = 0.6986 (multiple linear regression)									
P-value = 0.000*** (multiple linear regression)									

Source: Prepared by authors.

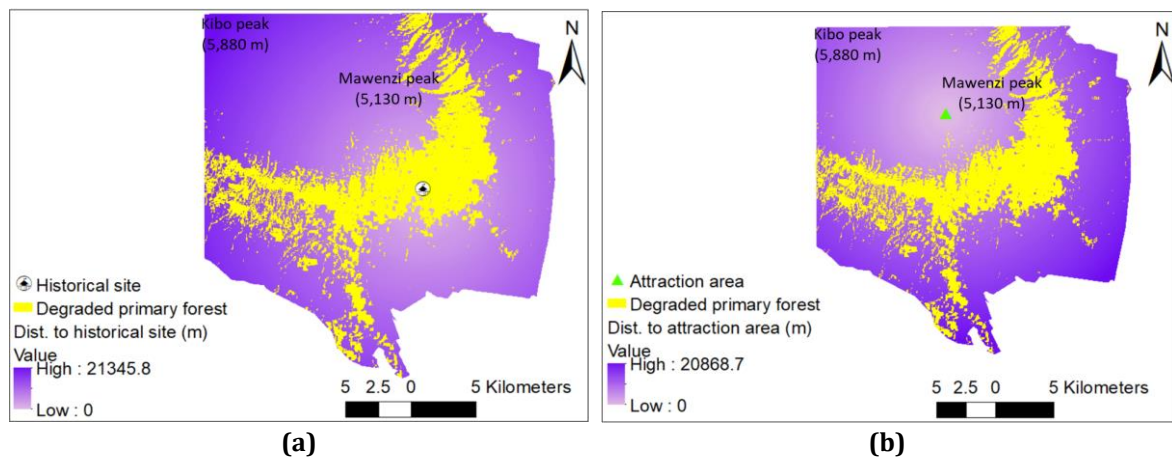


Figure 10. Maps showing relationships between the degraded primary forest and Euclidean distances to (a) the historical site and (b) the attraction area.

Source: Produced by authors.

5. DISCUSSION

Our study provides the first comprehensive investigation of spatial determinants of forest degradation in the Kilimanjaro WHS, Tanzania to support strategic policies for forest landscape protection and natural heritage sustainability.

5.1. Findings

Considering the scale of the site holistically, our findings (Table 5) show that the topographic elevation and slope as natural features are positively associated with forest degradation, indicating the lower the level of elevation and degrees of slope, the higher the likelihood of forest degradation. The results are similar to the findings from Htun, et al. [48] and Freitas et al. [49] who reported forest degradation at the low level of elevation and degrees of slope in the Popa Mountain Park, Central Myanmar, and the Plateau of Ibiuna, near Sao Paulo, Brazil, respectively. Other human factors are associated negatively, indicating the farther from those locations, the higher the likelihood of forest degradation. This could be due to the scale of the entire study area. Comparison of spatial determinants at the local scale, the degrees of the slope are negatively associated with forest degradation in the northwest and southwest Kilimanjaro WHS, indicating the higher the degrees of slope, the higher the likelihood of forest degradation in those areas. This can be visualized in Figures 7d and 9d. Considering previous studies e.g., Htun et al. [48] and Freitas et al. [49] that report the degradation of the forest at the low degrees of slope, other factors other than the degrees of slope may be responsible for forest degradation in the northwest and southwest Kilimanjaro WHS. Distances to tourist routes, campsites, and picnics are positively associated with forest degradation in the northwest area, indicating the closer the locations of those tourist activities in the northwest, the higher the likelihood of forest degradation. These are visualized in Figures 7a, b, and c). Contrarily, distances to the historical site and the attraction area are negatively associated with forest degradation in the same northwest. In the northeast Kilimanjaro WHS, our findings (Table 7) show the only human features that are positively associated with forest degradation are tourist routes and campsites but in the southwest, all the identified human features are associated with forest degradation positively, indicating the contribution of tourism activities on forest degradation. These are visualized in e.g., Figures 9a, b, and c. These results support the findings from Pongpattananurak [50] who reported the impact of tourism on forest degradation in the overlapping area between Thap Lan National Park and the Thai Samakkhi subdistrict of Thailand. In the southeast, the only human feature that is positively associated with forest degradation is the attraction area. However, picnic turned out to be the only human feature that is negatively associated at the multiple linear regression level in the same southeast area.

