



Article

Analyzing Drivers of Tropical Moist Forest Dynamics in the Kahuzi-Biega National Park Landscape, Eastern Democratic Republic of Congo from 1990 to 2022

Nadège Cizungu Cirezi ^{1,2,3,*}, Jean-François Bastin ¹, Yannick Mugumaarhahama ², Yannick Sikuzani Useni ⁴, Katcho Karume ², Raymond Sinsi Lumbuenamo ³ and Jan Bogaert ¹

- TERRA Research and Teaching Center, Gembloux Agro-Bio Tech, University of Liège, 5030 Gembloux, Belgium; jfbastin@uliege.be (J.-F.B.); j.bogaert@uliege.be (J.B.)
- Natural Resource Management Department, Faculty of Agricultural and Environmental Sciences, Université Evangélique en Afrique, Bukavu P.O. Box 3323, Democratic Republic of the Congo; mugumaarhahama@uea.ac.cd (Y.M.); katcho.karume@uea.ac.cd (K.K.)
- Protected areas management, Ecole Régionale Post-Universitaire d'Aménagement et de Gestion Intégrés des Forêts et Territoires Tropicaux (ERAIFT), Kinshasa P.O. Box 15373, Democratic Republic of the Congo; raymond.lumbuenamo@unikin.ac.cd
- Ecology, Ecological Restoration and Landscape Unit, Faculty of Agronomic Sciences, University of Lubumbashi, Lubumbashi P.O. Box 1825, Democratic Republic of the Congo; sikuzaniu@unilu.ac.cd
- * Correspondence: nadegecirezi@gmail.com or n.cirezi@doct.uliege.be; Tel.: +243-993435999

Abstract: The protected areas (PA) of the Democratic Republic of the Congo serve as vital carbon reservoirs and are crucial for biodiversity conservation and climate regulation. Despite their significance, these areas face escalating rates of deforestation and degradation, often poorly understood at the local level. This study focuses on the dynamics of tropical moist forest (TMF) and the relative importance of the driving factors in the landscape of Kahuzi-Biega National Park (KBNP), one of the country's prominent PAs. Analyzing annual TMF dynamics from 1990 to 2022 using data classified by Vancutsem and his collaborators in 2021 from Landsat imagery alongside spatial datasets of deforestation and degradation drivers, we employed a comprehensive analytical approach. This included meshing, multi-scale analysis, principal component analysis, zoning, multiple linear regression, and relative importance analysis through bootstrapping. The findings indicate that the grid size considered does not significantly influence TMF dynamics in the KBNP landscape (p-value = 0.67, α = 0.05). The edge and outer zones experienced substantial dynamics, with approximately 30% forest cover loss in both areas, contrasting with the relatively stable TMF cover (~100%) in the inner zone. Fire emerged as the most influential driver, explaining TMF dynamics with a relative importance of approximately 55%, 30%, and 23% in the inner, edge, and outer zones, respectively. This study underscores KBNP's efficacy in curbing TMF loss but highlights the need for enhanced protection around its periphery. Management efforts should prioritize sustainable land use practices, livelihood improvement, and the establishment of an officially recognized buffer zone.

Keywords: tropical moist forest; deforestation; degradation; protected area; natural resource management and Kahuzi-Biega National Park



Academic Editor: Guillermo J. Martinez-Pastur

Received: 28 November 2024 Revised: 24 December 2024 Accepted: 27 December 2024 Published: 29 December 2024

Citation: Cirezi, N.C.; Bastin, J.-F.; Mugumaarhahama, Y.; Useni, Y.S.; Karume, K.; Lumbuenamo, R.S.; Bogaert, J. Analyzing Drivers of Tropical Moist Forest Dynamics in the Kahuzi-Biega National Park Landscape, Eastern Democratic Republic of Congo from 1990 to 2022. Land 2025, 14, 49. https:// doi.org/10.3390/land14010049

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Home to more than 60% of the Congo Basin's forests [1–3], the Democratic Republic of the Congo (DRC) contains 99 million hectares of dense moist forest, with around 63 million hectares of intact forest landscapes [4,5]. These forests hold significant ecological

Land 2025, 14, 49 2 of 22

integrity and biodiversity and play an important role in the provision of global ecosystem services, including regulation of the climate and water cycle, carbon sequestration, and biodiversity conservation [6–8]. Despite their global importance, the DRC's forests face numerous pressures, including climate change, anthropogenic pressures, and other combined factors [9,10]. Since 2001, the DRC has lost over one million hectares of forest cover annually [9], including 450,000 hectares of primary forest [2,6], mainly due to forest clearance by smallholders for agriculture and charcoal production [9,11,12]. They often move into forests to escape conflict and insecurity [13–15].

The DRC's terrestrial protected areas (PAs) cover around 324,289.7 km² (approximately 13.8% of the country's territory) [16,17] and are crucial for conserving tropical biodiversity and mitigating climate change by reducing deforestation and degradation [18–23]. Despite their importance, protected areas face intense anthropogenic pressures, [16,20,24] which are compounded by high population density (exceeding 100 inhabitants per km²) in the eastern region [6,22] and widespread poverty (human development index of 0.479 [25]). The Kahuzi-Biega National Park (KBNP), one of the most important PAs for the conservation of Grauer's gorilla (*Gorilla beringei graueri*) in the DRC, faces severe threats primarily due to insecurity, which impedes the conservation and restoration of its integrity [26–28].

Straddling the Albertine Rift and the Congo Basin, the KBNP covers around 6700 km² of tropical forest, ranging from carbon-rich Afromontane forests to mid-altitude equatorial rainforests [26]. It is the second most important site in the Albertine Rift in terms of species richness, endemism, and threatened species [26,29–31]. The park is renowned for its extensive tracts of primary and secondary forest, with about 60% of the total area comprising intact forest landscapes with high ecological integrity [32]. These forests host a vast array of flora and fauna, with thousands of species documented [29,33,34]. Despite its importance, the KBNP is one of the DRC PAs where forest losses and degradation are severe [29,33].

The KBNP is in one of the DRC's most densely populated regions, with a population density of about 400 inhabitants per km², much higher than the national average [35]. The park faces significant challenges from human activities, such as bushmeat hunting, firewood collection, charcoal production, bushfires, and the establishment of villages in and around the park. Additional threats include encroachment from agriculture, mining operations, and the spread of the invasive vine *Sericostachys scandens* [28–30]. Lacking an officially recognized buffer zone, the PNKB shares its borders directly with villages where all kinds of activities take place, making it more vulnerable to anthropogenic threats [36]. Although the KBNP was inscribed on the UNESCO World Heritage List in 1980 under criterion (x), the threats have increased, particularly after the mass eviction of people from the park during its enlargement in 1975 and the civil wars of 1996–1997 and 1998–2003, leading to conflicts over land between indigenous Pygmy peoples and local communities [37,38]. Consequently, KBNP has been on the UNESCO list of World Heritage in Danger since 1997 [26,39,40].

Analyzing the impact of human activities on the park's forest dynamics and conservation status is crucial for understanding and guiding conservation efforts in this protected area, whose importance is recognized worldwide. To answer this question, we used remote sensing data and approaches. Remote sensing is recognized as an essential tool for monitoring tropical rainforest ecosystems, which are often inaccessible and large-scale [41,42]. This study uses Landsat archives, machine learning tools, and satellite image processing to analyze the KBNP landscape from 1990 to 2022. This analysis supports conservation efforts in the DRC, offering insights into deforestation and degradation (DFD) to ensure the long-term survival of Kahuzi-Biega's intact forest. Previous studies have highlighted drivers of DFD in the DRC without focusing on protected areas [11,13,43], while global

Land 2025, 14, 49 3 of 22

studies using remote sensing have examined general threats to protected areas [44–46]. Local analyses are necessary to understand the specific issues of forest loss in the context of each protected area.

This study hypothesizes that Kahuzi-Biega National Park, a Category II protected area (as defined by the UICN and national categorization) [47], experiences a lower rate of tropical moist forest (TMF) loss compared to its unprotected surroundings. Without well-defined buffer zones [40], the park faces increasing centripetal pressures. The inner zone is less exposed to forest loss than the peripheral and outer zones, which are more vulnerable. Several studies have shown that protected areas, despite various pressures, play a significant role in mitigating DFD compared to unprotected surroundings [14,22,48]. Fire, used for agriculture, charcoal production, hunting, and savannah regeneration, is expected to be the main driver of TMF loss in the KBNP landscape [49–51]. In this study, we define a driver as any human activity that directly affects TMF cover and biomass [52–54]. As supported by Ref. [52], the term driver is more appropriate as an adjunct to discuss factors that are typical causes of land or environmental change, where there is evidence of a causal relationship, but not enough to establish causal effects and explain the causal mechanisms of a particular phenomenon. It is used here as a synonym for the direct cause of deforestation and degradation [10,53] of TMF. TMF dynamics here include any TMF disturbance that leads to TMF degradation and/or deforestation [6].

2. Materials and Methods

2.1. Study Area

Covering 6700 km² [29,55], KBNP is located in central Africa, eastern DRC, spanning the South Kivu, North Kivu, and Maniema provinces (Figure 1). The park stretches from the Congo River basin near Itebero-Utu to its western border northwest of Bukavu, between 1°36′–2°37′ south latitude and 27°33′–28°46′ east longitude. The KBNP comprises two distinct zones, the high-altitude and the low-altitude regions, connected by a narrow ecological corridor [26,40,56]. The high-altitude zone features an ombrophilous forest, reaching its highest point at Mount Kahuzi (3308 m), and experiences an Afroalpine climate with occasional night frosts on the peaks of Kahuzi and Biega. This region receives an average annual rainfall of up to 1900 mm, with a long dry season from June to August and a short dry season in February. In contrast, the low-altitude zone consists of the Guineo–Congolian ombrophilous forest, located between 700 and 1700 m above sea level. This region enjoys a warm climate during the day and throughout the year, with an annual average temperature of 20.5 °C and very high rainfall [26,40,57]. The park is interspersed with numerous watercourses and is traversed by National Road 2 in the highlands [40].

