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Remote Sensing for Analyzing Forested Landscape Structure and Land-Use Histories in Guyana's Bauxite Mining Landscapes

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Abstract

Monitoring secondary forest regrowth is a priority in forest restoration strategies. A site history helps in understanding the present status of natural regeneration in the three landscapes impacted by bauxite mining. Nonetheless, high rainfall in bauxite residue storage areas can facilitate natural regeneration of forest. This research analyzed the natural regeneration of forest after thirty years of different land use histories at three bauxite mining areas of the Upper Demerara—Berbice region of Guyana. There are no man made forest plantations in the three landscapes being reviewed. The methodology included: 1) the selection of three sampling landscapes with different land use histories 2) the generation Land Use/Land Cover maps using KMeans unsupervised classification of satellite images in each landscape and 3) the assessment of landscape structure of the land cover classes for year 2020 at class and landscape level using landscape metrics. The assessment of landscape structure of the land cover classes was carried-out with landscape metrics for the comparisons at class and landscape level. Principal component analysis enables the identification of main patterns among landscape-level metrics and land cover classes. Discriminant classification of the landscape classes was analyzed with the different metrics. The results suggest that Normalized Difference Vegetation Index and KMeans unsupervised classification can be used to evaluate the difference in natural forest regeneration among landscapes with differing land use histories. The landscape metrics revealed secondary stages of forest succession. The Landscape Shape Index and Edge Density were the most significant for landscape differentiation. The result of the various land uses reveals a mosaic of early, intermediate, and late successional sequences.

Keywords

NDVI, KMeans, Natural Forest Regeneration, Landscape Approach

1. Introduction

Open-pit bauxite mining and its associated infrastructure are anthropogenic activities that lead to drastic changes in the landform, converting forest ecosystems into fragmented forest [1]. This type of surface mining generates 2 - 11 times more degraded land than underground mining [2]. Every single operation involved in open-cast bauxite mining has negative environmental impacts globally, regionally, and locally [3]. At first, the vegetation is completely removed from the land, subsequently, the topsoil is removed and the soil profile is heavily disturbed leading to the destruction of soil seed banks [4]. The most identifiable impacts of bauxite mining are associated with landscape transformations, especially high urbanization, landform alteration, soil erosion, and unstable waste spoils [5]. Waste dumps change the overall topography of the landscape due to the increases in elevation and slopes [6]. Mining infrastructure and emergent settlements require additional clearing of forestlands [7]. Forest fragmentation and loss of habitat connectivity are two major consequences of continual reduction of forest cover [4]. [8] studied successional patterns after five years following a hurricane disturbance event found that land use history of different sites influenced forest regeneration at the seedling stage and therefore the successional pathway. [9] reviewed extensively the role of land use history in successional processes and concluded that they are very important for the restoration of tropical forests. In Guyana, bauxite deposits occur on approximately 104,000 ha of the sandy rolling terrain and are mined in large open cast pits [10]. Bauxite mining has been conducted for over 100 years and was the main land use activity practiced within the Upper-Demerara Berbice Region (UDBR), a region dominated by rain forests until the early 1980s, when the industry closed operations. Bauxite mining was the principal cause of land and forest degradation and no reclamation or restoration program for these degraded lands has ever been established by the mining industry. Land use histories in different landscapes might have influenced different successional pathways as land uses diversified surrounding the three old mining towns (Linden, Ituni and Kwakwani) [11]. The Guyana Geology and Mines Commission's (GGMC) restoration unit is involved in restoration initiatives and is favourable to restoring vegetation on unstable spoil dumps in bauxite mined lands. GGMC relies on local knowledge of the areas, which is valuable but still limited and fragmented. The number and size of closed and active bauxite mines is key information that is not well documented in Guyana specifically in terms of natural vegetation colonization. Besides the aforementioned, the age and status of bauxite residue storage areas are important for restoration studies and this is unknown in Guyana [17]. There is a serious lack of data in regard to age, status and spatial distribution of natural regeneration on bauxite mined lands. In order to fill these gaps, this study aims to assess the status of landuse/landcover using a landscape ecology approach involving remote sensing to analyze successional patterns of forest regeneration in relation to landuse history, which can be considered a pre-requisite for landscape level research in areas impacted by bauxite mining in Guyana.