Our findings on spatial patterns of land cover types (Table 4 and Figures 3 and 4) show the primary forest was about 69.52% in 1976 and decreased to 50.01% in 2020. This result is consistent with those of

Hamunyela, et al. [4] and Kilungu, et al. [5], who reported a decrease in primary (montane) forest in the Kilimanjaro WHS, Tanzania. Also, the result is similar to those of Adeyemi & Owolabi [51]; Sievers, et al. [13]; Zeb [52], and Htun, et al. [48] who showed decreasing primary/mangrove/dense/closed forests in Effan Forest Reserve in Nigeria, Sundarbans natural WHS in India, the District Chitral in Pakistan, and Popa Mountain Park in Central Myanmar, respectively. Also, the result is similar to those of Morin, et al. [29] and Ullah, et al. [53] who reported reductions in forest land cover in the Dilijan National Park of Armenia and Teknaf Wildlife Sanctuary of Bangladesh, respectively. However, the result differs from the report from Liu, et al. [54] who showed increasing forestland in the Jiuzhaigou natural WHS, China. The study shows a little decrease in the forest between 2000, 2012, and 2020 and this may be associated with the stronger implementation of strategic policies and WHC on forest protection as the primary forest was included in the site in 2005 [11]. Our study showed that the moorland vegetation decreased from 1976 to 2000 and started increasing from 2000 to 2020. The moorland vegetation increase is similar to those of Kilungu, et al. [5]. Our observation shows that while the bare land surface encroached into the moorland vegetation, the moorland vegetation encroached into the primary forest over the years. This can be visualized on spatial patterns of land cover types (Figure 3) and the transition mapping (Figure 4a). The computation of the transition mapping shows that about 19.83% of the study area has been degraded within the primary forest between 1976 and 2020 (Figure 4b).

5.1. Implications of the findings

One implication of our findings is the clarification that spatial determinants of forest degradation in the Kilimanjaro WHS vary with different locations in the site, similar to the report from Shapiro et al. [18] for the Democratic Republic of the Congo and Zeb [52] for the District Chitral, Pakistan. This would help site managers to look beyond the reports deduced from the holistic viewpoint of the entire site in general to specific areas of the site in particular when implementing the WHC and other strategic policies for forest protection and natural heritage sustainability. For example, considering the site as a protected area that allows tourism activities, tourist routes, development of campsites, and picnics pose threats to the primary forest in the southwest area and the historical site and attraction areas pose threats in the southeast area. This may be the case for other natural WHS that serve as tourism destinations in Sub-Saharan Africa and other parts of the Global South. Human activities such as the development of campsites and picnics have the possibility of causing fire outbreaks that can degrade forest landscapes [26,55,56]. Tourism is one of the major activities posing a significant threat to forest protection [50,57,58,59].

An important implication of our findings is the decrease in primary forests that may be associated with the loss of habitats for wildlife in those areas, which may lead to wildlife migration/extinction and a decrease in tourism demand [11,60]. Also, the decrease in primary forest may put the site in danger, considering the forest as one of the outstanding universal values of the natural heritage [11]. Additionally, degradation of the primary forest may expose the site to denudation and increases soil erosion that may later develop into gully erosions [26]. Gully erosions may affect existing tourist routes, which may lead to the development of additional routes with additional negative impacts on forest protection and wildlife disturbances.

The positive implication of our findings shows that various strategic policies and WHC implementations on forest protection may have improved over the last two decades, considering a slight decrease in the primary forest from 2000 to 2020. In 2005, the Kilimanjaro WHS was expanded from the initial boundary of the moorland vegetation of the mountain to the primary (montane) forest of the mountain [11,26] and that may have enhanced the protection of the primary forest. However, there is a need to regenerate forest within lower parts of moorland vegetation for effective forest protection due to the encroachment of moorland vegetation into the primary forest between 1976 and 2020. Regeneration of forests in those areas would improve forest and natural heritage sustainability, as well as habitat protection for wildlife on the site.

