Journal of Geoscience and Environment Protection, 2022, 10, 64-81
https://www.scirp.org/journal/gep
ISSN Online: 2327-4344
ISSN Print: 2327-4336

Remote Sensing and Landscape Metrics-Based Forest Physical Degradation: Two-Decades Assessment in Gishwati-Mukura Biological Corridor in Rwanda, East-Central Africa

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How to cite this paper: Uwiringiyimana, H., & Choi, J. (2022). Remote Sensing and Landscape Metrics-Based Forest Physical Degradation: Two-Decades Assessment in Gishwati-Mukura Biological Corridor in Rwanda, East-Central Africa. *Journal of Geoscience and Environment Protection, 10,* 64-81.
https://doi.org/10.4236/gep.2022.104005

Received: March 8, 2022
Accepted: April 16, 2022
Published: April 19, 2022

Abstract

The management of forest corridors and related ecology is one of the effective strategies to minimize the adverse effects of forest degradation. It controls the connectivity of inhabitant species and the connection of the isolated patches. This study analyzed spatial and temporal forest physical degradation based on forest cover change and forest fragmentation in the Gishwati-Mukura biological corridor from 1990-2019. Remotely sensed datasets, Geographical Information System (GIS) and FRAGSTATS software were used to analyze the spatial and temporal physical degradation and changes in forest cover. The results indicated that the Gishwati-Mukura corridor experienced massive deforestation where approximately 7617.1 ha (64.22%) of forest cover was completely cleared out, which implies an annual forest loss of 262.6 ha·year^{-1} (2.21%) during 1990-2019. The forest cover transitions patterns and geostatistical analysis indicated that extensive deforestation was associated with intensive agriculture. The results demonstrated that agriculture has dramatically increased from 29.46% in 1990 to 57.22% in 2019, with an annual increase of 1.97%. Since Gishwati-Mukura has changed to National Park (NP), it lacks diversified scientific studies addressing the analysis of the remote and spatial patterns to investigate its physical degradation and landscape dynamics. This research study will serve as remote forest analysis gap-filling and as the cornerstone of numerous other research that will contribute to the improvement of the connectivity assessments along the Gishwati-Mukura corridor and other related ecosystems.

Keywords

Landscape Metrics, Remote Sensing, Geographic Information System (GIS), Forest Physical Degradation, Biological Corridor, National Park

1. Introduction

Forest physical degradation has been the most visible and prominent factor of present change in tropical forests (Alvarez-Berrios & Mitchell Aide, 2015), which affects the delivery of most ecosystem services, including the loss of biodiversity that more than 75% of terrestrial biodiversity resides in tropical forest (Kareiva et al., 2007). The Food and Agriculture Organization—forest report assessment indicated an approximate rate of 5.4 million ha·yr^{-1} of deforestation over this century (Malhi et al., 2013). Recently the African tropics accounts for about 23% of forest loss of the global forest (Kayiranga et al., 2016) and in East Africa, deforestation is reported to have increased in several important tropical forests of Kilimanjaro, Tanzania with a loss of 13.39% of its forest areas during the periods between the 1980s and 2000s due to the agricultural land expansion and increase of population pressure (Singh, 2013). The Gatamaiyo forest close to Nairobi city in Kenya decreased about 28,499 ha from 1980 to 2000 (Wu, 2011). Deforestation in Rwanda was a big issue, especially in the periods between 1994 and 2005 when the country accounted for at least 8299 ha of forest cover loss (692 ha/year) (de la Paix et al., 2013) and this was due to the demand for land for the relocation of refugees and displaced people, agriculture, firewood, logging for settlements and road constructions that followed the genocide (Solomon & Grazia, 2014), where natural forests came under strain as is evidenced by the reduction in the area of the Nyungwe and Akagera National Parks (Rwanda Environment Management Authority, 2020). The two patches of Gishwati and Mukura used to be in the complex system of natural forests of the Congo Nile Ridge comprised with Nyungwe National Park, the natural forests of Volcanoes National Park and contiguous Kibira National Park in Burundi (Chancellor et al., 2021) until it is degraded and fragmented due to enormous increase of population, the establishment of cattle ranching and an increase of agricultural land reclamation in its border until the forest becomes unproductive followed by degradation related disasters including soil erosion, landslides, reduced water quality and soil infertility (Mc Guinness & Taylor, 2014). Protected areas are an essential element of any strategy to conserve tropical forest and its biodiversity (Gardner et al., 2009). The establishment of corridors and protected areas is one of many strategies to reduce the negative effects of landscape fragmentation in human-dominated landscapes (Applying Landscape Ecology in Biological Conservation, 2002). Biological corridors connect isolated patches of habitats and support the movement of migratory species from one place to another (Kafle et al., 2020), are the contributors to the functional connectivity of a landscape and provide higher conservation value to the linked fragments (Diamond, 1975). The governmental and non-governmental initiatives restoration project has started in 2006 to extend the Gishwati forest to 1570 ha. In 2015 the management plan to support the transition from forest reserves was made to strengthen management and accelerate ecological restoration in support of upgrading to National Park status and improve key biodiversity refugees within the Nile-Congo crest. Therefore, the plan to go beyond the core forests and focus on the larger landscape, a potential biological corridor has been proposed to link-up Gishwati with Mukura forest reserves and Nyungwe National Park to enable the historical bio-ecotourism linkage in this area. The establishment of the Gishwati-Mukura forest corridor was adopted as a national goal and is reflected in the national land use management use master plan (Rwanda Land Management and Use Authority, 2017). Therefore, there is still a need for more research to provide baseline information and data for monitoring progress and changes, managing places and species as well as the ecological changes in the corridor and buffering parts of the landscape. The forest cover change studies based on the interpretation of multi-remotely sensed data and GIS have increased over the past years and have been identified as an accurate and cost-effective method for monitoring forest changes (Cohen & Goward, 2004; Masek et al., 2008). They can be used to evaluate the historical forest cover changes and landscape-scale status to provide specific facts for future planning (Midha & Mathur, 2010) and the spatial and temporal pattern can be analyzed to assess the net effects on both forest cover change and the analysis of its landscape scale as well (Wayne Forsythe & McCartney, 2014). Remote Sensing technology and GIS mapping evolved in the 1960s and have been of great support in the collection of detailed multispectral data that led to improved understanding of minerals, soil, urban growth, agriculture and other geographic features (Weilin et al., 2000). In the tropical forests of the Brazilian Amazon, remotely sensed data were used to analyze farm-level property by overlapping property boundary grid in the GIS in the year 1990 (McCracken et al., 1999). Remote Sensing and GIS techniques were used to map the land cover, assess the forest cover change and identify the deforestation hot-spots for forest conservation priorities in the North-Kivu Congo (Philippe & Karume, 2019). Landsat datasets acquired from several sensor instruments were used in numerous research to delineate wetland, analyze deforestation, soil erosion and runoff in different areas of Rwanda. However, there is still very little research that has so far used the combination of remotely sensed data, GIS and landscape-based metrics to detect deforestation patterns and structures. Spatial pattern analysis program for quantifying landscape structure and patterns plays a prominent role in landscape ecology and process. In Gishwati-Mukura biological corridor, there were no remote sensed studies on its physical degradation based on landscape metrics conducted in the new park and the corridor in general yet. Therefore, in this study GIS and FRAGSTATS were applied to investigate the spatial and temporal physical degradation and changes in forest cover in Gishwati-Mukura biological corridor from 1990 to 2019. The objectives of this study were as follows: 1) to monitor the spatial and temporal forest cover change; 2) to determine the degradation level and forest transition probabilities; and 3) to analyze the forest landscape dynamics from 1990 to 2019 in Gishwati-Mukura biological corridor.