Natural forest regeneration and the design of successful future restoration and reclamation activities are dependent on the direction of secondary forest successional processes. Therefore, based upon recent postulates from applications of the landscape ecology theory, we questioning how land use histories could influence different directions of natural forest regeneration in the successional processes. The study aims to discuss observed changes in the forested landscape structure of vegetation cover in relation to different land use history after thirty years of post-bauxite mining in Guyana. It is focused on a landscape ecology approach using a remote sensing. Vegetation classes are considered as surrogate variables for multivariable analyses seeking to find factors that could explain the dynamics of natural forest regeneration.

This is the first study to investigate the relationships between natural forest regeneration and land use in Guyana's bauxite mining areas using remote sensing analysis. Previous studies have been experimental, but never attempted remote sensing techniques and landscape ecology approaches.

2. Materials and Methods

2.1. Study Area

Guyana is part of the Guiana Shield, which is one of the oldest geological formations in the world [12] and is dominated by the largest track of dense tropical forest [13]. Inside this region, the Upper-Demerara watershed (UDW) covers 189,000 ha [14], between 60˚00' North and 58˚30' West (**Figure 1**, **Figure 2**).

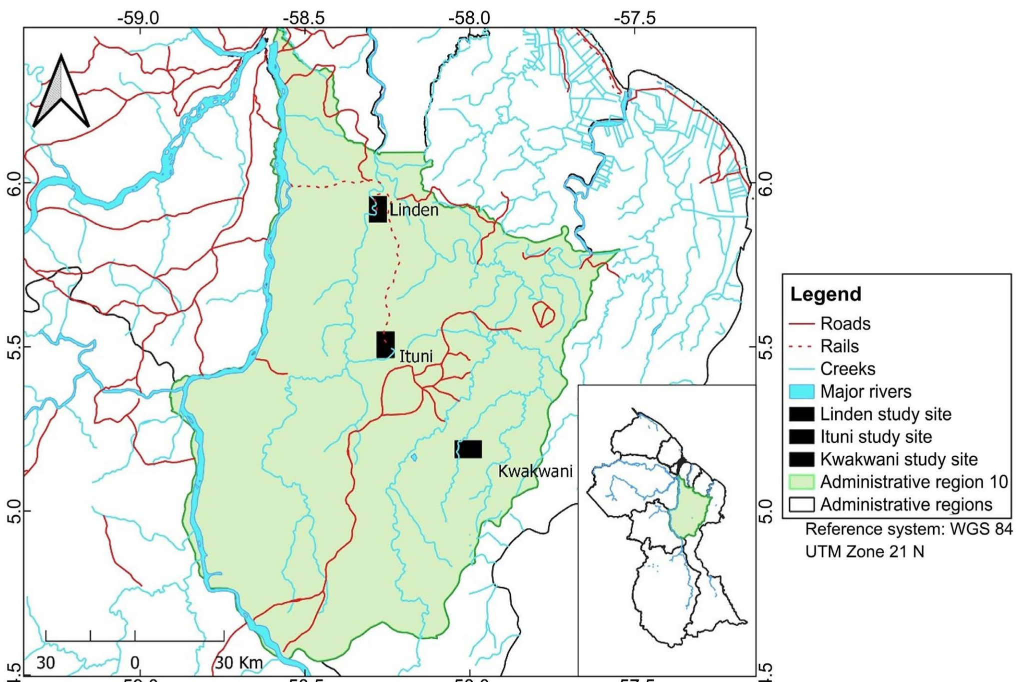

Figure 1. Location of the study sites. (Source: Administrative regions of Guyana, Waterbodies, Roads and Rails shapefiles from DIVA-GIS: https://www.diva-gis.org/).