The KBNP landscape considered includes the park and a 15 km surrounding area, based on research suggesting that protected areas should be studied along with their surroundings for better understanding [44,48,58]. To better analyze the dynamics of TMF in the KBNP landscape, the landscape was subdivided into three main zones: the inner zone (consisting of the inner of the park minus the buffer zone), an edge zone (including an inner buffer and outer buffer with a total width of 10 km), and the outer zone (located outside the KBNP and the buffer zone. The width of the edge zone was determined based on the literature [36,59] estimating how far communities can travel in search of forest products (timber and non-timber).

Land 2025, 14, 49 4 of 22

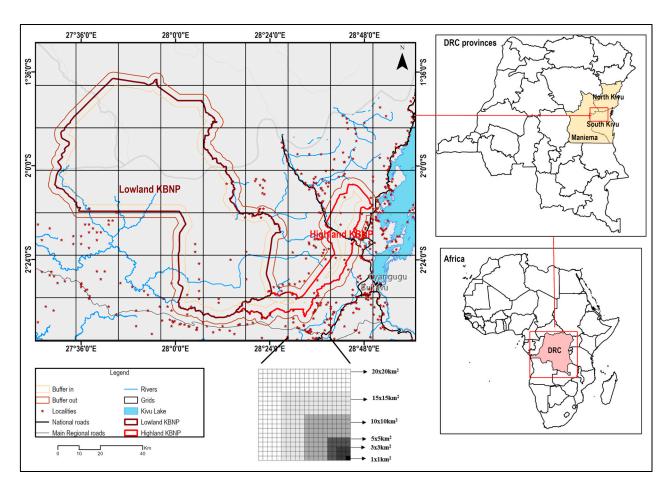


Figure 1. Study area. Landscape of the Kahuzi-Biega National Park (KBNP) with a 15 km outer zone. The park is located in central Africa, eastern Democratic Republic of Congo (DRC) between three provinces (North Kivu, South Kivu, and Maniema).

2.2. Dataset

The data analyzed were obtained from several sources (Appendix A.1). The tropical moist forest data provided by Vancutsem et al. [6] were used as the response variable and relevant deforestation/degradation factors, referred to here as drivers, as explanatory variables. The drivers considered (Appendix A.2) in the models were selected based on the literature on the main drivers of forest disturbance in the Congo Basin [11,13,60,61] and locally [29,30,62,63], but also on the availability of spatial data. The data set lacks consideration of factors such as logging activities, as well as the underlying causes of deforestation and degradation as described by Ref. [53].

2.3. Data Analysis

2.3.1. Image Quality and Adaptability Assessment

Following the acquisition, extraction, and preprocessing (Appendix A.1) of annual classified images from Ref. [6] and covering 1990 to 2022, we tested their effectiveness in analyzing TMF dynamics in Kahuzi-Biega National Park landscape. The images were chosen for their annual availability, quality (free cloud), high estimate accuracy (91.40%) [6], and high similarity rate (91.28%) with a Landsat 8 OLI/TIRS surface reflectance (2021) image classified using Google Earth Engine and the methodology proposed by Ref. [64]. Appendix A.3 shows the results of the similarity test between the two images. This test involved extracting differences between the two images and assessing their ratio to the total surface area using the Raster Calculator and Field Calculator tools in ArcMap 10.8.1.

Land 2025, 14, 49 5 of 22

2.3.2. Model and Variable Selection

The selection of the model and variables was carried out through the following steps:

Deforestation quantification: To assesses the impact of spatial grain selection on TMF dynamics, we quantified deforestation in square grids of varying sizes (1 km², 9 km², 25 km², 100 km², 225 km², and 400 km²) as tested by Ref. [65]. Given the study area size, we focused on the smallest grid sizes (1 km², 9 km², 25 km²).

- Variable selection: Considering the various grid sizes retained, a selection of variables was made. The variable selection reduced the original set of variables based on Pearson correlation tests and principal component analyses (PCA) using, respectively, corrplot [66] and FactoMineR [67] packages in R 4.2.2. For the PCA analysis, eigenvalues and eigenvectors were computed to identify principal components and a correlation circle was used to visualize relationships. When two variables were highly correlated (r > 85%) and formed an acute angle on the correlation circle, the variable with the highest expression (high cos2) rate was selected.
- Model testing and scale selection: After testing models at different scales, one scale was chosen to analyze the zoning effects on our landscape. The choice was guided by Ref. [68]'s principle of fine scales for local disturbances and the model's ability to explain most variables used [69]. The analysis of variance (ANOVA) also helped to detect the differences between models and different scales.
- Analysis of zoning effects on TMF dynamics: To better understand the dynamics of TMF in the Kahuzi-Biega National Park landscape, three groups of grids were considered for the three previously defined zones: inner grids, edge grids, and outer grids. Grids located entirely within the park (excluding the buffer zone) were classified as inner grids. Grids that were entirely or predominantly within the buffer zone were classified as edge grids, while those located outside both the buffer zone and the park were classified as outer grids. At this step, the variable selection was performed again for the different zones using the same methodology described above.

2.3.3. Model Construction

The model construction involved several steps:

 Model development: At the first level, we developed TMF dynamics models across selected spatial scales using multiple linear regressions. The formula used for the multiple linear regression model is provided in Equation (1):

$$Y = \beta_0 + \beta_1 X_1 + \beta_1 X_1 + \ldots + \beta_n X_n + \epsilon$$
 (1)

where

Y is the dependent variable (Δf),

 $X_1, X_2, ..., X_n$ are the independent variables (predictors),

 $\beta_0, \beta_1, \ldots, \beta_n$ are the coefficients,

and ϵ is the error term.

Model validity assessment: The normality tests for residuals [70] and Durbin–Watson tests for autocorrelations [71] were used to assess the model validity. Equation (2) describes the Durbin–Watson test statistic formula:

$$DW = \frac{\sum_{t=2}^{T} (e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2}$$
 (2)

where e_t is the residual at time t.

Land 2025, 14, 49 6 of 22

 Analysis of Variance (ANOVA): We determined scale-dependent TMF variation based on studied parameters. All variables were centered and normalized to assess their individual impacts. The results were visualized using dot-whisker plots [72]. The normalization formula used is presented in Equation (3).

$$Z = \frac{X - \mu}{\sigma} \tag{3}$$

where

X is the original value, μ is the mean, and σ is the standard deviation.

• Zoning and Relative important analysis: Once the optimal scale for KBNP TMF dynamics was established, we analyzed different predefined zones. Initially, we computed TMF variation statistics across all years (1990–2022) and developed multiple linear regression models for the variation of TMF (Δf) as per earlier methods. The relative importance analysis (Equation (4)) was conducted using Lindemann, Merenda, and Gold's method (lmg) with bootstrapping to estimate variability [73] by employing the relaimpo package in R 4.2.2.

$$lmg(X_j) = \sum_{S \subseteq \{X_1, ..., X_p\} \setminus \{X_j\}} \frac{|S|!(p-|S|-1)!}{p!} \left(R^2(S \cup \{X_J\}) - R^2(S) \right)$$
(4)

where

 X_j is the variable of interest, S is a subset of predictors, R^2 is the coefficient of determination, and p is the total number of predictors.

Figure 2 depicts the methodological workflow.

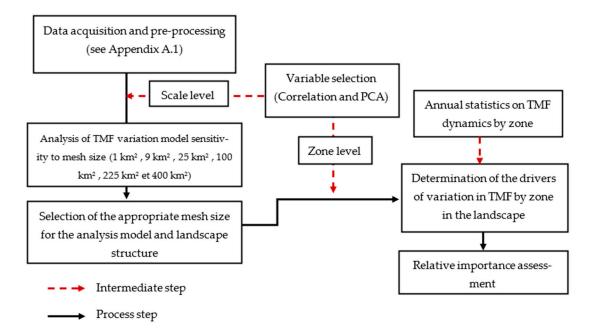


Figure 2. Methodology workflow used to assess tropical moist forest loss and quantify the contribution of factors explaining this loss in the landscape of Kahuzi-Biega National Park, eastern Democratic Republic of Congo, from 1990 to 2022.

Land 2025, 14, 49 7 of 22

3. Results

3.1. Analysis of Model Sensitivity to Mesh Size

Figure 3 and Appendix A.4 depict variable relationships in the model for moist forest variation in KBNP. While the first two principal components explain < 75% variance, correlation circles show relationships between original variables and components. Relationships were tested across scales (1 km 2 (a), 9 km 2 (b), 25 km 2 (c), 100 km 2 (d), 225 km 2 (e), and 400 km 2 (f)). Variables like Euclidean distance to roads and rivers are highly correlated across scales. However, rivers' Euclidean distances were not considered due to low Cos2 compared to roads. This information is assumed to be included in the latter. Other variables show scale-dependent relationships significant for model construction.

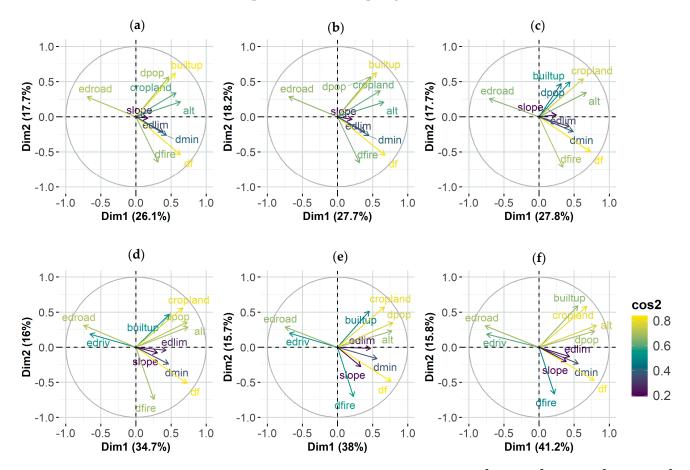


Figure 3. Correlation circles from different grid sizes (1 km² (**a**), 9 km² (**b**), 25 km² (**c**), 100 km² (**d**), 225 km² (**e**), and 400 km² (**f**)) tested for assessing tropical moist forest dynamic (df) as a function of the factors analyzed, including, edroad: Euclidean distance to roads, edriv: Euclidean distance to rivers, cropland: cropland area, builtup: built-up density, dpop: population density, edlim: Euclidean distance to limits, dmin: mining site densisty, df: TMF loss, dfire: fire.