2. Materials and Methods

2.1. Study Area

This study was conducted in the Gishwati-Mukura corridor, located in the Western Province of Rwanda (Figure 1 Left). Gishwati-Mukura biological corridor consists of two inter-connected protected forests namely, Gishwati and Mukura; and was designated as a National Park in 2015. Gishwati covers 1484 ha of the remnant rainforest while Mukura covers approximately 1988 ha and is located approximately 20 km in the southeast of Gishwati (see Figure 1 Right). The Gishwati-Mukura National Park (GMNP) lies in Congo-Nile ridge which is expanding over 35.58 km^2 in the Rutsiro and Ngororero districts in the Western Province of Rwanda. Gishwati-Mukura forest corridor lies at 10˚49'S, 290˚22'E in mountainous and hilly landscape (mean slope = 25.6˚), the elevation ranges from 2000 to 3000 m above sea level. The vegetation consists of primarily secondary

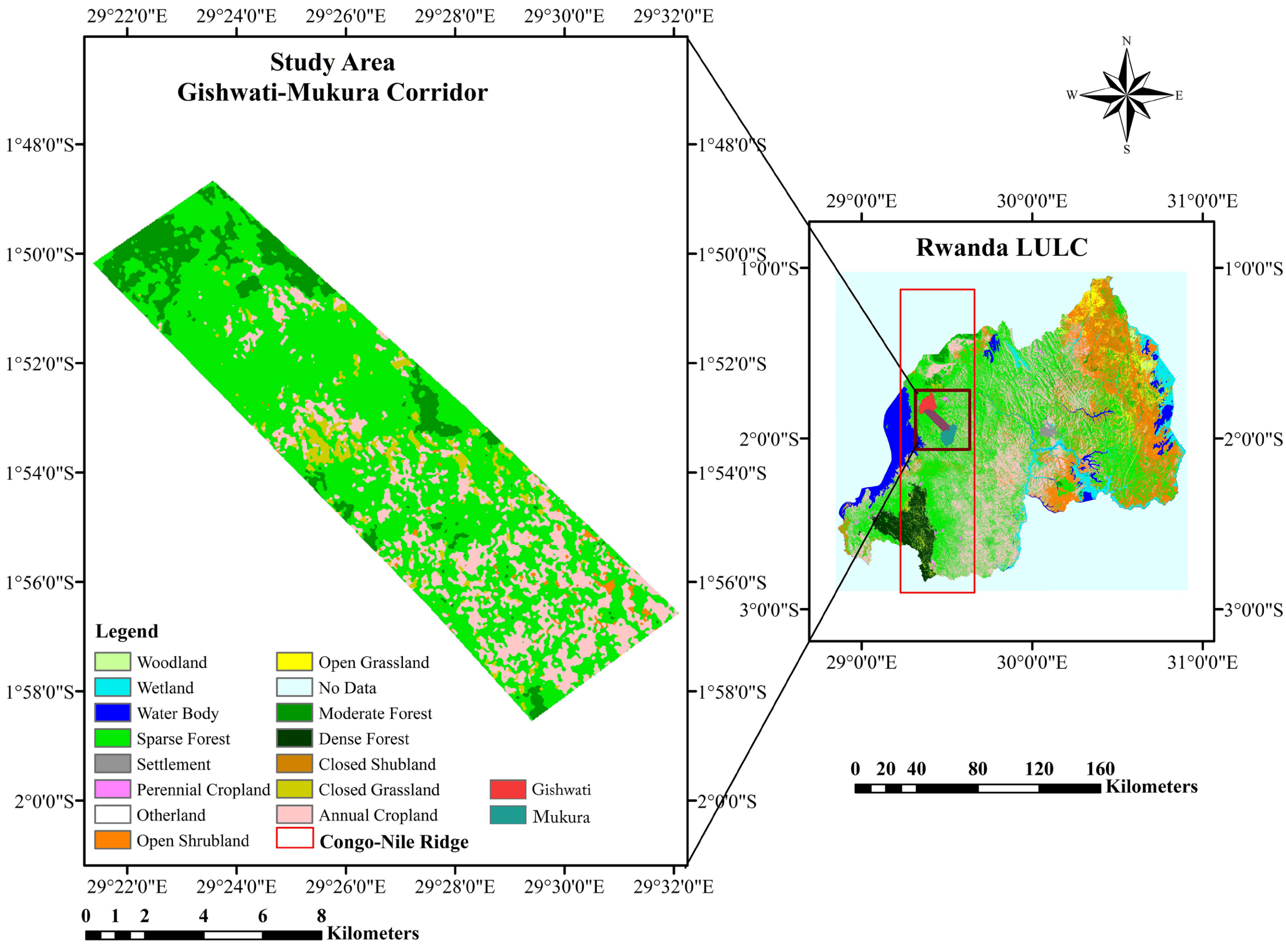

Figure 1. Location of Gishwati-Mukura corridor showing dominant land-use/land-cover types with reference of the Rwanda map.

growth tree species such as *Dombeya torrida*, *Maracanga kilimandsharica* and *Maesa lanceolate.* The annual average rainfall approximately ranges between 1200 - 1500 mm and the mean daily minimum and maximum temperatures average 15.7˚C and 24.2˚C, respectively (Chancellor, Rundus, & Nyandwi, 2012). GMNP is one of the few remaining natural forests and biodiversity hotspots in the Congo-Nile following the Albertine rift region which accounts for more than 120 species of birds and more than 250 plants species. Among the biodiversity animal species, GMNP accommodates multiple eastern chimpanzees, mountain and golden monkeys, serval, genet, civet, small mammals, amphibians, reptiles. Regardless of almost its complete conversion into an agricultural area, it has been adopted as a national goal and is reflected in the national land-use master plan in 2015 for conserving critical habitats and linking Gishwati and Mukura forests with an ecologically meaningful corridor that would allow the continuation of long term ecological and evolutionary process and heal fragmented landscapes (Humphrey Kisioh, 2015a). The management of this corridor is a far-reaching strategy to increase connectivity between the two fragmented forests of Gishwati and Mukura. Therefore, research in this estimated 28,000 ha corridor is of massive importance for the movement of multiple populations of vertebrates, rejuvenating disturbed habitat and landscape conservation.