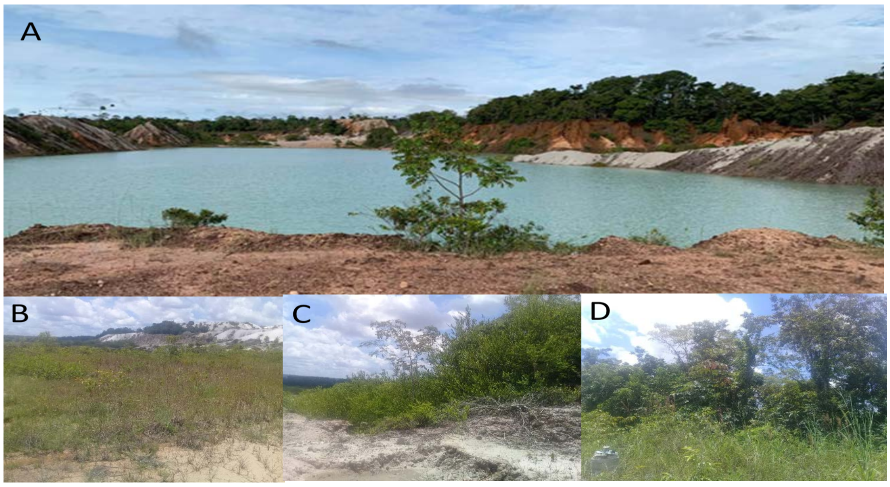

Figure 2. The photograph (A) is a section of an isolated remnant forest at the right and passive restoration in residues storage areas (BRAS) at the left and an artificial bauxite mining pond in Kwakwani at the center of the photograph. Photograph taken in May 2021 by Ewart Smith. Examples of natural regeneration in Linden abandoned BRAS, (B) of natural regeneration by grasses. (E) Natural regeneration by trees, shrubs and scrubs. (G) Natural regeneration by grasses and trees in (B, C, D). Photographs taken in 2020 Photo Credits: Gordon Lorrimer.

The bauxite mining belt is located on the white sand plateau that dominates the northeastern area of Guyana. This plateau covers an area of approximately 64,000 km^2 and has a topography that appears rather homogeneous and monotonous. The elevation ranges from 16 meters along the coast to more than 150 meters inland [15]. The white sand plateau corresponds to the Berbice formation (Pliocene and Pleistocene), which consists of sub-continental and old deltaic sand and clay deposits interbedded with kaolinitic clay, laterite, and bauxite. The soil of the white sand plateau consisted of well-drained Ultisols, Oxisols, and Entisols [16].

The study area was previously covered by Wallaba (*Eperua falcata*) and Dakama (*Dimorphandra conjugata*) forests in mosaic with Muri (*Humiria balsamifera*) shrubland and savannah grasslands [5].

2.2. Methods

2.2.1. Research Design

The work was concentrated in three landscapes namely Ituni, Kwakwani and Linden known as mining towns that were created around the mines. After their closure these towns were no longer administered by the bauxite companies and thereby derived different histories of land use [17]. In Ituni, there has not been any further bauxite mining operation. Instead, the community of Ituni has resorted to low impact logging (Community Forestry) as means of earning livelihood. Nevertheless, there has been considerable expansion of bauxite mining as well as logging in Kwakwani. Whilst in Linden the bauxite mining operation has been constant throughout the whole period. One main fair-weather road connects the three landscapes in Region 10, Guyana, Upper Demerara-Berbice administrative region.

2.2.2. Remote Sensing

Three areas with similar surfaces were selected from each of the landscapes for remote sensing analysis. The satellite image that showed the vegetation cover within the mining closure period in the nineteenth century is the Landsat 5 TM top atmospheric reflectance (TOA) images of the period of 1989. These images were obtained from the Google Earth Engine (GEE), which provides a visual depiction of the three landscapes at this specific year (Table 1). The satellite images were used to calculate the normalized difference vegetation index (NDVI) and to compute a KMEANS Unsupervised Classification to generate secondary succession map which includes six (6) land use/landcover classes (forest, shrublands, grassland, non-vegetation, water bodies and built-up areas) for each study site (Table 2). In this study, forest is referred to the dominant woody life forms such as forest regeneration, secondary regrowth of woody trees and shrubs or dwarf woody scrubs. Landcover changes in surface were analyzed from the landuse/landcover (LULC) maps 1998 to 2020.