Figure 4 displays standardized estimate coefficients (β) with standard errors on the x-axis and predictors (variables) on the y-axis. The results indicate increasing coefficient variance with grid size, and R² values rose across models: 0.44, 0.57, 0.62, 0.70, 0.76, and 0.87 for models 1 to 6 (see Appendices A.5 and A.6). However, variance analysis found no significant difference (p = 0.67, α = 0.05) in grid size impact on TMF variation in KBNP. Therefore, the 25 km² grid size was deemed optimal for zoning effect analysis on the landscape.

Land 2025, 14, 49 8 of 22

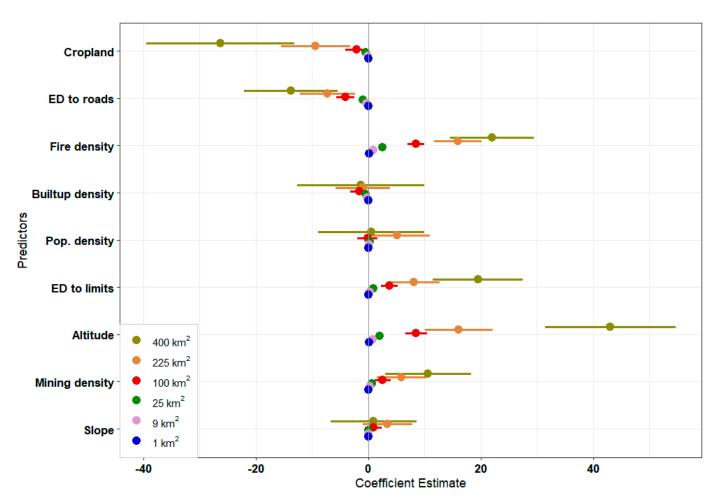


Figure 4. Influence of grid cell size on TMF dynamics. Summary results of the linear regressions carried out to analyze the contribution of the variables studied to the variation in tropical moist forest (df) in the KBNP landscape at different scales (1 km², 9 km², 25 km², 100 km², 225 km², and 400 km²) and considering drivers analyzed (cropland, ED to roads: Euclidean distance to roads, fire density, built-up density, pop. density: population density, ED to limits: Euclidean distance to limits, altitude, mining site density, and slope). The points represent the median value associated to the standard error(line).

3.2. Assessing Zoning Effect on TMF Variation

Figures 5 and 6 depict the spatial variation of TMF (Δf) and TMF change statistics by sub-zone in KBNP from 1990 to 2022 for the 25 km² grid size. The results reveal significant TMF regression in the outer and edge zones compared to the less dynamic inner zone. The median proportion of dense moist forest in inner patches remained stable at around 100% from 1990 to 2022, while in the edge zone, it decreased from approximately 98% to 76%, and in the outer zone, from 98% to about 72% (Figure 6). Figure 6 highlights significant TMF variations, particularly outside the park (losses > 40%) and in the highlands.

The construction of the models was preceded by an evaluation of the relationships between the variables, as shown in Figure 7a–c and Appendix A.7. The results obtained show the existence of strong correlations between variables according to the zone of the KBNP landscape. Upon analysis of the data from each zone, it becomes evident that there is a strong correlation between the variables cultivated area and altitude, as well as the density of built-up areas and fire density, in the inner zone (Figure 7a). Similarly, in the edge zone (Figure 7b), population density is also strongly correlated with built-up density. In the outer zone (Figure 7c), there was also a strong correlation between population density and built-up density, as well as slope and elevation. In constructing the final model for

Land 2025, 14, 49 9 of 22

each zone, one of two highly correlated variables, having high \cos^2 , was considered. The variables excluded were cultivated land and building density for the inner zone, population density for the edge zone, and population density and slope for the outer zone.

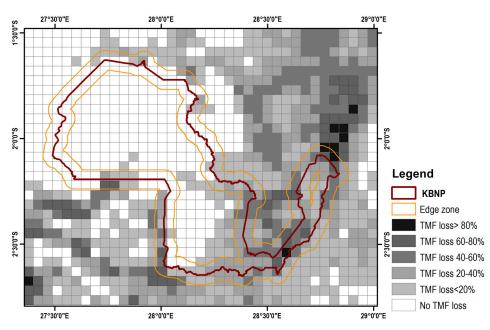


Figure 5. Change in tropical moist forest at 25 km² scale from 1990 to 2022 in the considered sub-zones (inner zone, edge zone, and outer zone) of the Kahuzi-Biega National Park landscape.

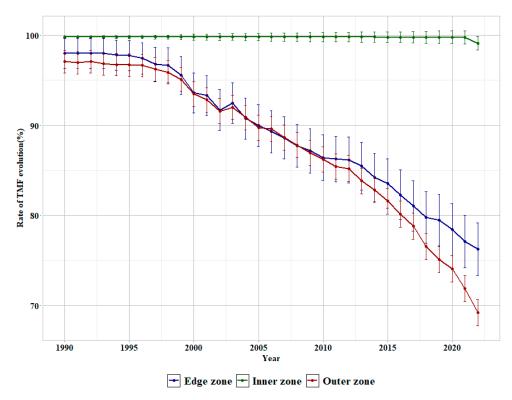


Figure 6. Rate of tropical moist forest (TMF) evolution (median associated to standard errors) from 1990 to 2022 at the scale of 25 km² grids in the landscape of the Kahuzi-Biega National Park.

Land 2025, 14, 49 10 of 22

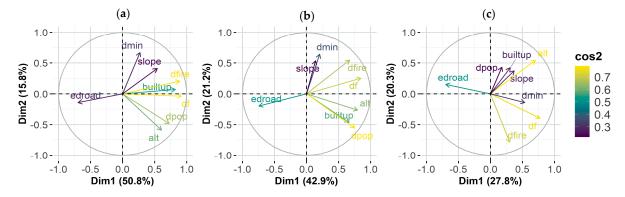


Figure 7. Correlation circles for different sub-zones. (a) Inner zone, (b) edge zone, and (c) outer zone. Legend: edroad: Euclidean distance to roads, cropland: cropland area, builtup: built-up density, dpop: population density, edlim: Euclidean distance to limits, dmin: mining site density, df: TMF loss, dfire: fire density.

The results in Table 1 show the main drivers (predictors) that act differently in the inner, edge, and outer zones. Population density, fire density, and the density of mining sites are the main drivers of forest degradation whether inside, on the edge, or outside the boundaries of the KBNP (p-value < 0.0001). DFD in the edge zone is in turn more influenced by fire density, altitude, and distance from roads (p-value < 0.0001). The expansion of agricultural areas and the density of mining sites also have a significant effect (p-value < 0.05). In the outer zones, the loss of tropical moist forest was strongly influenced by all the drivers analyzed in this study (p-value < 0.0001 for all the drivers analyzed). The different correlation coefficients obtained in the model show a strong correlation between degradation and deforestation and the drivers analyzed in the inner zone (R^2 = 0.87) compared to the other zones, including the edge zone and the outer zone (R^2 of 0.73 and 0.56, respectively), where other drivers not analyzed here may also have a significant impact on the DFD of the tropical moist forest in the KBNP.

Table 1. Multiple linear regression between tropical moist forest loss and the drivers analyzed as a function of the zones making up the landscape of Kahuzi-Biega National Park. Legend: β : Coefficient estimate, t = t value, P = p-value, ED: Euclidean distance.

Predictors		ner Zone (·Value: <2	$(R^2 = 0.87) \times 10^{-16})$		lge Zone (1 ·Value: <2		Outer Zone ($R^2 = 0.56$) (p -Value: $< 2 \times 10^{-16}$)			
	β	t	Pr (> t) (*)	β	t	Pr (> t) (*)	β	t	Pr (> t) (*)	
Built-up density	-	-	-	-1.38	-1.10	0.27	-0.52	-4.07	0.00 ***	
Cropland area	-	-	-	1.98	2.24	0.03 *	-0.56	-3.83	0.00 ***	
ED to roads	0.02	0.27	0.79	-1.10	-3.40	0.00 ***	-1.24	-7.04	0.00 ***	
Altitude	0.30	1.79	0.07.	1.63	5.26	0.00 ***	2.24	14.14	<2 × 10 ⁻¹⁶ ***	
Fire Density	4.87	24.24	<2 × 10 ¹⁶ ***	2.82	8.15	0.00 ***	2.46	18.39	<2 × 10 ⁻¹⁶ ***	
Population density	6.72	4.69	0.00 ***	-	-	-	-	-		
Mining density	-4.90	-3.82	0.00 ***	1.11	2.05	0.04 *	0.56	4.74	0.00 ***	
Slope	-0.10	-0.65	0.52	-0.69	-1.71	0.09.	-	-	-	
ED to park limits	-	-	-	5.25	1.19	0.24	0.80	5.49	0.00 ***	

^(*) The probability values (Pr) obtained do not consider the existence of spatial autocorrelations. Consequently, they should be treated with caution when interpreting trends. The values in bold showed significant difference. Significance Index (p value \leq): «***» 0.001 «**» 0.01 «*» 0.05 «.» 0.1 «» 1.

Land 2025, 14, 49 11 of 22

The assessment of the relative importance of the drivers studied on the variation of tropical moist forest in the KBNP landscape shown in Figure 8a–c indicates that fire is the main driver of deforestation and degradation whether inside, on the fringe, or outside the protected area with a relative importance (RI) of about 55%, 30%, and 23% for the three zones, respectively. In the inner zone, it is followed by population density (\sim 15%), road ED (\sim 9%), and altitude (\sim 7%). The density of mining sites in turn contributes less. In the edge zone, fire density is followed by altitude (\sim 17%), road ED (\sim 15%), and built-up density (\sim 10%). In the outer zone, it is altitude (\sim 12%), road ED (\sim 11%), and mining density (\sim 7%). As one moves away from the protected area, the density of mining sites has an increasing influence on the variation of tropical moist forest in the KBNP landscape.