2.2. Data Acquisition

Land use/Land Cover (LULC) maps of Rwanda for years 1990, 2000, 2010, 2015 and 2019 were used to evaluate the changes in forest cover and were generated from the RCMRD (Regional Centre for Mapping of Resources for Development) Geoportal a platform that has partnered with SERVIR-Eastern and Southern Africa for disseminating open geospatial datasets and maps for the Eastern and Southern Africa region. The RCMRD-LULC consists of 14 LULC classes, including dense forest, moderate forest, sparse forest, woodland, closed grassland, open grassland, closed shrubland, open shruband, perennial cropland, annual cropland, wetland, waterbody, urban settlement and others (RCMRD, 2012). This RCMRD data are raster data available at 30m resolution in WGS84 Geoid reference datum Sphere were projected to WGS 1984 Web Mercator Auxiliary. These datasets were chosen because of their finer spatial resolution of 30m and comparable accuracies of 0.80 kappa and 86.42% overall classification accuracies respectively (Cheng et al., 2017). Datasets from the same month were used to minimize errors due to seasonal variations and provide worthwhile information about the quantity of conversion from one particular class to another. Gishwati-Mukura forest corridor was delineated based on the potential protection of forest areas within Gishwati-Mukura-NNP Corridor in Gishwati Forest Reserve, three years interim management plan 2015-2018 (Humphrey Kisioh, 2015b).

2.3. Data Processing and Land Cover Change Detection

Data processing was performed using ArcGIS 10.6 into 3 stages: 1) Raster projection and extraction of the study area, projections and transformations tools were used to create a spatial reference for the Gishwati-Mukura polygon and to project the raster images of Rwanda LULC for the 5 different study years based on the Gishwati-Mukura corridor shapefile got from Gishwati Forest Reserve, three-year management plan 2015-2018 spatial references. 2) Image reclassification, and change detection stages. Second stage all land use/land cover maps were clipped to match with the study area boundaries; a clip tool for raster processing in data management tools was used to extract the LULC maps for the years 1990, 2000, 2010, 2015 and 2019 and reclassified in two distinctive classes namely forest and non-forest. In this case, forest land cover classes were combined to form one class called forest and the combination of all other land cover classes were named non-forest using the reclassify tool of the spatial analyst tools in ArcGIS 10. 6 and the same process was applied to all 5 land cover maps. 3) Forest cover change detection, this stage consisted of detecting space and time changes in forest cover in the Gishwati-Mukura forest corridor from 1990 to 2019, only forested areas were considered and raster image differencing was used by subtracting the new forest maps with elder maps to detect spatial and temporal patterns of forest changes in time (**Figure 2**). The raster calculator tool developed in ArcGIS 10.6 was utilized to differentiate and statistically evaluate the forested area to non-forest areas and estimate the deforestation rate or forest loss.

2.4. Annual Rate of Deforestation

The annual deforestation rate was calculated using the compound interest formula due to its explicit biological meaning (Puyravaud, 2003).

$$r = \left(\frac{1}{t2 - t1}\right) \times \ln\left(\frac{A2}{A1}\right)$$

where r is the percentage of forest loss per year, $A1$ and $A2$ represent the area of forest cover at time $t1$ and $t2$ respectively.

2.5. Landscape Metrics Measurement and the Evaluation of Landscape Patterns at Class Levels

FRAGSTATS a spatial pattern analysis software program offers a comprehensive choice of landscape metrics for quantifying the structure of the ecological landscape. This software is implemented by decision-makes, forest managers and ecologists to analyze landscape fragmentation, describe the characteristics and components of landscapes. The advantage of FRAGSTATS is that calculations are implemented in an integrated form of GIS whereby it is easy to apply to digital maps (McGarigal & Marks, 1995). This study analyzed Gishwati-Mukura forest corridor landscape fragmentation, landscape metrics at the class level, which served to quantify the forest landscape composition and configurations (Turner & Gardner, 2015). The particular fragmentation metrics were chosen based upon their correspondence to the evaluation of forest physical landscape

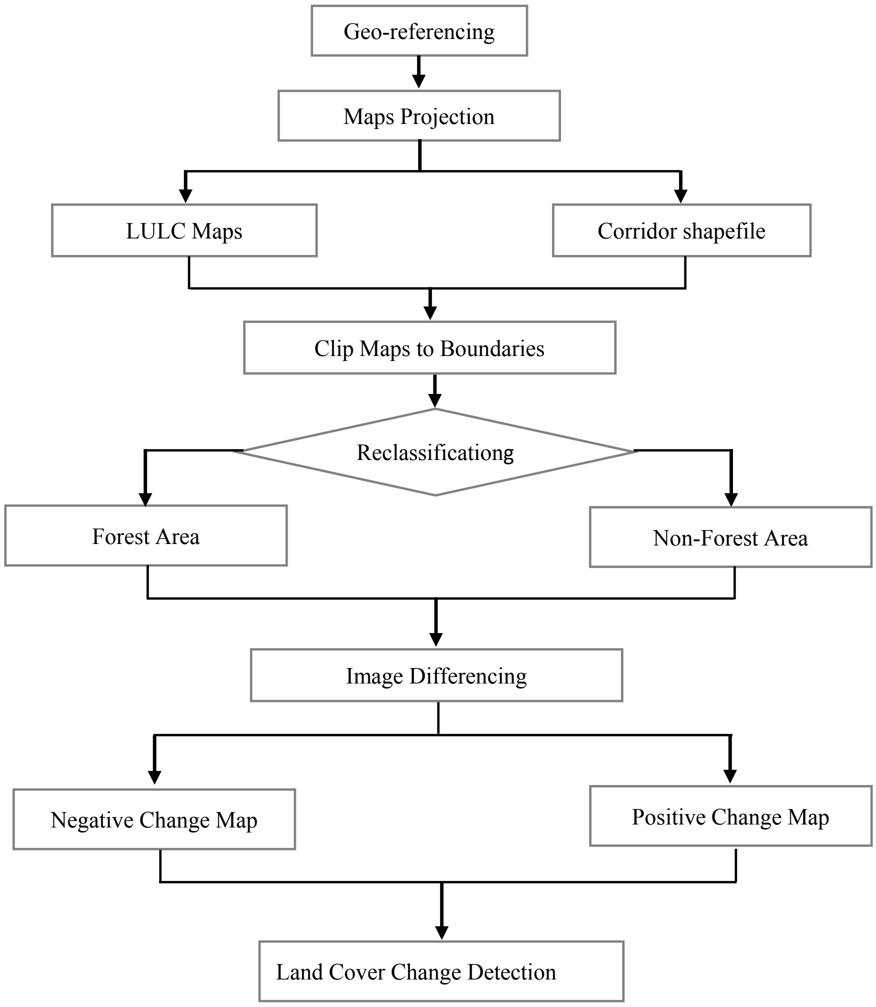

Figure 2. Flow chart showing the procedure of the data processing and land cover change detection.

fragmentation (Flowers et al., 2020) and several of landscape metrics widely used in the literature were selected and statistically assessed in this study, including Class Area (CA), Number of Patches (NP), Mean Patch Size (MPS), Core Area Percentage of Landscape (CPLAND), Landscape Patch Index (LPI), Patch Density (PD), Mean Shape Index (MSI) and Euclidian Nearest Neighbor (ENN). **Table 1** indicates the detailed description of the selected FRAGSTATS indices and metrics.