2.2.3. Data Acquisition and Image Preparation

The boundary of each landscape (Linden, Ituni and Kwakwani) was stored as a shapefile. Ortho-rectified Level 2A Sentinel-2 Multispectral Instrument satellite images (MSI) with resolutions 10-m were acquired for the same time (August to November 2020) to avoid seasonal variation. In addition, Landsat 5 TM 10-m resolution top atmospheric reflectance (TOA) images for the period 1989 were also obtained (Table 1). Satellite images Landsat 5 and Sentinel 2 were used for the calculation of the normalized difference vegetation index (NDVI) and the KMeans Unsupervised Classification.

2.2.4. Computation of KMeans Unsupervised Classification

The KMeans unsupervised method created a land cover classification using SAGA-GIS version 2.3.2. The multi-spectral bands in the study included Blue (B2), Green (B3), Red (B4), and near infrared (NIR) (B8). In addition to these spectral bands, the normalized difference vegetation index (NDVI) was added to the image. The classification used fifty (50) number of spectral classes and the Hill

Table 1. Satellite data used in landcover classification (Sentinel-2) and reference images (Landsat 5).

Satellite	Number of bands	Resolutions	Data of Observation	Landscapes
Sentinel-2 MSI, Level-2A	12	10	16 August 2020	Linden
Sentinel-2 MSI, Level-2A	12	10	18 August 2020	Ituni
Sentinel-2 MSI, Level-2A	12	10	20 August 2020	Kwakwani
	7	30	19 August 1989	Linden, Ituni, Kwakwani

Table 2. Normalized difference vegetation index (NDVI) range values and description of landcover classes.

Class ID	Name	NDVI	Description
1	Forest	0.4 to 1	This class comprises areas occupied by secondary forest regeneration and residual forest tracks along major rivers and creeks. Woody trees.
2	Shrubland	0.35 to 0.39	This class comprises areas occupied by volunteer forest developed after severe disturbances such as mining and forest fires. A mixture of short trees and multiple-stem woody plants.
3	Grassland	0.19 to 0.34	A land mainly composed of grass with sparse scrubs.
4	Non-Vegetation	0.1 to 0.18	Lands without vegetation cover, barren soil, open white sandy areas.
5	Water bodies	−0.01 to −0.05	Artificial ponds, irregular shape, rivers. Some of these waterbodies have small and low vegetation cover.
6	Built-up areas	0.01 to −0.09	An area that is appropriate for a mix of residential and office uses, Major Impact Facilities (strip mines, quarries, mine pits), roads, trials.

climbing method. The rule that selection for the number of spectral classes should be much larger than the number of informational classes was considered in this study [18]. The resulting image was then reclassified using the land cover classes of **Table 2**.

The images classification used six landuse/landcover classes: forest, shrubland, grassland, non-vegetation, water bodies and built up areas. The true and false RGB composites, NDVI values, the land cover classification scheme and the seven elements for image interpretation [19] aided in the reclassification of clusters.

The accuracy of each classified Sentinel image was determined using stratified random selection [20]. An error matrix was produced from the accuracy assessment. The result of the accuracy assessment provides an overall accuracy of the land use/land cover map and the accuracy for each class shown on the map. The number of sampling point (N) was calculated by means of the following formula:

$$\text{"Equation (1)": } N = \left(\sum i = 1 \left(Wi * Si \right) / So\right)^2$$

where:

Wi is the mapped area proportion of class I;

Si is the standard deviation of stratum I;

So is the expected standard deviation of overall accuracy;

c total number of classes.

2.2.5. Landscape Metrics Analysis

The classified images of Sentinel-2 2020 were used for the calculation of landscape metrics with FRAGSTATS ver. 4 software [21]. While the software has numerous landscape metrics available for assessing landscape structure and fragmentation [22]. Studies in restoration of mine landscape worldwide were reviewed where several landscape metrics were proposed as appropriate [22]-[27], then determined the best suited method for this study. The authors considered avoiding metrics that were highly correlated [28] [29] and selected the metrics most suitable for the quantification of landscape structure and connectivity at the class- and landscape-levels (**Table 3**).

Table 3. Description of the landscape metrics used in this study.