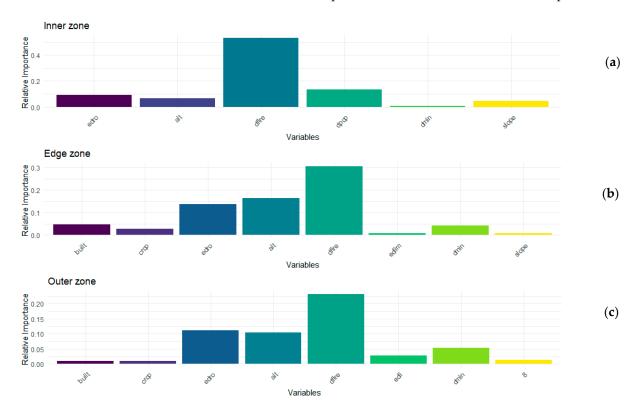


Figure 8. Drivers' relative importance assessment for forest variation with 95% bootstrap confidence intervals with LMG (Lindemann, Merenda, and Gold) method in the Kahuzi-Biega Landscape from 1990 to 2022. (a) Inner zone, (b) edge zone, and (c) outer zone. Legend: built: built-up density, crop: cropland area, edro: Euclidean distance to roads, alt: altitude(elevation), dpop: population density, dfir: fire density, edli: distance to park limits, dmin: mining site density.

4. Discussion

4.1. Data, Methods, and Limits of the Study

Human-induced habitat change profoundly impacts biodiversity, including forest degradation and loss [74]. This study examines tropical moist forest dynamics in the Kahuzi-Biega National Park from 1990 to 2022. The typological methodology used assesses the relative importance of contributing drivers. The IUCN mission in 2017, evaluating the park's UNESCO World Heritage status, noted gaps in forest dynamics and deforestation submissions. This observation prompted further reflection. Indeed, the intact forest block represents the third conservation objective of the park [40], but monitoring has been hindered by persistent cloud cover, especially from 1980 to 2000. Leveraging advancements in remote sensing and machine learning [15,42,64], we sourced global tropical moist forest dynamics data [6]. This dataset distinguishes disturbances over three decades, revealing the extent of undisturbed primary and secondary forests [6]. A 15 km outer zone around KBNP

Land 2025, 14, 49

enhances the assessment of park effectiveness in mitigating disturbances, as highlighted by other studies [20,44,75]. The drivers analyzed include global, regional [11,22,60,61,76], and local-scale literature [30,35,38]. We could not use the global data on the human footprint on biodiversity conservation by Venter et al. [61] due to its low spatial resolution (1 km²), lack of updates, and numerous gaps in the study area. Our analysis includes a broader range of drivers than those considered in Venter et al.'s study, which focused solely on infrastructure, land cover, and human access to natural areas.

The study's primary limitation is the sparse and uneven spatial distribution of available data on the variables analyzed (e.g., population data limited to health zone scales), preventing a comprehensive multi-temporal analysis. To mitigate this challenge, a mesh method for multi-spatial analysis aggregated variables spatially within the landscape [77]. This approach facilitated assessing each variable's contribution and constructing analytical models by statistically comparing values across cells. Adopting a zoning approach, uncommon in such studies, addressed dynamics near boundaries by isolating and treating them separately as an 'edge zone'. This isolation may introduce biases beyond control but likely does not alter overall trends. Variable selection combined PCA with Pearson correlation tests, focusing on variables explaining less than 70% variance [67]. Linear regression models commonly used for spatial phenomena face spatial autocorrelation in residuals, indicating specification errors [78]. Thus, the conclusions relied on relative importance analysis over probability values, employing bootstrap resampling to address these challenges [73].

4.2. TMF Dynamics and the Influence of Deforestation and Degradation Drivers

Given that ecological processes operate across diverse spatial and temporal scales [79], we tested how aggregation scale affects moist forest dynamics in the KBNP landscape. The analysis found no significant differences across scales (p = 0.67, $\alpha = 0.05$), aligning with Ref. [80] on biomass scale independence. Regression coefficients rose from 0.44 to 0.87 from 1 km² to 400 km², reflecting reduced unit variation and increased within-unit variance at larger scales [79]. Yet, this scale increase does not guarantee better modeling, as finer scales better capture local disturbances [68]. Among the 1 km², 9 km², and 25 km² scales tested, 25 km² was optimal ($R^2 = 0.62$), with seven of nine variables being significant. At 25 km², a detailed sub-zone analysis from 1990 to 2022 showed varying TMF reductions across the inner, edge, and outer zones.

Among the three zones analyzed, the inner zone showed less tropical moist forest (TMF) loss from 1990 to 2022. However, fire use, human presence, distance from roads, and altitude influenced its dynamics. Consistent with other studies [11,15,48,49,81–84], forest loss correlated positively with higher fire and population densities and greater accessibility (distance to roads and slope). It is generally perceived that the exploitation of fragmented forests and forest edges is a more straightforward process than that of dense tropical forests [85]. Interestingly, TMF loss in the inner zone contrasts with larger-scale analyses, possibly due to limited, artisanal mining activities in remote park areas, mainly exploiting gold and coltan on non-forested sites like rocks [86]. Historical factors, including park boundary expansions in 1975 without community consultation [35,39], followed by armed conflicts from 1996 to 2004 [14,39], exacerbated cultural conflicts and led to widespread illegal activities like logging, fires, and mining, significantly impacting TMF regression in this once-intact landscape [35-37,40]. By analyzing the dynamics of TMF in the edge zone and the outer zone, it can be observed that the greatest losses occurred during the periods in which wars were reported to have begun and during which there were major civil invasions in and around the KBNP [26,37,39,40]. This confirms the results already found by other authors [14,87], who have reported the significant impacts of population movements on forest conservation, notably the increased need for agricultural land, firewood, and Land 2025, 14, 49 13 of 22

building materials. The impact of altitude noted for both zones can be attributed to the fact that the high-altitude zones of the park are more susceptible to human influence due to their high population density [35,40]. Conversely, the low-lying areas are less dynamic, largely due to their isolation and limited accessibility.

Compared to the inner zone, both the edge zone and outer zones have experienced greater dynamics due to various deforestation and degradation drivers, making them more vulnerable to external pressures. In these zones, TMF loss rates are almost identical, reflecting the vulnerability of areas close to the park boundaries. Although Article 33 of Law No. 14/003 on nature conservation in the DRC [88] stipulates that buffer zones may be created and delimited by a decree for protected areas declared to be of national interest (as in the case of Lomami NP [89]), the situation in the KBNP is different. To date, no buffer zone has been officially established, which increases the vulnerability of peripheral areas. Studies conducted in protected areas [46,75,90] highlight the role of buffer zones in alleviating pressure on inner forests. For example, Ref. [48] observed significantly higher forest losses (up to four times higher) in buffer zones surrounding protected areas in the DRC compared to the inner zones, where losses were well below the national average.

The edge zone of Kahuzi-Biega National Park is particularly affected by fire use, altitude, and distance from roads, as well as built-up density, mining density, and agriculture. These relationships align with findings from previous studies mentioned above. Furthermore, the study conducted by Ref. [91] in the eastern DRC revealed that agriculture and urban expansion contribute significantly (25 times greater) to deforestation than artisanal mining. Interestingly, built-up density shows a negative correlation with TMF loss, indicating that deforestation occurs farther away from urban areas characterized by densification rather than expansion. As population density rises, so does the demand for forest resources, leading communities to penetrate deeper into the forest for survival needs. The study conducted by Ref. [59] in Falgore Game Reserve (Nigeria) revealed that communities are willing to travel up to 10.25 km from their villages to the forest in search of forest products. The edge zone, covering significant highlands of the park, faces intense human pressure exacerbated by local poverty, driving activities such as logging, charcoal production, non-timber forest product collection, slash-and-burn agriculture, and small-scale livestock farming [29,40,86]. Proximity to National Road No. 2 within the park's internal boundaries further amplifies these effects. In the outer zone of Kahuzi-Biega National Park, TMF variation is influenced by analyzed drivers, particularly fire, altitude, distance from roads, mining density, and proximity to the park boundary. These trends echo findings from previous studies [11,92,93], highlighting them as primary drivers of deforestation and degradation in the DRC, albeit at varying rates compared to this study. For instance, small-scale agriculture, driven by population growth and recent conflicts, is a major factor according to Ref. [11]. Comparing the contributions of factors between the outer and edge zones reveals distinct patterns; mining site density plays a more significant role in the outer zone, while built-up areas and agricultural land have a lesser impact. These observations underscore how despite similarities, these regions face differing pressures.

5. Conclusions and Implications for Conservation

The use of novel remote sensing approaches and multi-scale analysis enabled us to analyze the drivers of deforestation and degradation (DFD) influencing tropical moist forest (TMF) dynamics in KBNP. These methods mitigated data scarcity, enhancing our understanding of TMF dynamics in this understudied landscape. The results confirmed that fire significantly affects TMF loss, with varying impacts across zones. Fire's relative importance was highest in the inner zone (55%), followed by the edge (30%) and outer zones

Land 2025, 14, 49 14 of 22

(23%). Population density, altitude, and distance from roads also emerged as significant factors, with their impacts varying by zone.

Overall, KBNP mitigates DFD compared to surrounding areas, which face substantial anthropogenic pressures. Centripetal pressures threaten park integrity, necessitating strategies to promote sustainable land use practices like agroforestry and restoration. Sustainable conflict management and livelihood diversification are crucial, given historical injustices and ongoing land conflicts exacerbated by population growth and poverty. Establishing and recognizing a buffer zone around KBNP could safeguard its resources and surrounding areas.

Future research should focus on characterizing fires and their uses. Identified as a major driver of TMF loss in the landscape, deeply analyzing fire dynamics is critical for understanding TMF loss dynamics. Assessing the ecological implications of TMF loss will guide conservation efforts in KBNP, informing management decisions crucial for this unique forest landscape.

Author Contributions: Conceptualization, N.C.C., J.-F.B. and J.B.; methodology, N.C.C., Y.M. and J.-F.B.; validation, Y.S.U., R.S.L., J.-F.B., K.K. and J.B.; formal analysis, N.C.C. and Y.M.; data curation, N.C.C. and Y.M.; writing—original draft preparation, N.C.C.; writing—review and editing, N.C.C., Y.S.U., R.S.L., J.-F.B., K.K. and J.B.; visualization, N.C.C., Y.S.U., R.S.L., J.-F.B., K.K. and J.B.; supervision, R.S.L. and J.B. All authors have read and agreed to the published version of the manuscript.