Such spatial information is crucial for site managers and decision-makers in strategic policies and WHC implementations on forest protection in the Kilimanjaro WHS, Tanzania and other natural WHS found in Sub-Saharan Africa, as well as other parts of the Global South. By integrating various methods to derive new findings on, e.g., how human (various tourism activities) and natural (elevation and degrees of

slope) factors determine spatial patterns of forest degradation at different scales in a WHS, our study, therefore, contributes to Heritage Studies and Management for natural heritage sustainability.

5.3. Limitations and recommendations

One limitation of the current study is the non-availability of data related to other uses of the site. This makes it impossible to identify additional human factors (e.g., illegal logging) [61,26] in the site as spatial determinants of forest degradation. Also, the use of 30 m spatial resolution of remotely sensed data did not allow the identification of the locations of such illegal logging. However, the openly accessible remotely sensed data are useful for monitoring primary forest trends of the Kilimanjaro WHS at no cost. Additionally, our inability to obtain 100% accuracies shows that there are some misclassifications of land cover types despite the high accuracies obtained for the current study.

Based on the limitations of the current study and the findings, we recommend the following: First, the information on spatial determinants of forest degradation provided in the current study should be considered when implementing strategic policies and WHC on forest landscape protection of the site. For example, tourism activities such as the development of campsites and picnics that are associated with forest degradation should be monitored effectively to prevent further degradation (e.g., fire outbreaks). Second, the strategic policies and WHC implementations on forest landscape protection can still be improved to regenerate forest along the lower parts of the moorland vegetation to compensate for the loss of primary forest over the years. This can be done by initiating forest regeneration programs within the context of the strategic policies and WHC. Finally, future research should be conducted by integrating high spatial resolution remotely sensed data and additional data on other uses of the site (including illegal logging), as well as the qualitative survey-based data to investigate spatial determinants and other driving factors of forest landscape degradation of the site.

6. CONCLUSIONS

Our study investigated spatial determinants of forest degradation in the Kilimanjaro WHS, Tanzania to support strategic policies for forest landscape protection and natural heritage sustainability. The analysis of spatial patterns of land cover types showed a decrease in primary forest and a decrease in moorland vegetation over the years. The computation of transition mapping showed the encroachments of bare land surface into moorland vegetation and that of moorland vegetation into the primary forest, indicating a large area of primary forest degraded over the years. While spatial determinants of the degraded primary forest vary with different locations in the site, human (tourism) activities, including locations of tourist routes, campsites, picnics, the historical site, and the attraction area are mostly associated with the degradation of forest in the southern parts of the site.

The study showed that spatial determinants of forest degradation in the Kilimanjaro WHS vary with different locations in the site, similar to the report from previous studies in the Democratic Republic of the Congo and the District Chitral, Pakistan. Additionally, while tourism activities such as tourist routes, development of campsites, and picnics pose threats to the primary forest in the southwest area, the historical site and the attraction area of tourism activities pose threats to the same forest category in the southeast area of the site. For sustainable protection of the forest landscape in the Kilimanjaro WHS, additional efforts are required to intervene the lost primary forest by regenerating the forest in the lower parts of the moorland vegetation. By investigating the spatial patterns of primary forest of a protected WHS and how distances to various tourist activities (e.g., the attraction area, picnic locations, campsites, tourist routes, and the historical site), as well as other environmental factors (e.g., topography), are associated with the degradation, this paper contributes to Heritage Studies and Management for natural heritage sustainability.

Spatial information provided in the current study is crucial to support site managers and decision-makers in strategic policies and WHC implementations on forest landscape protection for natural heritage sustainability of the Kilimanjaro WHS, Tanzania and other sites located in the Global South. Future research is required to integrate high spatial resolution satellite images and additional location data e.g., illegal logging, as well as qualitative survey-based data to investigate other driving factors along with spatial determinants of forest landscape degradation.

ACKNOWLEDGMENT

We acknowledge Paul and Maria Kremer Stiftung for the PhD scholarship awarded to the first author that contributed financially to the success of this article. Also, we appreciate the United States Geological Survey (USGS) for making the remotely sensed data used in this study freely available and accessible.

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