Scale	Name of landscape metric	Abbreviations	Description	Unit
Area-Edge indices				
Class	Class percent of landscape	PLAND	The proportion of total is occupied by a particular patch type: It a measures of dominance of patch type.	Percent
Landscape/Class	Largest Patch Index	LPI	The proportion of total area occupied by the largest patch of a patch type.	Percent
Landscape/Class	Patch Size Coefficient of Variation	AREA_CV	Patch size standard deviation divided by the mean patch size; a measure of relative variability. CV (coefficient of variation) equals the standard deviation divided by the mean, multiplied by 100 to convert to a percentage, for the corresponding patch metric.	None
Landscape/Class	Edge Density	ED	Describe the distance of an ecosystem from its centroid (the center of the patch).	m/ha
Shape index				
Landscape/Class	Area-Weighted Mean Shape Index	SHAPE_AM	A mean patch-base shape weighted by patch size.	None
Aggregation Indices				
Landscape/Class	Number of Patches	NP	Express the number of patches identified for each class.	None
Landscape/Class	Patch Density	PD	The number of patches of per hectare.	#100 ha
Landscape/Class	Landscape Shape Index	LSI	The landscape boundary and total edge within the landscape divided by the total area, adjusted by a constant for a square standard.	None
Landscape/Class	Patch Cohesion Index	COHESION	Patch cohesion index at the class level measures the physical connectedness of the corresponding patch type.	None
Landscape	Clumpiness Index	CLUMPY	Clumpiness index is calculated from the adjacency matrix, which shows the frequency with which different pairs of patch types (including like adjacencies between the same patch type) appear side-by-side on the map. Clumpiness is scaled to account for the fact that the proportion of like adjacencies (Gi) will equal Pi for a completely random distribution.	Percent

Continued

Diversity and connectivity indices				
Landscape	Patch richness	PR	This index reflects the number of patch types (vegetation types) in the bauxite mining landscape. It is a measure of diversity of patch type.	None
Landscape	Shannon's Diversity Index	SHDI	Express the proportional abundance of every patch of a certain type of patch multiplied by a proportion.	Information
Landscape	Perimeter Area Fractal Dimension Index	PAFRACMN	It reflects shape complexity across a range of spatial scales (patch sizes). Perimeter-area fractal dimension at the landscape level is identical to the class level.	None
Landscape	Radius of Gyration Area Weighted Mean	GYRATE_AM	Radius of gyration is a measure of patch extent (*i.e.*, how far-reaching it is); thus, it is effected by both patch size and patch compaction.	Meters

2.2.6. Multivariate Analysis

A multivariate analysis of the selected landscape metrics was conducted using the principal component analysis PCA [22] [30] [31]. Libraries package within RStudio software [32] enabled the statistical analysis of multivariate ecological data. The library packages Vegan, BiodiversityR, FactoMineR [33] were used. A spatial pattern analysis with PCA was performed to find the main patterns among landscape level metrics and land cover classes. A Wilks-test was used to compute the p-value that best explains the distance between the land cover classes. The PCA provided an individual factor map that showed the contribution of each landscape metrics. Discriminant analysis classification of the landscapes was carried out with the resulting metrics of the landscape classes using stepwise variation; F values and Wilks-Lambda.

3. Results

3.1. Land Cover Classification

The LULC classification results showed that forest was the predominant land cover class in the three landscapes (**Figure 3**, **Table 4**). The forest surface increased from year 1998 to year 2020 in Ituni and Linden, while there was a reduction in Kwakwani. Scrublands increased in Ituni while it was less in Kwakwani and Linden; there was a reduction in Grasslands for Ituni and Linden but an increase in Kwakwani; Waterbodies increased in Ituni and Kwakwani while reduced in Linden. There was a reduction in Non-vegetated areas of the three landscapes, especially in Linden.

3.2. Landuse/Landcover Level Vegetation Metrics for Years 2020

In 2020, Table 5 shows the vegetation metrics indicating that highest percentage of forest regeneration in Kwakwani (72.5%) followed by Linden (64.5%), and the least was found in Ituni (59.9%), but the scrubland class for Ituni showed the highest percentage (32.4%) when compared to Linden (8.8%) and Kwakwani

Table 4. Landcover class metrics of the three studied landscapes for the year 2020.