3. Results

3.1. Spatial Patterns and Temporal Forest Cover Change

The assessment of forest cover change and land cover transitions indicated that forest was covering about 8936 ha (75.34%) of the Gishwati-Mukura corridor during the year 1990 and highly reduced and falling to 1319.34 ha (11.12%) in 2019 (**Figure 3**). This degradation of forest cover increased relatively with the conversion for refugee settlement, agricultural land and pasture. The statistical

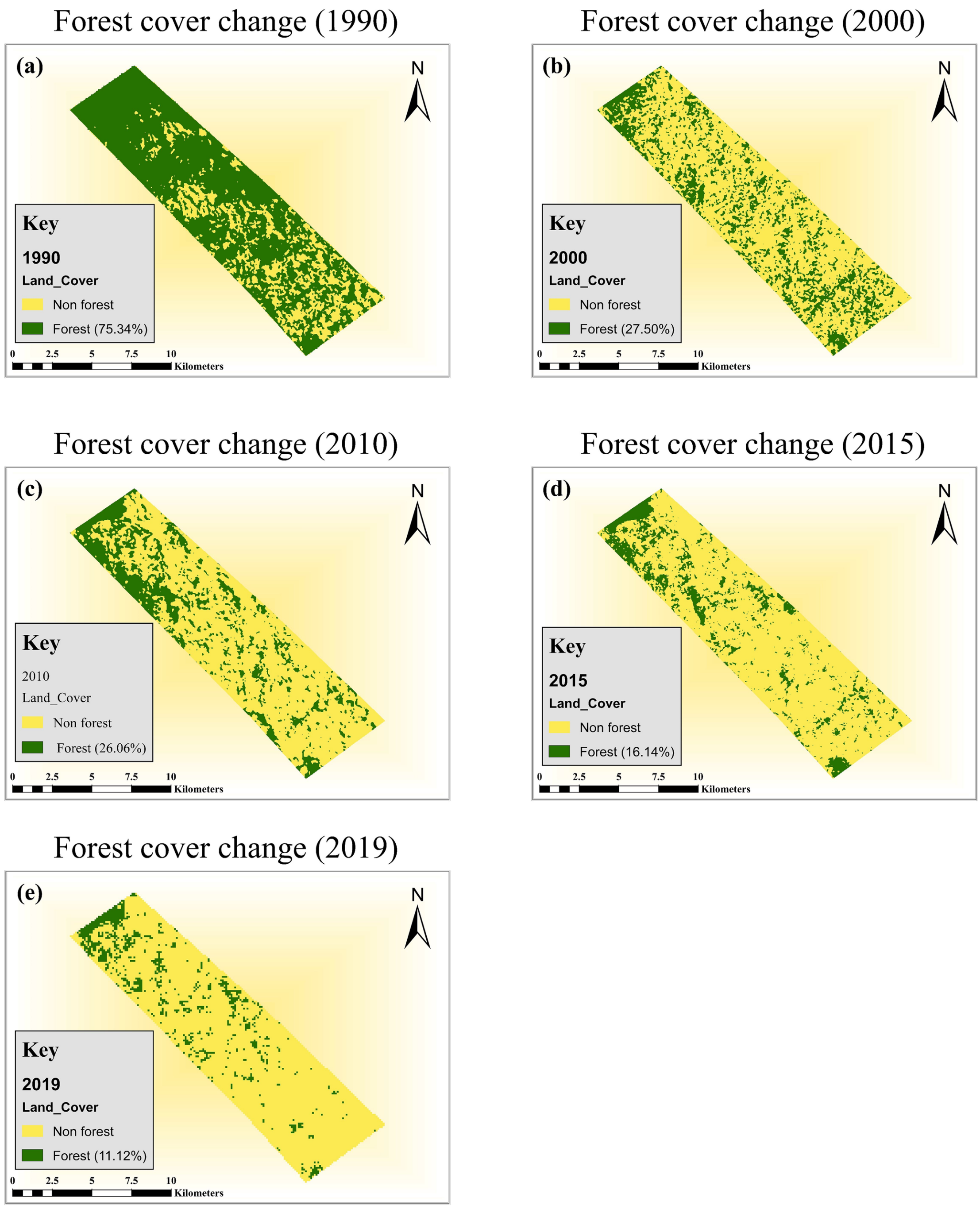

Figure 3. Thematic maps showing the spatial and patterns of forest land cover on Gishwati-Mukura biological corridor of (a) 1990, (b) 2000, (c) 2010, (d) 2015, (e) 2019.

Table 1. Landscape metrics used to quantify forest cover in the Gishwati-Mukura forest corridor their detailed descriptions.

Landscape metrics (unit)	Description
Class Area—CA (ha)	Class area; sum of areas of all patches belonging to a given class, in map units.
Number of Patches—NP	NP > 1, without limit, NP = 1 when a landscape or class type.

Continued

Mean Patch Size—MPS (ha)	Contains one patch, number of patches corresponding to class type at a landscape. The average area of patches corresponding to the forest cover type. Greater MPS indicate slightly fragmented forests.
Core Area Percentage of Landscape—CPLAND (%)	Percentage of the center of the landscape, similar to patch level core.
Landscape Patch Index—LPI (%)	Percentage of the landscape comprised by the largest path.
Patch Density—PD (Patches/100 ha)	Patches corresponding to the total forest cover divided by the total Area multiplied by 100. If forest class represents a greater PD, it indicates that it is subdivided into many patches and thus could be considered as fragmented.
Mean Shape Index—MSI	Shape complex measurement. The more irregular the shape, the larger the values and the closer the quadrilateral the closer it is to 1.
Euclidian Nearest Neighbor—ENN-MN	The average distance between patches of corresponding forest type, based on edge-to-edge distance.

Source: FRAGSTATS help (Mcgarigal, 2015).

representation of forest changes within the corridor showed the highest level of deforestation in the very first period of the study, where the forest cover reduction counted about 5673.75 ha (47.84%) of the total forest loss in the 10 years of 1990 to 2000. Therefore, deforestation continued to occur but at a small pace. For the period between 2000 to 2010, forest losses were accounted for 1.44%, 9.92% by 2010-2015 and 5.02% by 2015-2019. Therefore, the overall analysis indicated that at least 7617 ha (64.22%) of forest cover was completely cleared out, which implies an annual forest loss of 262.6 ha·year^{-1} (2.21%) during 1990-2019.