Funding: This study received funding from ENABEL (Agence Belge de Développement) in the Democratic Republic of Congo: a PhD grant through PRECOB (Programme de Renforcement des Capacités par l'Octroi des Bourse) program. The PhD funder played no role in the study design, data collection and analysis, preparation of the manuscript, or decision to publish.

Data Availability Statement: The data used for this study is available from the corresponding author on reasonable request.

Acknowledgments: The authors thank all the stakeholders who graciously participated in this study.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Appendix A.1

A1. Description, source, and pre-processing steps applied to data used for explaining variation of TMF loss in the KBNP landscape from 1990 to 2022.

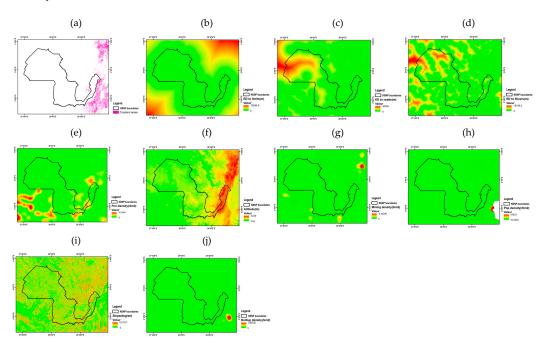
Id	Data	Description	Source	Pre-Processing
1	Collection of annual changes in land use (1990–2022)	 Landsat images classified into seven classes (undisturbed TMF, degraded TMF, TMF regrowth, deforested land, ongoing deforestation and degradation, water, other landcover including afforestation) Spatial resolution (29.90 m) Acquisition: Google Earth Engine on 17 October 2023 Asset ID: projects/JRC/TMF/v1_2022/AnnualChar 	Forest Observations (europa.eu) [6]	 Reclassification (two classes: TMF and other classes) Calculation of the annual proportion of forest for each grid Calculation of the change in the TMF (Δf) from the reference year (1990) to the final year (2022) at all scales
2	Landsat image (2021)	Landsat 8 OLI/TIRS surface reflectance: USGS Landsat 8 Level 2, Collection 2, Tier 1, cloud cover < 1%	Google Earth Engine (GEE): https: //code.earthengine. google.com/	Supervised classification via GEE using the Random Forest algorithm (two classes: TMF and other classes) [64]
3	Built-up areas	Buildings provided by Open Street Map	Geofabrik Download Server	Calculation of the density of buildings/km ² for each grid at different scales

Land **2025**, 14, 49 15 of 22

Id	Data	Description	Source	Pre-Processing		
4	Roads	Road and waterway data provided by Open Street Map	Geofabrik Download Server	Calculation of the average Euclidean distance to roads in km for each grid at different scales		
5	Rivers	Watercourse data provided by Open Street Map	Geofabrik Download Server	Calculation of the average Euclidean distance to rivers in km for each grid at different scales		
6	Altitude and Slope	Digital terrain model with 30 m resolution	OpenTopography— Shuttle Radar Topography Mission (SRTM GL1)	Calculation of the average altitude (m) of each grid at different scales		
7	Population data	Population at health zone level	Humanitarian Data Exchange (humdata.org)	Calculation of population density/km ² for each grid at different scales		
8	Agricultural areas	Land cover map for 2021 at 10 m resolution based on Sentinel-1 and Sentinel-2 data	https://esa- worldcover.org/en [94]	Determination of the agricultural area (km²) in each grid at different scales		
9	Lights	Active fires and hot spots derived from the MODIS collection 6.1	https://firms.modaps. eosdis.nasa.gov/	Calculation of the average density of fires/km ² for each grid at different scales		
10	Mining areas	Small-scale artisanal mining sites	IPIS—Opendata (shinyapps.io)	Calculation of the average density of mining sites/km ² for each grid at different scales		
11	Distance from park boundaries	Euclidean distance of the boundaries of the KBNP in the study landscape	Analyses in Arc Map 10.8.1	Determination of the Euclidean distance of the park boundaries in km		

Appendix A.2

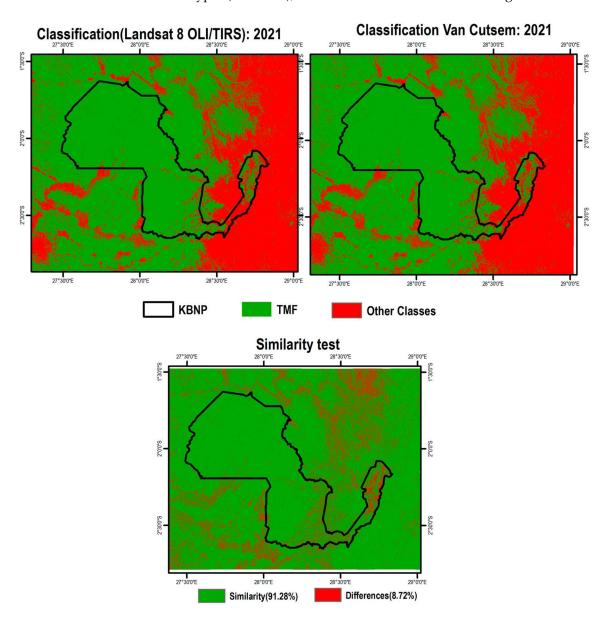
A2: Drivers considered for explaining tropical moist forest loss in Kahuzi-Biega National Park, eastern Democratic Republic of Congo from 1990 to 2022 (see also attached figures).(a): cropland areas,(b): ED to limits,(c): Ed to roads,(d): ED to rivers,(e): fire density,(f)altitude,(g)mining density,(h): population density,(i): slope and (j): built up density.



Land 2025, 14, 49 16 of 22

Appendix A.3

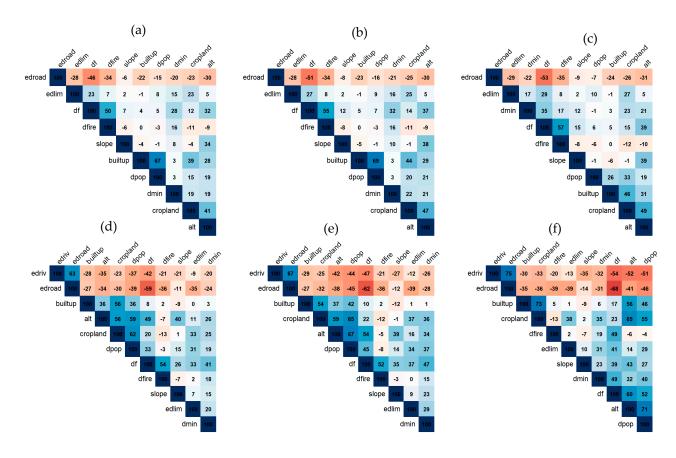
A3: Test of the adaptability of images used to analyze tropical moist forest (TMF) dynamic: Comparison of [6] classification from Landsat image and our own classification using Landsat image (2021), collected training points from Google Earth and supervised classification using a Random Forest algorithm in the landscape of Kahuzi-Biega National Park. The classification considers two classes, including the undisturbed TMF and the other landcover types (Other LC), which include deforestation and degradation.



Appendix A.4

A4: Plots of correlations at different grid sizes ($(1 \text{ km}^2 \text{ (a)}, 9 \text{ km}^2 \text{ (b)}, 25 \text{ km}^2 \text{ (c)}, 100 \text{ km}^2 \text{ (d)}, 225 \text{ km}^2 \text{ (e)}, and <math>400 \text{ km}^2 \text{ (f)}$) tested for analysis of variation in tropical moist forest in the Kahuzi-Biega National Park landscape from 1990 to 2022. The blue color indicates a positive correlation and the red color indicates a negative correlation. Dark colours indicate a strong correlation and light colours a weak correlation.

Land 2025, 14, 49 17 of 22



Appendix A.5

A5: Multiple linear regression between the loss of tropical rainforest and the drivers analyzed at scales of $400~\rm km^2$, $225~\rm km^2$, and $100~\rm km^2$ in the Kahuzi-Biega National Park landscape.

Predictors		(F	Size: 400 km^2 $R^2 = 0.87$) e: $< 2 \times 10^{-16}$)		Grid Size: 225 km^2 ($R^2 = 0.76$) (p -Value: $<2 \times 10^{-16}$)					Grid Size: 100 km^2 $(R^2 = 0.70)$ $(p\text{-Value: } < 2 \times 10^{-16})$			
	β	t	Pr (> t) (*)		β	t	Pr (> t) (*)		β	t	Pr (> t) (*)		
Built-up density	-26.33	-4.02	0.00	***	-9.38	-3.03	0.00	**	-2.07	-1.96	0.05		
Cropland area	-13.74	-3.31	0.00	**	-7.27	-2.94	0.00	**	-4.07	-4.92	1.60×10^{-6}	***	
Distance to roads	43.04	7.46	8.20×10^{-10}	***	16.04	5.28	7.70×10^{-7}	***	8.51	8.72	4.50×10^{-16}	***	
Distance to rivers	21.99	5.94	2.30×10^{-7}	***	15.91	7.38	5.10×10^{-11}	***	8.46	11.5	<2 × 10 ⁻¹⁶	***	
Altitude	-1.37	-0.24	0.81		-1.04	-0.43	0.67		-1.59	-1.9	0.06		
Fire density	0.49	0.1	0.92		5.08	1.73	0.09		-0.14	-0.15	0.88		
Population Density	19.51	4.88	1.00×10^{-5}	***	8.12	3.57	0.00	***	3.74	4.91	1.60×10^{-6}	***	
Ext. distance to limits	10.60	2.79	0.01	**	5.9	2.67	0.01	**	2.55	3.59	0.00	***	
Mining site density	0.93	0.24	0.81		3.42	1.54	0.13		0.84	1.13	0.26		

^(*) The probability values (Pr) obtained do not consider the existence of spatial autocorrelations. Consequently, they should be treated with caution when interpreting trends. Significance Index (p value \leq): «***» 0.001 «**» 0.01 «*» 0.05 «.» 0.1 « » 1.

Land 2025, 14, 49 18 of 22

Appendix A.6

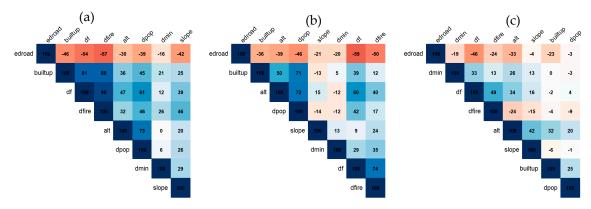
A6: Multiple linear regression between the loss of tropical rainforest and the drivers analyzed at scales of 25 km², 9 km², and 1 km² in the Kahuzi-Biega National Park landscape.