LN	LULC	TA (ha)	PLAND (%)	LPI (%)	AREA_MN (ha)	AREA_CV (ha)	ED (meters/ha)	SHAPE_AM (ha)	NP	PD (#/100 ha)	LSI	COHESION	CLUMPY (%)
Ituni	Forest	2987.20	59.86	31.25	1.69	**2754.91**	**501.41**	**70.08**	**1763**	**35.33**	**115.16**	99.84	0.48
Kwakwani	Forest	**3614.26**	**72.45**	**60.94**	**4.88**	2318.43	98.22	14.6	740	14.83	21.38	99.90	**0.88**
Linden	Forest	3220.98	64.52	23.68	**3.85**	1476.78	84.54	4.66	836	16.75	23.68	99.40	**0.91**
Ituni	Shrubland	**1616.24**	**32.39**	**1.76**	**0.15**	**854.82**	**539.68**	**7.57**	**10371**	**207.83**	**167.88**	**94.67**	0.39
Kwakwani	Shrubland	203.60	4.08	0.16	0.05	506.97	81.89	2.31	4167	83.53	71.63	79.00	**0.48**
Linden	Shrubland	438.29	8.78	0.24	0.06	535.74	183.49	3.43	6685	133.91	0.24	85.21	0.43
Ituni	Grassland	26.06	0.52	0.02	0.02	186.07	14.31	1.38	1027	20.58	34.74	52.65	0.32
Kwakwani	Grassland	**292.58**	**5.86**	**0.11**	**0.08**	**313.91**	**127.18**	**3.30**	**3767**	**75.51**	**92.61**	**84.14**	**0.43**
Linden	Grassland	108.23	2.17	0.02	0.03	189.62	58.39	1.61	3505	70.20	0.02	60.08	0.31
Ituni	Waterbodies	29.33	0.59	0.02	0.03	236.15	14.28	1.68	866	17.35	32.93	65.25	0.39
Kwakwani	Waterbodies	**132.76**	**2.66**	**0.19**	**0.09**	**413.89**	**41.95**	**2.59**	**1493**	**29.93**	**45.35**	**85.29**	**0.61**
Linden	Waterbodies	3.65	0.07	0.02	**0.06**	234.09	1.28	1.54	65	1.30	0.02	72.90	**0.59**

LN: Landscape Name; LULC: Lnad Use/Land Cover Name; TA: Total Area; PLAND: Percentage of Landscape; LPI: Largest Patch Index; AREA_MN: Mean Patch Size; AREA_CV: Coefficient of Variation in Patch Area; ED: Edge Density; SHAPE_AM: Area Weighted Mean Shape Index; LSI: Landscape Shape Index.

Table 5. Area size (ha) and percentage of landuse/landcover classes in 1989 and 2020 for each landscape. I = Increase in area size (has) covered by the landuse/landcover class.

Landscape	Class	Landsat (1989)		Sentinel 2 (2020)		Difference (1989-2020)	
		Area[ha]	%	Area[ha]	%	[ha]	
Ituni	Forest	2548.98	50.59	2987.20	59.86	**438.22**	I
Kwakwani	Forest	3735.18	74.15	3614.26	72.45	120.92	
Linden	Forest	2900.34	41.07	3220.98	64.52	**320.64**	I
Ituni	Shrubland	1430.55	28.39	1616.24	32.39	**185.69**	I
Kwakwani	Shrubland	512.55	10.17	203.60	4.08	308.95	
Linden	Shrubland	465.84	22.47	438.29	8.78	27.55	
Ituni	Grassland	460.62	9.14	26.06	0.52	434.56	
Linden	Grassland	161.01	3.20	292.58	5.86	**131.57**	I
Kwakwani	Grassland	202.32	2.38	108.23	2.17	94.09	
Ituni	Waterbodies	8.55	0.17	29.33	0.59	**20.78**	I
Linden	Waterbodies	58.95	1.17	132.76	2.66	**73.81**	I
Kwakwani	Waterbodies	164.97	3.27	3.65	0.07	161.32	