3.2. Transition Matrix among Forest Cover Types

The transition matrix of forest conversion to other land cover types indicated that about 62.09% of forest transitioned into non-forest, where at least 52.05% of forest was converted from sparse forest to annual cropland followed by 5.77% of the moderate forest changed to annual cropland and 2.73% of the sparse forest changed to closed grassland (**Table 3**). A total of 1.04% of forest cover was gained from other non-forest covers. While 13.44% of the forest cover remained unchanged; a large area of 5.95% of sparse forest was remained the same compared to other forest types. This study found that only 23.40% of other non-forest cover remained proportionally interchanging to closer other non-forest types patterns. However, this study accounted also for about 17.73% of annual cropland remained unchanged (**Table 2**).

3.3. Spatial Patterns and Forest Landscape Dynamics

The spatial patterns and landscape dynamics was used to analyze forest subdivision:

Table 2. Transition matrix table showing the amount of forest cover area converted to other land cover types during the period of 1990-2019.

Land cover	Area changed (ha)	Percentage (%)
FOREST LOSS	**7322.51**	**62.09**
Moderate Forest—Annual Cropland	680.78	5.77
Moderate Forest—Closed Grassland	35.75	0.3
Moderate Forest—Open shrub land	14.05	0.11
Moderate Forest—Wetland	6.06	0.05
Sparse Forest—Annual Cropland	6138.85	52.05
Sparse Forest—Closed Grassland	323.04	2.73
Sparse Forest—Open shrub land	101.23	0.85
Sparse Forest—Settlement	8.05	0.06
Sparse Forest—Wetland	14.66	0.12
UNCHANGED FOREST	**1586.01**	**13.44**
Moderate Forest—Closed Forest	109.84	0.93
Moderate Forest—Dense Forest	135.75	1.15
Moderate Forest—Moderate Forest	0.513	0.004
Moderate Forest—Sparse Forest	185.87	1.57
Sparse Forest—Closed Forest	346.61	2.93
Sparse Forest—Dense Forest	103.64	0.87
Sparse Forest—Moderate Forest	1.52	0.01
Sparse Forest—Sparse Forest	702.23	5.95
GAINED FOREST	**123.1**	**1.04**
Annual Cropland—Closed Forest	10.15	0.08
Annual Cropland—Sparse Forest	61.32	0.52
Closed Grassland—Closed Forest	4.78	0.04
Closed Grassland—Sparse Forest	43.04	0.36
Open shrub land—Closed Forest	0.005	0
Open Shrub land—Sparse Forest	3.79	0.03

Number of Patches (NP), Mean Patch Size (MPS), Mean Shape Index ((MSI), Patch Density (PD), Largest Patch Index (LPI) and Mean Euclidian Nearest Neighbor (ENN_MN) indices (metrics) to determine the forest physical degradation level. This assessment indicated that the Gishwati-Mukura forest was subdivided into multiple patches where the number of patches increased from 60 in 1990 to 672 in 2000 which shows the highest level of forest fragmentation over this period. The ecosystem conservation activities in this forest reconsolidated the degradation up to 359 patches in 2010. A little degradation of 1.44% was marked between 2000 and 2015 where the number of patches increased again to 563 by 2015 and significantly decreased to 175 patches in 2019. The entire analysis indicates an increase of the number of forest patches of 115 which implies an increase of forest patches at rate of 4% in the Gishwati-Mukura forest corridor during 1990-2019 (**Table 3**).

This assessment indicated that the number of patches was increasing, in association with the decreased mean patch size (MPS) where the geostatistical evaluation indicated that MPS extremely decreased from 148.9 ha to 74.53 ha. Patch density (PD) increased from 0.5 to 5.66, the largest patch index (LPI) decreased from 72.7% to 2.66% and the mean shape index values gradually decreased from 1.5 to 1.2 with the agreement that the PD > 1, indicates the high level of fragmentation.

The Euclidian Nearest Neighbor which indicates the proximity and the shortest edge to edge distance between patches of a given land use indicated an increasing distance between the subdivided patches from 101.6 meters in 1990 to 352.1 meters in 2019 which indicated a mean gradual patches isolation in the Gishwati-Mukura forest corridor during 1990-2019.

4. Discussion

Analysis of the changes in forest cover and landscape dynamics in the Gishwati-Mukura forest corridor using LULC time series revealed that the interchanges among the cover types were rendered by changes of forest cover from 1990 to 2019. The results revealed tremendous deforestation where approximately 64.22% of forest cover was completely cleared out over 29 years. This expresses an annual loss of 262.6 ha (2.21%) from 1990 to 2019. This loss in forest cover has been converted into different classes among land cover types found in the corridor. The geo-statistical analysis indicated that extensive deforestation was associated with intensive agriculture that occupied approximately 29.46% in 1990, which is highly increased 57.22% in 2019. The analysis highlighted that conversions among the land cover types triggered the reduction of forest cover in this biological corridor. Given that in the very first years, dense forest type changed into the sparse forest and after major transitions mainly occurred to sparse forest class, the results indicated that 52.05% of the sparse forest were transformed into

Table 3. Selected landscape metrics applied on forest land cover of Gishwati-Mukura biological corridor in 1990 to 2019.

Year	CA	NP	MPS	CPLAND	LPI	PD	MSI	ENN_MN
1990	8936.44	60	148.94	75.34	72.72	0.5	1.514	101.67
2000	3262.69	672	4.85	27.5	2.65	5.66	1.36	117.67
2010	3090.87	359	8.6	26.06	11.19	3.02	1.34	151.05
2015	1914.63	563	3.4	16.14	3.97	4.74	1.27	143.79
2019	1319.34	175	7.53	11.12	2.97	1.47	1.2	352.12

CA: Class Area; NP: Number of Patches; MPS: Mean Patch Size; CPLAND: Core Area Percentage of Landscape; LPI: Landscape Patch Index; PD: Patch Density; ENN_MN: Euclidian Nearest Neighbor; MSI: Mean Shape Index.

annual cropland. Therefore, these transitions among land cover classes exerted a certain influence on forest cover change (Deforestation/degradation). The assessment of forest degradation/fragmentation based on landscape analysis at the class level, revealed that the values of MPS decreased proportionally with an increase of NP, the lowest MPS values were calculated in 2000 and 2015 during the whole study period. The analysis of MPS indicated that the forest inside the Gishwati-Mukura corridor was extremely fragmented. Since Gishwati-Mukura was named a National Park and even before nomination from normal forest to ecological reserve, the diverse scientific studies addressing the new officialised have occurred, however there was little to non-remote sensed information about the physical degradation based on landscape metrics was yet assessed in this region. However, as reported by previous studies (Bettinger et al., 2017; Keleş et al., 2008; Frohn & Hao, 2006) similar investigations highlighted that the greater the MPS the lower the degradation, conforming to the findings of this study especially the analysis of several patches and edge density (**Table 2**). The MPS has considerably reduced over the years, which indicated the high level of forest fragmentation, hence the forest was highly fragmented, the following assumption that the greater the number of patches the greater the subdivision of forest cover that may have occurred until some patches started to get disappeared due to gradual forest degradation.