Predictors		(F	Size: 25 km^2 $R^2 = 0.62$) e: $<2 \times 10^{-16}$)			(F	Size: 9 km^2 $8^2 = 0.57$) e: $<2 \times 10^{-16}$)	Grid Size: 1 km^2 ($R^2 = 0.44$) ($p\text{-Value}$: $<2 \times 10^{-16}$)				
	β	t	Pr (> t) (*)		β	t	Pr (> t) (*)		β	t	Pr (> t) (*)	
Built-up density	-0.45	-3.31	0.00	***	-0.45	-3.31	0.00	***	-0.01	-4.2	2.70×10^{-5}	***
Cropland area	-1.03	-8.85	<2 × 10 ⁻¹⁶	***	-1.03	-8.85	<2 × 10 ⁻¹⁶	***	-0.04	-32.64	$<2 \times 10^{-16}$	***
Distance to roads	2.06	15.83	<2 × 10 ⁻¹⁶	***	2.06	15.83	<2 × 10 ⁻¹⁶	***	0.08	56.06	$<2 \times 10^{-16}$	***
Distance to rivers	2.53	23.33	<2 × 10 ⁻¹⁶	***	2.53	23.33	<2 × 10 ⁻¹⁶	***	0.10	87.76	$<2 \times 10^{-16}$	***
Altitude	-0.48	-4.24	2.40×10^{-5}	***	-0.48	-4.24	2.40×10^{-5}	***	-0.03	-16.87	$<2 \times 10^{-16}$	***
Fire density	0.23	2.22	0.02647	*	0.23	2.22	0.03	*	0.01	6.57	5.20×10^{-11}	***
Population Density	0.87	8.12	1.30×10^{-15}	***	0.87	8.12	1.30×10^{-15}	***	0.03	23.18	$<2 \times 10^{-16}$	***
Exterior distance to limits	0.65	6.31	4.20×10^{-10}	***	0.65	6.31	4.20×10^{-10}	***	0.03	22.82	<2 × 10 ⁻¹⁶	***
Mining site density	-0.03	-0.31	0.76		-0.03	-0.31	0.76		-0.01	-8.21	2.30×10^{-16}	***

^(*) The probability values (Pr) obtained do not consider the existence of spatial autocorrelations. Consequently, they should be treated with caution when interpreting trends. Significance Index (p value \leq): «***» 0.001 «**» 0.01 «*» 0.05 «.» 0.1 « » 1.

Appendix A.7

A7: Plots of correlations between different variables at the scale of zones (inner (a), edge (b), and outer (c)) within the KBNP landscape from 1990 to 2022. The blue color indicates a positive correlation and the red color indicates a negative correlation. Dark colours indicate a strong correlation and light colours a weak correlation.



References

- Karsenty, A. Géopolitique Des Forêts d'Afrique Centrale. Herodote 2020, 179, 108-129. [CrossRef]
- Tchatchou, B.; Sonwa, D.J.; Tiani, A.M. Deforestation and Forest Degradation in the Congo Basin State of Knowledge, Current Causes and Perspectives; Center for International Forestry Research (CIFOR): Bogor, Indonesia, 2015.
- Mayaux, P.; Pekel, J.F.; Desclée, B.; Donnay, F.; Lupi, A.; Achard, F.; Clerici, M.; Bodart, C.; Brink, A.; Nasi, R.; et al. State and 3. Evolution of the African Rainforests between 1990 and 2010. Philos. Trans. R. Soc. B Biol. Sci. 2013, 368, 20120300. [CrossRef]
- Grantham, H.S.; Shapiro, A.; Bonfils, D.; Gond, V.; Goldman, E.; Maisels, F.; Plumptre, A.J.; Rayden, T.; Robinson, J.G.; Strindberg, S.; et al. Spatial Priorities for Conserving the Most Intact Biodiverse Forests within Central Africa. Environ. Res. Lett. 2020, 15, 0940b5. [CrossRef]

Land 2025, 14, 49 19 of 22

5. Eba'a Atyi, R.; Bayol, N. Les Forêts de La République Démocratique Du Congo En 2008. *Les Forêts Du Bassin Du Congo Etat Des Forêts* **2008**, 2009, 115–128.

- 6. Vancutsem, C.; Achard, F.; Pekel, J.-F.; Vieilledent, G.; Carboni, S.; Simonetti, D.; Gallego, J.; Aragão, L.E.O.C.; Nasi, R. Long-Term (1990–2019) Monitoring of Forest Cover Changes in the Humid Tropics. *Sci. Adv.* **2021**, *7*, eabe1603. [CrossRef]
- 7. Hill, S.L.L.; Arnell, A.; Maney, C.; Butchart, S.H.M.; Hilton-Taylor, C.; Ciciarelli, C.; Davis, C.; Dinerstein, E.; Purvis, A.; Burgess, N.D. Measuring Forest Biodiversity Status and Changes Globally. *Front. For. Glob. Chang.* **2019**, *2*, 70. [CrossRef]
- 8. Maxwell, S.L.; Evans, T.; Watson, J.E.M.; Morel, A.; Grantham, H.; Duncan, A.; Harris, N.; Potapov, P.; Runting, R.K.; Venter, O.; et al. Degradation and Forgone Removals Increase the Carbon Impact of Intact Forest Loss by 626%. *Sci. Adv.* **2019**, *5*, eaax2546. [CrossRef]
- 9. Eba'a Atyi, R.; Hiol Hiol, F.; Lescuyer, G.; Mayaux, P.; Defourny, P.; Bayol, N.; Saracco, F.; Pokem, D.; Sufo Kankeu, R.; Nasi, R. *Les Forêts Du Bassin Du Congo: État Des Forêts* 2021; Center for International Forestry Research (CIFOR): Bogor, Indonesia, 2022.
- Shapiro, A.; d'Annunzio, R.; Desclée, B.; Jungers, Q.; Kondjo, H.K.; Iyanga, J.M.; Gangyo, F.I.; Nana, T.; Obame, C.V.; Milandou, C.; et al. Small Scale Agriculture Continues to Drive Deforestation and Degradation in Fragmented Forests in the Congo Basin (2015–2020). Land Use Policy 2023, 134, 106922. [CrossRef]
- 11. Tyukavina, A.; Hansen, M.C.; Potapov, P.; Parker, D.; Okpa, C.; Stehman, S.V.; Kommareddy, I.; Turubanova, S. Congo Basin Forest Loss Dominated by Increasing Smallholder Clearing. *Sci. Adv.* **2018**, *4*, aat2993. [CrossRef]
- 12. Ickowitz, A.; Slayback, D.; Asanzi, P.; Nasi, R. *Agriculture and Deforestation in the Democratic Republic of the Congo: A Synthesis of the Current State of Knowledge*; Center for International Forestry Research (CIFOR): Bogor, Indonesia, 2015.
- 13. Turubanova, S.; Potapov, P.V.; Tyukavina, A.; Hansen, M.C. Ongoing Primary Forest Loss in Brazil, Democratic Republic of the Congo, and Indonesia. *Environ. Res. Lett.* **2018**, *13*, 074028. [CrossRef]
- 14. Butsic, V.; Baumann, M.; Shortland, A.; Walker, S.; Kuemmerle, T. Conservation and Conflict in the Democratic Republic of Congo: The Impacts of Warfare, Mining, and Protected Areas on Deforestation. *Biol. Conserv.* **2015**, *191*, 266–273. [CrossRef]
- 15. Nackoney, J.; Molinario, G.; Potapov, P.; Turubanova, S.; Hansen, M.C.; Furuichi, T. Impacts of Civil Conflict on Primary Forest Habitat in Northern Democratic Republic of the Congo, 1990–2010. *Biol. Conserv.* **2014**, *170*, 321–328. [CrossRef]
- 16. WWF-PARAP. Le Réseau Des Aires Protégées de La République Démocratique Du Congo. Available online: https://www.wwf.de/fileadmin/fm-wwf/Publikationen-PDF/Afrika/WWF-Parap-Poster-French.pdf (accessed on 6 December 2023).
- 17. UNDP. Aichi Biodiversity Target 11 Country Dossier: Congo (Democratic Republic Of); UNDP: New York, NY, USA, 2021.
- 18. Bruner, A.G.; Gullison, R.E.; Rice, R.E.; da Fonseca, G.A.B. Effectiveness of Parks in Protecting Tropical Biodiversity. *Science* **2001**, 291, 125–128. [CrossRef]
- 19. Gibson, L.; Lee, T.M.; Koh, L.P.; Brook, B.W.; Gardner, T.A.; Barlow, J.; Peres, C.A.; Bradshaw, C.J.A.; Laurance, W.F.; Lovejoy, T.E.; et al. Primary Forests Are Irreplaceable for Sustaining Tropical Biodiversity. *Nature* **2011**, *478*, 378–381. [CrossRef]
- Damnyag, L.; Saastamoinen, O.; Blay, D.; Dwomoh, F.K.; Anglaaere, L.C.N.; Pappinen, A. Sustaining Protected Areas: Identifying and Controlling Deforestation and Forest Degradation Drivers in the Ankasa Conservation Area, Ghana. *Biol. Conserv.* 2013, 165, 86–94. [CrossRef]
- 21. UNEP-WCMC; IUCN; NGS. Protected Planet Report 2018: Tracking Progress towards Global Targets for Protected Areas; UNEP-WCMC: Cambridge, UK; IUCN: Gland, Switezerland; NGS: Wahsington, DC, USA, 2018; ISBN 9789280737219.
- 22. Jones, K.R.; Venter, O.; Fuller, R.A.; Allan, J.R.; Maxwell, S.L.; Negret, P.J.; Watson, J.E.M. One-Third of Global Protected Land Is under Intense Human Pressure. *Science* 2018, 360, 788–791. [CrossRef]
- 23. Watson, J.E.M.; Iwamura, T.; Butt, N. Mapping Vulnerability and Conservation Adaptation Strategies under Climate Change. *Nat. Clim. Chang.* **2013**, *3*, 989–994. [CrossRef]
- 24. Ngabinzeke, J.S.; Linchant, J.; Quevauvillers, S.; Muhongya, J.K.; Lejeune, P. La Détection Des Activités Humaines Illégales Dans Les Aires Protégées En République Démocratique Du Congo. *NRC Res. Pract.* **2016**, *159*, 151–159.
- 25. UNEP. Human Development Index (HDI); UNEP: Nairobi, Kenya, 2022.
- 26. UICN. Rapport de La Mission Conjointe de Suivi Réactif Centre Du Patrimoine Mondial/UICN Au Parc National de Kahuzi-Biega; UICN: Gland, Switzerland, 2017.
- 27. Misser, F. Les Aires Protégées En République Démocratique Du Congo: Menaces et Défis. In *L'action de l'Union Européenne*; European Union: Brussels, Belgium, 2013.
- 28. Plumptre, A.J.; Behangana, M.; Davenport, T.; Kahindo, C.; Kityo, E.; Ndomba, E.; Nkuutu, D.; Owiunji, I.; Ssegawa, P.; Eilu, G. *Albertine Rift Biodiversity*; WCS: New York, NY, USA, 2003.
- 29. Spira, C.; Mitamba, G.; Kirkby, A.; Katembo, J.; Kiyani Kambale, C.; Musikami, P.; Dumbo, P.; Byaombe, D.; Plumptre, A.J.; Maisels, F. *Inventaire de La Biodiversité Dans Le Parc National de Kahuzi-Biega, République Démocratique Du Congo*; WCS: New York, NY, USA, 2018.
- 30. Plumptre, A.J.; Nixon, S.; Kujirakwinja, D.K.; Vieilledent, G.; Critchlow, R.; Williamson, E.A.; Nishuli, R.; Kirkby, A.E.; Hall, J.S. Catastrophic Decline of World's Largest Primate: 80% Loss of Grauer's Gorilla (Gorilla Beringei Graueri) Population Justifies Critically Endangered Status. *PLoS ONE* **2016**, *11*, e0162697. [CrossRef]