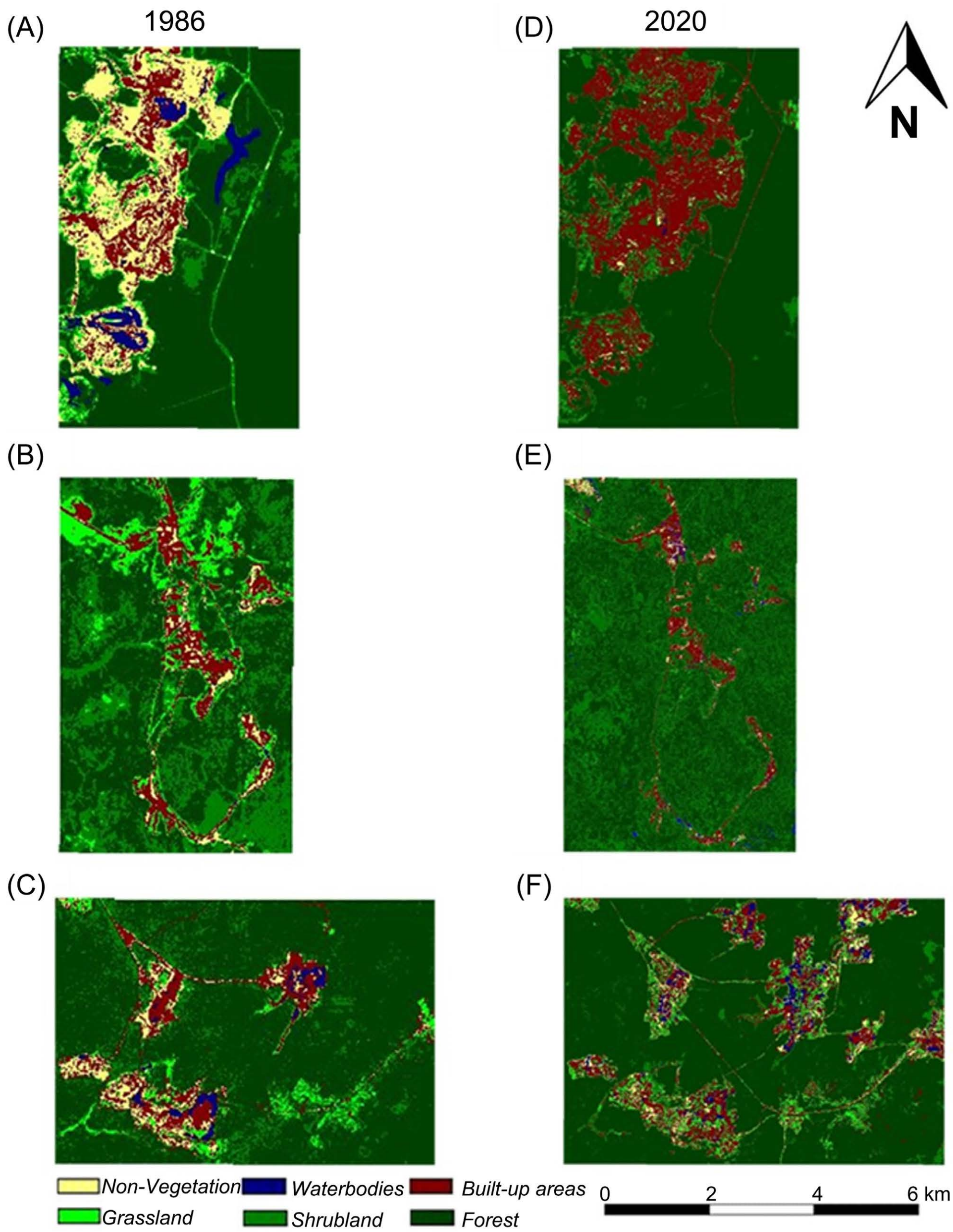

Figure 3. KMeans Unsupervised Image Classification of Land Use/Land Cover Classes (LULC) based on NDVI for images year 1989 (Landsat 5 TM) and 2020 (Sentinel-2 MSI). Left images: Landsat 5 TM for (A) Linden, (B) Ituni and Kwakwani (C); Right images: Sentinel MSI for (D) Linden, (E) Ituni and Kwakwani (F).