The NP revealed that the forest was heavily degraded and subdivided into numerous patches from 1990 until some of the patches disappeared as is explained by the CA and CPLAND which dramatically kept reducing over the years. The forest Largest Patch Index which is a simple measure of dominance revealed that in 1990 the forest land use class was in high dominance which reduced over the years according to the level of fragmentation of the forest. The PD which simply measures fragmentation expressed the transition period of 2000 as the most fragmented period over the study period as many other metrics revealed and the Mean Shape Index values continually decreased indicating a more regular shape; patch shape changed to a more regular one close to circle with straight lines (**Figure 4(a)**). The aggregation of forest patches also was analysed to check the shortest edge-to-edge distance between patches of given land use. Euclidian Nearest Neighbour is the simplest measure of patch context and has been used extensively to quantify patch isolation as reported by McGarigal et al. (McGarigal et al., 2002). This method helped to verify the degradation of forest given fragmentation due to understanding of the shortest edge to edge distance between patches of given land use where the greater ENN-MN signifies patches isolation in which implies high fragmentation. ENN is the shortest edge-to-edge distance between patches of given land use; for this case, the patch distance between edges has been increasing from 101.6 m in 1990 to 352.1 m in 2019 which means gradual patch isolation as the period has gone (**Figure 4(b)**).

Gishwati-Mukura Corridor is a potential biological corridor that was proposed by the management of the Gishwati-Mukura new National Park to be linking Gishwati and Mukura forest reserves which were two separate parts of

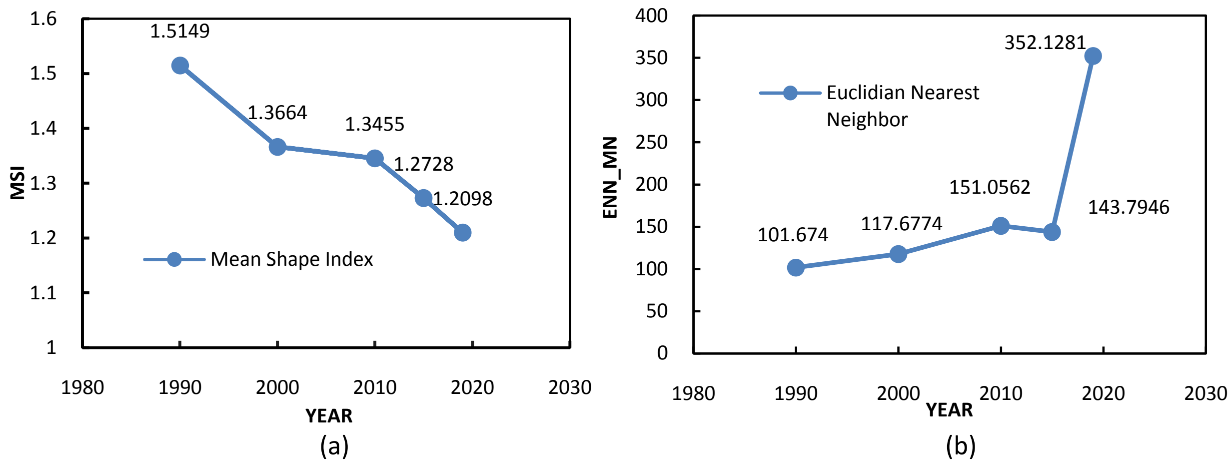

Figure 4. Landscape metrics of (a) variation of the MSI representing the mean patch shape; and (b) Mean Euclidian Nearest Neighbor (ENN_MN) values showing the shortest edge to edge distance between patches of a given land use.

the newly established park for restoring the connection that will allow animals to migrate between the protected areas and ensure gene exchange between the population of chimpanzees, improve environmental quality and quantity of life in rural communities and demonstrate the practices and benefits of sustainable conservation-compatible land uses (Clay, 2019). Thus, the results of this study highlighted extreme forest loss (deforestation/degradation) especially over the first decade, where the statistical trends imply that from 1990 to 2000 alone; a total of 567.3 ha (4.78%) of forest cover each year was lost which is extremely higher compared to other following year periods. The 1994 genocide and post-genocide situation was the cause of this boundless deforestation where about 15,000 ha of forests were destroyed and 35,000 ha damaged during the genocide countrywide (REMA, 2009) and after genocide mass clearing and removal of natural forests took place for the purpose of making more land available for the relocation of refugees and displaced people which reduced up to 92% of protected areas from 1993 to 2006, where for example some of the areas of the Akagera National Park, Gishwati and Mukura forests were partly cleared and reduced in size to build refugee camps and to resettle returnees (Moodley et al., 2011). Deforestation was also aggravated by households seeking wood as a source of energy wherein 2004 it was reported that the livelihoods of 90% of the rural population make forest resources the primary source of domestic energy and fuel (Minicofin, 2015). Several other factors have contributed to the observed losses including but not limited to the anthropogenic activities that have played a leading role throughout the degradation process. The effect of anthropogenic activities was generally evaluated based on population growth. Currently, the Rwandan population grew almost doubled from 7,288,882 in 1990 to 12,626,950 in 2019 (National Institute of Statistics of Rwanda (NISR), *Ministry of Finance and Economic Planning* (*MINECOFIN*) [*Rwanda*]; 2012. *Rwanda Fourth Population and Housing Census*., 2012), and this has considerably made a great pressure on natural resources including natural forest degradation and disappearance level due to most notably inside the forest and in surrounding areas (forest buffer zones) through exacerbation of intensive agricultural and pastoral activities.

Worldwide, agriculture has contributed hugely as the major cause of the deforestation and degradation of tropical forests (Carter et al., 2018; Ickowitz et al., 2015) for about 90% of forest loss was accounted to be cleared for agriculture extension purposes (Benhin, 2006). Assuming that agriculture and forestry are the two competing uses for land, the Gishwati-Mukura forest corridor also has experienced a tremendous increase in agriculture over the last two decades which has majorly led to the deforestation and degradation of the corridor. The correlation of forest change values and the annual cropland was higher with R^2 = 0.5646. The cultivated area has apparently increased each year which implied the spatial forest loss where the cropland increase adjacency was calculated (**Figure 5**).

Inconsistent with our hypothesis that deforestation has ceased since the establishment of the Gishwati-Mukura forest corridor in 2015, forest degradation continued despite. This might be related to the fact that the land within the corridor still belongs to the communities, the government is still seeking expropriation to reduce to the minimum the disruption and dislocation of the corridor communities (Bizimana et al., 2016).