Land 2025, 14, 49 20 of 22

- 31. UNEP. Africa Mountains Atlas; UNEP: Nairobi, Kenya, 2014.
- 32. Potapov, P.; Hansen, M.C.; Laestadius, L.; Turubanova, S.; Yaroshenko, A.; Thies, C.; Smith, W.; Zhuravleva, I.; Komarova, A.; Minnemeyer, S.; et al. The Last Frontiers of Wilderness: Tracking Loss of Intact Forest Landscapes from 2000 to 2013. *Sci. Adv.* **2017**, *3*, e1600821. [CrossRef]
- 33. Plumptre, A.J.; Davenport, T.R.B.; Behangana, M.; Kityo, R.; Eilu, G.; Ssegawa, P.; Ewango, C.; Meirte, D.; Kahindo, C.; Herremans, M.; et al. The Biodiversity of the Albertine Rift. *Biol. Conserv.* **2007**, *134*, 178–194. [CrossRef]
- 34. UICN/PACO. Parcs et Réserves de La République Démocratique Du Congo: Evaluation de l'Efficacité de La Gestion Des Aires Protégées Programme Aires Protégées d'Afrique Du Centre et de l'Ouest (PAPACO); UICN/PACO: Ouagadougou, Burkina Faso, 2010.
- 35. Spira, C.; Kirkby, A.; Kujirakwinja, D.; Plumptre, A.J. The Socio-Economics of Artisanal Mining and Bushmeat Hunting around Protected Areas: Kahuzi-Biega National Park and Itombwe Nature Reserve, Eastern Democratic Republic of Congo. *Oryx* **2019**, 53, 136–144. [CrossRef]
- 36. Contino, F. Rapport Sur L'observation de La Zone Tampon Du PNKB; Graduate Institute: Geneva, Switzerland, 1996.
- 37. Mudinga, M.E.; Ngendakumana, S.; Ansoms, A. Analyse Critique Du Processus de Cogestion Du Parc National de Kahuzi-Biega En République Démocratique Du Congo. *La Rev. Électronique En Sci. De L'Environ.* **2013**, *17*. [CrossRef]
- 38. Iyomi, B. Parc National de Kahuzi Biega (PNKB), Fact Sheet PNKB No1, mars 2005, SYGIAP ICCN 2005. p. 2.
- 39. Busane, R.M.; Kaganda, M.; Sheria, N.; Mushagalusa, J.-P.; Mugoli, M.N.; Maramuke, B.J.; Wakandwa, C.M. *Analyses Des Dynamiques Des Conflits Autour Du PNKB*; 2021. Available online: https://pdf.usaid.gov/pdf_docs/PA00XK66.pdf (accessed on 6 December 2023).
- 40. ICCN-PNKB. Plan Général de Gestion 2009–2019: Parc National de Kahuzi-Biega; ICCN-PNKB: Bukavu, Congo, 2010.
- 41. Dupuis, C.; Lejeune, P.; Michez, A.; Fayolle, A. How Can Remote Sensing Help Monitor Tropical Moist Forest Degradation?—A Systematic Review. *Remote Sens.* **2020**, *12*, 1087. [CrossRef]
- 42. Bullock, E.L.; Woodcock, C.E.; Olofsson, P. Monitoring Tropical Forest Degradation Using Spectral Unmixing and Landsat Time Series Analysis. *Remote Sens. Environ.* **2020**, 238, 110968. [CrossRef]
- 43. Zhuravleva, I.; Turubanova, S.; Potapov, P.; Hansen, M.; Tyukavina, A.; Minnemeyer, S.; Laporte, N.; Goetz, S.; Verbelen, F.; Thies, C. Satellite-Based Primary Forest Degradation Assessment in the Democratic Republic of the Congo, 2000–2010. *Environ. Res. Lett.* **2013**, *8*, 024034. [CrossRef]
- 44. Allan, J.R.; Venter, O.; Maxwell, S.; Bertzky, B.; Jones, K.; Shi, Y.; Watson, J.E.M. Recent Increases in Human Pressure and Forest Loss Threaten Many Natural World Heritage Sites. *Biol. Conserv.* **2017**, *206*, 47–55. [CrossRef]
- 45. Heino, M.; Kummu, M.; Makkonen, M.; Mulligan, M.; Verburg, P.H.; Jalava, M.; Räsänen, T.A. Forest Loss in Protected Areas and Intact Forest Landscapes: A Global Analysis. *PLoS ONE* **2015**, *10*, e0138918. [CrossRef]
- 46. Laurance, W.F.; Carolina Useche, D.; Rendeiro, J.; Kalka, M.; Bradshaw, C.J.A.; Sloan, S.P.; Laurance, S.G.; Campbell, M.; Abernethy, K.; Alvarez, P.; et al. Averting Biodiversity Collapse in Tropical Forest Protected Areas. *Nature* **2012**, *489*, 290–294. [CrossRef]
- 47. Dudley, N. Lignes Directrices Pour l'Application Des Catégories de Gestion Aux Aires Protégées; IUCN: Gland, Switezerland, 2008.
- 48. Potapov, P.V.; Turubanova, S.A.; Hansen, M.C.; Adusei, B.; Broich, M.; Altstatt, A.; Mane, L.; Justice, C.O. Quantifying Forest Cover Loss in Democratic Republic of the Congo, 2000–2010, with Landsat ETM+ Data. *Remote Sens. Environ.* 2012, 122, 106–116. [CrossRef]
- 49. Tyukavina, A.; Potapov, P.; Hansen, M.C.; Pickens, A.H.; Stehman, S.V.; Turubanova, S.; Parker, D.; Zalles, V.; Lima, A.; Kommareddy, I.; et al. Global Trends of Forest Loss Due to Fire From 2001 to 2019. Front. Remote Sens. 2022, 3, 825190. [CrossRef]
- 50. WWF. Les Fronts de Déforestation: Moteurs et Réponses Dans Un Monde En Mutation; WWF: Gland, Switezerland, 2020.
- 51. Eva, H.; Lambin, E.F. Fires and Land-Cover Change in the Tropics: A Remote Sensing Analysis at the Landscape Scale. *J. Biogeogr.* **2000**, 27, 765–776. [CrossRef]
- 52. Meyfroidt, P. Approaches and Terminology for Causal Analysis in Land Systems Science. *J. Land Use Sci.* **2016**, 11, 501–522. [CrossRef]
- 53. Geist, H.J.; Lambin, F.E. Proximate Causes and Underlying Driving Forces of Tropical Deforestation. *Bioscience* **2002**, *52*, 143–150. [CrossRef]
- 54. Shapiro, A.C.; Grantham, H.S.; Aguilar-Amuchastegui, N.; Murray, N.J.; Gond, V.; Bonfils, D.; Rickenbach, O. Forest Condition in the Congo Basin for the Assessment of Ecosystem Conservation Status. *Ecol. Indic.* **2021**, 122. [CrossRef]
- 55. Hall, L.S.; Krausman, P.R.; Morrison, M.L. Plea for Standard Terminology: The Habitat Concept and a Plea for Standard Terminology Key Words Peer Refereed. *Wildl. Soc. Bull.* **1997**, 325.
- 56. Aveling, C. Le Patrimoine Mondial Dans Le Bassin Du Congo; UNESCO: Paris, France, 2010.
- 57. Masumbuko, N. Ecologie de Sericostachys Scandens, Liane Envahissante Dans Les Forêts de Montagne Du Parc National De Kahuzi-Biega, République Démocratique Du Congo. Ph.D. Thesis, Université Libre de Bruxelles, Bruxelles, Belgium, 2010.

Land 2025, 14, 49 21 of 22

58. Cizungu, N.C.; Tshibasu, E.; Lutete, E.; Mushagalusa, C.A.; Mugumaarhahama, Y.; Ganza, D.; Karume, K.; Michel, B.; Lumbuenamo, R.; Bogaert, J. Fire Risk Assessment, Spatiotemporal Clustering and Hotspot Analysis in the Luki Biosphere Reserve Region, Western DR Congo. *Trees For. People* **2021**, *5*, 100104. [CrossRef]

- 59. Suleiman, M.S.; Wasonga, V.O.; Mbau, J.S.; Suleiman, A.; Elhadi, Y.A. Non-Timber Forest Products and Their Contribution to Households Income around Falgore Game Reserve in Kano, Nigeria. *Ecol Process* **2017**, *6*, 23. [CrossRef]
- 60. Curtis, P.G.; Slay, C.M.; Harris, N.L.; Tyukavina, A.; Hansen, M.C. Classifying Drivers of Global Forest Loss. *Science* **2018**, *361*, 1108–1111. [CrossRef]
- 61. Venter, O.; Sanderson, E.W.; Magrach, A.; Allan, J.R.; Beher, J.; Jones, K.R.; Possingham, H.P.; Laurance, W.F.; Wood, P.; Fekete, B.M.; et al. Sixteen Years of Change in the Global Terrestrial Human Footprint and Implications for Biodiversity Conservation. *Nat. Commun.* **2016**, *7*, 12558. [CrossRef]
- 62. Hart, J.A.; Hall, J.S. Status of Eastern Zaire's Forest Parks and Reserves. Conserv. Biol. 1996, 10, 316–327. [CrossRef]
- 63. Scholte, P. International Conference on the Impact of Sericostachys Scandens on the Conservation of Nyungwe National Park, Rwanda. *Rw. Env. Man. Authority* **2008**.
- 64. Zurqani, H.A.; Post, C.J.; Mikhailova, E.A.; Schlautman, M.A.; Sharp, J.L. Geospatial Analysis of Land Use Change in the Savannah River Basin Using Google Earth Engine. *Int. J. Appl. Earth Obs. Geoinf.* **2018**, *69*, 175–185. [CrossRef]
- 65. Jaffé, R.; Nunes, S.; Dos Santos, J.F.; Gastauer, M.; Giannini, T.C.; Nascimento, W.; Sales, M.; Souza, C.M.; Souza-Filho, P.W.; Fletcher, R.J. Forecasting Deforestation in the Brazilian Amazon to Prioritize Conservation Efforts. *Environ. Res. Lett.* **2021**, *16*, 084034. [CrossRef]
- 66. Wei, T.; Simko, V.; Levy, M.; Xie, Y.; Jin, Y.; Zemla, J.; Freidank, M.; Cai, J.; Protivinsky, T. Package "Corrplot": Visualization of a Correlation Matrix. 2022. Available online: https://cran.r-project.org/web/packages/corrplot/corrplot.pdf (accessed on 17 July 2024).
- 67. Kenett, R.S.; Longford, N.T.; Piegorsch, W.W.; Ruggeri, F. Wiley StatsRef: Statistics Reference Online, 1st ed.; Balakrishnan, N., Colton, T., Everitt, B., Piegorsch, W., Ruggeri, F., Teugels, J.L., Eds.; Major Reference Works; Wiley: Hoboken, NJ, USA, 2014; ISBN 9781118445112.
- 68. Delcourt, H.R.; Delcourt, P.A. *Quaternary Landscape Ecology: Relevant Scales in Space and Time*; SPB Academic Publishing: Amsterdam, The Netherlands, 1988; Volume 2.
- 69. Benítez-López, A.; Viñuela, J.; Mougeot, F.; García, J.T. A Multi-Scale Approach for Identifying Conservation Needs of Two Threatened Sympatric Steppe Birds. *Biodivers. Conserv.* **2017**, *26*, 63–83. [CrossRef]
- 70. Khaliq, Y.; Dwyer, G.P., Jr. Tests of Normality for Time Series Data. Econ. Lett. 2005, 89, 83–88. [CrossRef]
- 71. Farebrother, R.W. The Durbin-Watson Test for Serial Correlation When There Is No Intercept in the Regression. *Econometrica* **1980**, 48, 1553–1563. [CrossRef]
- Wickham, H. Ggplot2: Elegant Graphics for Data Analysis; Springer International Publishing: Cham, Switzerland, 2016; ISBN 978-3-319-24275-0.
- 73. Groemping, U. Relative Importance for Linear Regression in R: The Package Relaimpo. J. Stat. Softw. 2006, 17, 1–27. [CrossRef]
- 74. Mestre, F.; Silva, B. Lconnect R Package: A Versatile Tool for Evaluating Landscape Connectivity and Prioritizing Habitat Patches in Conservation Research. *Ecol. Model.* **2023**, 484, 110489. [CrossRef]
- 75. Campbell, A.; Clark, S.; Coad, L.; Miles, L.; Bolt, K.; Roe, D. Protecting the Future: Carbon, Forests, Protected Areas and Local Livelihoods. *Biodiversity* **2008**, *9*, 117–121. [CrossRef]
- 76. Ouattara, B.; Sanou, L.; Koala, J.; Hien, M. Perceptions Locales de La Dégradation Des Ressources Naturelles Du Corridor Forestier de La Boucle Du Mouhoun Au Burkina Faso. *Bois For. Des Trop.* **2022**, 352, 43–60. [CrossRef]
- 77. Bagan, H.; Yamagata, Y. Land-Cover Change Analysis in 50 Global Cities by Using a Combination of Landsat Data and Analysis of Grid Cells. *Environ. Res. Lett.* **2014**, *9*, 064015. [CrossRef]
- 78. Thayn, J.B.; Simanis, J.M. Accounting for Spatial Autocorrelation in Linear Regression Models Using Spatial Filtering with Eigenvectors. *Ann. Assoc. Am. Geogr.* **2013**, *103*, 47–66. [CrossRef]
- 79. Fürst, C.; Avirmed, B.; Clerici, N.; Khoroshev, A.; Kofi Nyarko, B.; Prishchepov, A.; Scheller, R.M.; Silbernagel Balster, J.; Watanabe, T. *Principles and Methods in Landscape Ecology*; Springer Nature: Cham, Switzerland, 2022; Volume 3.
- 80. Qi, Y.; Wu, J. Effects of Changing Spatial Resolution on the Results of Landscape Pattern Analysis Using Spatial Autocorrelation Indices; SPB Academic Publishing: Amsterdam, The Netherlands, 1996.
- 81. Molinario, G.; Hansen, M.; Potapov, P.; Tyukavina, A.; Stehman, S. Contextualizing Landscape-Scale Forest Cover Loss in the Democratic Republic of Congo (DRC) between 2000 and 2015. *Land* 2020, *9*, 23. [CrossRef]
- 82. Cirezi, N.C.; Bastin, J.F.; Tshibasu, E.; Lonpi, E.T.; Chuma, G.B.; Mugumaarhahama, Y.; Sambieni, K.R.; Karume, K.C.; Lumbuenamo, R.S.; Bogaert, J. Contribution of 'Human Induced Fires' to Forest and Savanna Land Conversion Dynamics in the Luki Biosphere Reserve Landscape, Western Democratic Republic of Congo. *Int. J. Remote Sens.* 2022, 43, 6406–6429. [CrossRef]
- 83. van Wees, D.; van der Werf, G.R.; Randerson, J.T.; Andela, N.; Chen, Y.; Morton, D.C. The Role of Fire in Global Forest Loss Dynamics. *Glob. Chang. Biol.* **2021**, 27, 2377–2391. [CrossRef]

Land 2025, 14, 49 22 of 22

84. Harris, N.L.; Goldman, E.; Gabris, C.; Nordling, J.; Minnemeyer, S.; Ansari, S.; Lippmann, M.; Bennett, L.; Raad, M.; Hansen, M.; et al. Using Spatial Statistics to Identify Emerging Hot Spots of Forest Loss. *Environ. Res. Lett.* **2017**, *12*, 024012. [CrossRef]

- 85. Alignier, A.; Deconchat, M. Patterns of Forest Vegetation Responses to Edge Effect as Revealed by a Continuous Approach. *Ann. For. Sci.* **2013**, *70*, 601–609. [CrossRef]
- 86. Kabonyi, C.; Salmon, M.; Roche, E. Le Parc National de Kahuzi-Biega (R. D. Congo), Patrimoine En Péril? Le Secteur «Haute Altitude», Situation et Perspectives. *Geo-Eco-Trop* **2011**, *35*, 1–8.
- 87. Arakwiye, B.; Rogan, J.; Eastman, J.R. Thirty Years of Forest-Cover Change in Western Rwanda during Periods of Wars and Environmental Policy Shifts. *Reg. Environ. Chang.* **2021**, 21, 27. [CrossRef]
- 88. Democratic Republic of the Congo. Loi N° 14/003 DU 11 Février 2014 Relative à La Conservation de La Nature. Available online: https://www.leganet.cd/Legislation/Droit%20administratif/Environnement/Loi14003.11.02.2014.htm (accessed on 17 December 2024).
- 89. Batumike, R.; Imani, G.; Bisimwa, B.; Mambo, H.; Kalume, J.; Kavuba, F.; Cuni-Sanchez, A. Lomami Buffer Zone (DRC): Forest Composition, Structure, and the Sustainability of Its Use by Local Communities. *Biotropica* **2022**, *54*, 289–300. [CrossRef]
- 90. Jusys, T. Quantifying Avoided Deforestation in Pará: Protected Areas, Buffer Zones and Edge Effects. *J. Nat. Conserv.* **2016**, *33*, 10–17. [CrossRef]
- 91. Ladewig, M.; Angelsen, A.; Masolele, R.N.; Chervier, C. Deforestation Triggered by Artisanal Mining in Eastern Democratic Republic of the Congo. *Nat. Sustain.* **2024**, *7*, 1452–1460. [CrossRef]
- 92. Harris, I.; Osborn, T.J.; Jones, P.; Lister, D. Version 4 of the CRU TS Monthly High-Resolution Gridded Multivariate Climate Dataset. *Sci. Data* **2020**, *7*, 109. [CrossRef]
- 93. Molinario, G.; Hansen, M.C.; Potapov, P. V Forest Cover Dynamics of Shifting Cultivation in the Democratic Republic of Congo: A Remote Sensing-Based Assessment for 2000–2010. *Environ. Res. Lett.* **2015**, *10*, 094009. [CrossRef]
- 94. Zanaga, D.; Van De Kerchove, R.; Daems, D.; De Keersmaecker, W.; Brockmann, C.; Kirches, G.; Wevers, J.; Cartus, O.; Santoro, M.; Fritz, S.; et al. *ESA WorldCover 10 m 2021 V200 (Version V200) [Data Set]*; International Institute for Applied Systems Analysis: Laxenburg, Austria, 2022.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.