This research was designed to deal with spatial and temporal forest physical degradation and delineated the proximity of forest change in the Gishwati-Mukura corridor over two decades; maps and the discussed forest cover change, and forest physical degradation through land cover and landscape metrics and statistical forest change provided were not yet assessed and presented by any other study so far. The limitation of this research was a lack of prior research. Due to the currency of this study, the fact that the biological corridor was proposed and established in 2015. Very few preceding research studies address this region. Generally, citing previous research studies usually lay a foundation for understanding

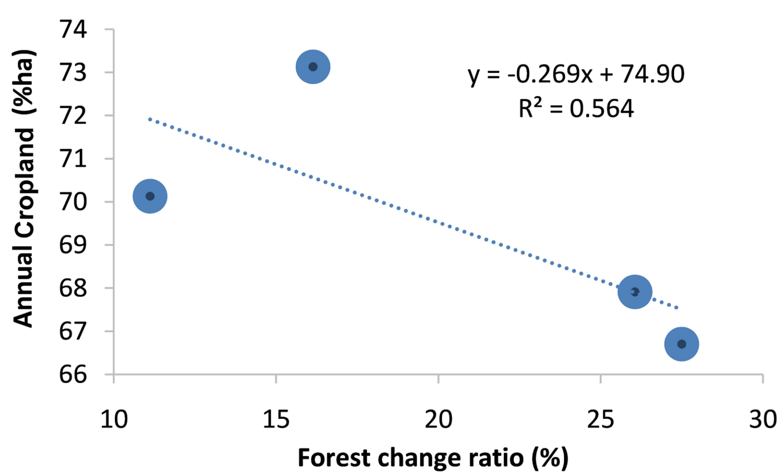

Figure 5. Linear correlation representing the relation between Gishwati-Mukura corridor deforestation and the increase of agriculture during the two last decades.

the research problem under investigation. Therefore, there is an urgent need for more research proposing different restoration scenarios and indigenous tree species to plant to preserve the natural habitat for further studies.

5. Conclusion

This study used remotely sensed datasets, Geographic Information System (GIS) techniques and Landscape metrics to quantify and analyze the spatial and temporal forest cover change and physical landscape dynamics in the Gishwati-Mukura corridor. The results revealed extreme forest loss (deforestation/degradation) in the Gishwati-Mukura corridor at least over 64.22% of the total forest cover was cleared during the period. The obtained high deforestation and fragmentation rates were totally associated with an inventoried extensive agriculture in this region. The study has focused on spatial and temporal changes of forest cover and physical degradation. Thus, the findings of this study will serve as the cornerstone of numerous other research that will contribute to the conservation and management of the corridor as well as the GMNP. Therefore, to strengthen the sustainability, resilience of the forest, and the National Park values and management, authors are encouraging and recommending a deep consideration of landscape ecological approaches (ecosystem-based conservation) with response to the economic and social concerns of the community living around. For, it is recognized that sustainability cannot thrive without the participation of the local population. In future, Restoration scenarios should consider planting indigenous tree species to restore the natural habitat conditions, the water balances and nutrient cycles. To support the biodiversity of native species, reduce the vulnerability to large outbreaks of insects' pests and diseases that set back reforestation efforts and species that will be well known and valued by local communities for their non-timber benefit.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

Alvarez-Berrios, N. L., & Mitchell Aide, T. (2015). Global Demand for Gold Is Another Threat for Tropical Forests. *Environmental Research Letters, 10,* Article ID: 014006. https://doi.org/10.1088/1748-9326/10/1/014006

Applying Landscape Ecology in Biological Conservation (2002). *Choice Reviews Online*.

Benhin, J. K. A. (2006). Agriculture and Deforestation in the Tropics: A Critical Theoretical and Empirical Review. *A Journal of Human Environment, 35,* 9-16. https://doi.org/10.1579/0044-7447-35.1.9

Bettinger, P., Zengin, H., & Değermenci, A. S. (2017). Analysis of Temporal Changes in Land Cover and Landscape Metrics of a Managed Forest in the West Black Sea Region of Northern Turkey: 1970-2010. *Journal of Forestry Research, 29,* 139-150. https://doi.org/10.1007/s11676-017-0423-6

Bizimana, J. P., Hategekimana, S., Habonimana, H. V., Nkurunziza, F., & Justin Nzayinambaho, E. T. (2016). Ecosystem Services and Land Degradation in Gishwati-Mukura Corridor, Rwanda: Cost Benefit Analysis. https://www.eld-initiative.org/fileadmin/Regreening_Africa_publications/Western_Group_Study_Poster_final.pdf

Carter, S., Herold, M., Avitabile, V., De Bruin, S., De Sy, V., Kooistra, L., & Rufino, M. C. (2018). Agriculture-Driven Deforestation in the Tropics from 1990-2015: Emissions, Trends and Uncertainties. *Environmental Research Letters, 13,* Article ID: 014002. https://doi.org/10.1088/1748-9326/aa9ea4

Chancellor, R. L., Rundus, A. S., & Nyandwi, S. (2012). The Influence of Seasonal Variation on Chimpanzee (*Pan troglodytes schweinfurthii*) Fallback Food Consumption, Nest Group Size, and Habitat Use in Gishwati, a Montane Rain Forest Fragment in Rwanda. *International Journal of Primatology, 33,* 115-133.

Chancellor, R., Rundus, A., Nyiratuza, M., Nyandwi, S., & Aimable, T. (2021). Community-Based Conservation and Chimpanzee Research in Gishwati Forest, Rwanda. *American Journal of Primatology, 83,* e23195. https://doi.org/10.1002/ajp.23195

Cheng, G., Han, J., & Lu, X. (2017). Remote Sensing Image Scene Classification: Benchmark and State of the Art. *Proceedings of the IEEE, 105*, 1865-1883. https://doi.org/10.1109/JPROC.2017.2675998

Clay, N. (2019). Fixing the Ecosystem: Conservation, Crisis and Capital in Rwanda's Gishwati Forest. *Environment and Planning E: Nature and Space, 2,* 23-46. https://doi.org/10.1177/2514848619826576

Cohen, W. B., & Goward, S. N. (2004). Landsat's Role in Ecological Applications of Remote Sensing. *BioScience, 54,* 535-545. https://doi.org/10.1641/0006-3568(2004)054[0535:LRIEAO]2.0.CO;2

de la Paix, M. J., Lanhai, L., Xi, C., Ahmed, S., & Varenyam, A. (2013). Soil Degradation and Altered Flood Risk as a Consequence of Deforestation. *Land Degradation and Development.*

Diamond, J. M. (1975). The Island Dilemma: Lessons of Modern Biogeographic Studies for the Design of Natural Reserves. *Biological Conservation, 7,* 129-146. https://doi.org/10.1016/0006-3207(75)90052-X

Flowers, B., Huang, K. T., & Aldana, G. O. (2020). Analysis of the Habitat Fragmentation of Ecosystems in Belize Using Landscape Metrics. *Sustainability (Switzerland), 12,* 3024. https://doi.org/10.3390/su12073024

Frohn, R. C., & Hao, Y. (2006). Landscape Metric Performance in Analyzing Two Decades of Deforestation in the Amazon Basin of Rondonia, Brazil. *Remote Sensing of Environment, 100,* 237-251. https://doi.org/10.1016/j.rse.2005.10.026

Gardner, T. A., Barlow, J., Chazdon, R., Ewers, R. M., Harvey, C. A., Peres, C. A., & Sodhi, N. S. (2009). Prospects for Tropical Forest Biodiversity in a Human-Modified World. *Ecology Letters, 12,* 561-582. https://doi.org/10.1111/j.1461-0248.2009.01294.x

Humphrey kisioh (2015a). *Gishwati Forest Reserve Three Years Interim Management Plan 2015-2018.*

Humphrey Kisioh. (2015b). *Gishwati Forest Reserve Three Years Interim Management Plan.*

Ickowitz, A., Slayback, D., Asanzi, P., & Nasi, R. (2015). *Agriculture and Deforestation in the Democratic Republic of the Congo: A Synthesis of the Current State of Knowledge.* Center for International Forestry Research (CIFOR).

Kafle, K., Thanet, D. R., Poudel, P., Gautam, D., Thapa, G., & Bhatt, P. (2020). Status and

Conservation Threats to Large Mammals of the Laljhadi Mohana Biological Corridor, Nepal. *Journal of Animal Diversity, 2,* 16-33. https://doi.org/10.29252/JAD.2020.2.2.3

Kareiva, P., Watts, S., McDonald, R., & Boucher, T. (2007). Domesticated Nature: Shaping Landscapes and Ecosystems for Human Welfare. *Science, 316,* 1866-1869. https://doi.org/10.1126/science.1140170

Kayiranga, A., Kurban, A., Ndayisaba, F., Nahayo, L., Karamage, F., Ablekim, A., Li, H., & Ilniyaz, O. (2016). Monitoring Forest Cover Change and Fragmentation Using Remote Sensing and Landscape Metrics in Nyungwe-Kibira Park. *Journal of Geoscience and Environment Protection, 4,* 13-33. https://doi.org/10.4236/gep.2016.411003

Keleş, S., Sivrikaya, F., Çakir, G., & Köe, S. (2008). Urbanization and Forest Cover Change in Regional Directorate of Trabzon Forestry from 1975 to 2000 Using Landsat Data. *Environmental Monitoring and Assessment, 140,* 1-14. https://doi.org/10.1007/s10661-007-9845-5

Malhi, Y., Adu-Bredu, S., Asare, R. A., Lewis, S. L., & Mayaux, P. (2013). African Rainforests: Past, Present and Future. *Philosophical Transactions of the Royal Society B: Biological Sciences, 368,* Article ID: 20120312. https://doi.org/10.1098/rstb.2012.0312

Masek, J. G., Huang, C., Wolfe, R., Cohen, W., Hall, F., Kutler, J., & Nelson, P. (2008). North American Forest Disturbance Mapped from a Decadal Landsat Record. *Remote Sensing of Environment, 112,* 2914-2926. https://doi.org/10.1016/j.rse.2008.02.010

Mc Guinness, S., & Taylor, D. (2014). Farmers' Perceptions and Actions to Decrease Crop Raiding by Forest-Dwelling Primates around a Rwandan Forest Fragment. *Human Dimensions of Wildlife, 19,* 179-190. https://doi.org/10.1080/10871209.2014.853330

McCracken, S. D., Brondizio, E. S., Nelson, D., Moran, E. F., Siqueira, A. D., & Rodriguez-Pedraza, C. (1999). Remote Sensing and GIS at Farm Property Level: Demography and Deforestation in the Brazilian Amazon. *Photogrammetric Engineering and Remote Sensing, 65,* 1311-1320.

Mcgarigal, K. (2015). *FRAGSTATS*.

McGarigal, K., & Marks, B. J. (1995). *FRAGSTATS: Spatial Patterns Analysis Program for Quantifying Landscape Structure*. General Technical Report PNW-351, U.S. Forest Service. https://doi.org/10.2737/PNW-GTR-351

McGarigal, K., Cushman, S. A., Neel, M. C., & Ene, E. (2002). *FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps*.

Midha, N., & Mathur, P. K. (2010). Assessment of Forest Fragmentation in the Conservation Priority Dudhwa Landscape, India Using FRAGSTATS Computed Class Level Metrics. *Journal of the Indian Society of Remote Sensing, 38,* 487-500. https://doi.org/10.1007/s12524-010-0034-6

Minicofin (2015). *The Government of Rwanda. Ministry of Finance and Economic Planning External Finance Unit. Documentation of Rwanda's Good Practices in Aid Coordination and Management since 2004*. Final Report.

Moodley, V., Gahima, A., & Munien, S. (2011). Environmental Causes and Impacts of the Genocide in Rwanda: Case Studies of the Towns of Butare and Cyangugu. *African Journal on Conflict Resolution, 10,* 103-119. https://doi.org/10.4314/ajcr.v10i2.63313

National Institute of Statistics of Rwanda (NISR), Ministry of Finance and Economic Planning (MINECOFIN) [Rwanda] (2012). *Rwanda Fourth Population and Housing Census*. Ministry of Finance and Economic Planning, National Institute of Statistics of Rwanda.

Philippe, M. T., & Karume, K. (2019). Assessing Forest Cover Change and Deforestation Hot-Spots in the North Kivu Province, DR-Congo Using Remote Sensing and GIS. *Amer-*

ican Journal of Geographic Information System, 8, 39-54.

Puyravaud, J. P. (2003). Standardizing the Calculation of the Annual Rate of Deforestation. *Forest Ecology and Management, 177,* 593-596. https://doi.org/10.1016/S0378-1127(02)00335-3

RCMRD (Regional Center for Mapping of Resources for Development) (2012). RCMRD GeoPortal. http://geoportal.rcmrd.org/

REMA (2009). *State of Environment Summary for Decision Makers* (pp. 5-6).

Rwanda Environment Management Authority (2020). *Republic of Rwanda 6th National Report to the Convention on Biological Diversity*.

Rwanda Land Management and Use Authority (2017). *Rwanda National Land Use Planning Guidelines* (p. 130).

Singh, K. D. (2013). *Global Forest Resources Assessments*. Environmental Science and Engineering (Subseries: Environmental Science), Springer. https://doi.org/10.1007/978-3-642-32292-1_19

Solomon, A., & Grazia, A. (2014). *How to Deal with People in Post Displacement—Reintegration*.

Turner, M. G., & Gardner, R. H. (2015). *Landscape Ecology in Theory and Practice*. Springer. https://doi.org/10.1007/978-1-4939-2794-4

Wayne Forsythe, K., & McCartney, G. (2014). Investigating Forest Disturbance Using Landsat Data in the Nagagamisis Central Plateau, Ontario, Canada. *International Journal of Geo-Information, 3,* 254-273. https://doi.org/10.3390/ijgi3010254

Weilin, L., Buo, X., & Yu, L. (2000). Applications of RS, GPS and GIS to Forest Management in China. *Journal of Forestry Research, 11,* 69-71. https://doi.org/10.1007/BF02855502

Wu, Y. (2011). *Investigation of Deforestation in East Africa on Regional Scales* (p. 47).