(4.1%). Kwakwani had the highest percentage of grassland (5.9%) when compared to Linden (2.1%) and Ituni (0.52%) respectively. A similar pattern was shown with the metrics, Largest Patch Index and Mean Patch Size and Clumpiness Index. On the other hand, the metrics Patch Size Coefficient of Variation, Edge Density Area, Weighted Mean Shape Index, Aggregation Indices, Number of Patches, Patch Density and Landscape Shape Index and Patch Cohesion Index showed the highest values for Ituni in both landuse/landcover forests and scrublands.

3.3. Landscape Level Vegetation Metrics for Years 2020

Computation of diversity, shape and connectivity metrics assisted in describing the diversity, complexity and landscape connectivity. Associated with the dominance of the forest class, Shannon's diversity index (SHDI) was in general low between 0.90 and 1 and the Patch richness (PR) remained constant across the three landscapes. The results of the Perimeter Fractal Dimension (PAFRAC) did not show significant differences indicating similar processes in the three landscapes. The radius of gyration (GYRATE_AM) however showed a gradient of relative reduction of complexity in the landscapes from Kwakwani (1823.72 m) to Ituni (1732.29 m) to Linden (1503.40 m).

3.4. Multivariate Analysis of Class Level Metrics

The PCA model indicated that about 80.8% of the total variability in the set of landscape pattern metrics that was generated by FRAGSTATS is explained by the first two components: PC1 accounted for 40.71% of the variation while PC2 accounted for 31.59%. The first axis was highly aligned with AREA_CV and PLAND having its metric increasing to the right, whereas the second axis was highly associated with PD, NP and ED. The first axis was dominated by fewer land cover classes as opposed to the high number of land cover classes at the left side of the plane (Figure 4(A)).

The organization of centers of landuse/landcover classes in relation to the Components 1 and 2 indicate that Forest cover was positively correlated to Component 1 (D1M1) as opposed to Waterbodies and Grasslands. However, Shrubland was positively correlated to Component 2 (D1M2) (Figure 4(B)).

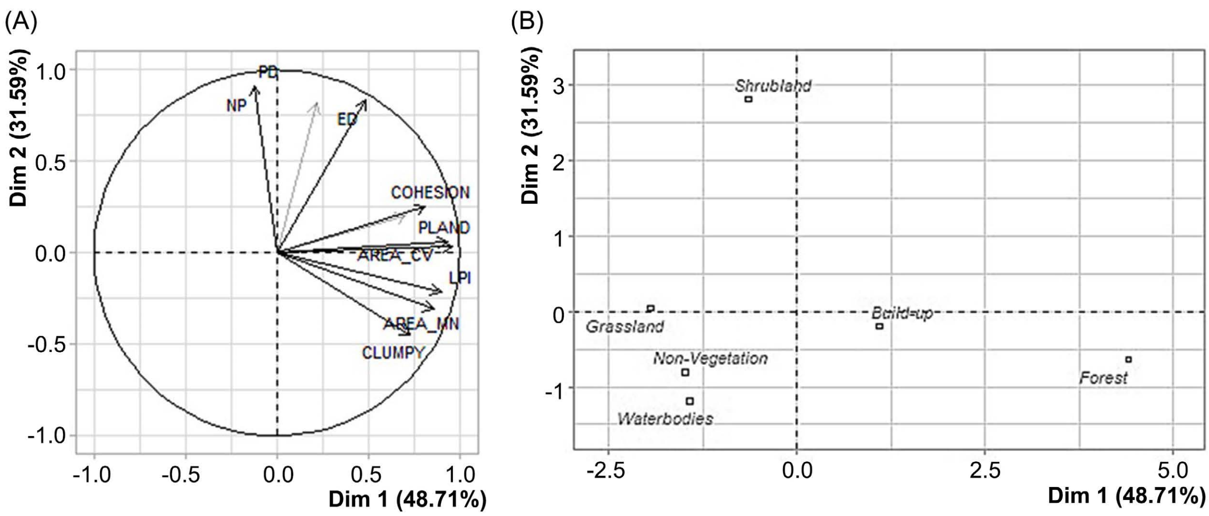

Figure 4. Multivariate statistics using principal component analysis (PCA). (A) Variables factor map showing class and landscape level metrics (PLAND = Class Percent of Landscape; LPI = Largest Patch Index; AREA_MN = Mean Patch Size; AREA_CV = Patch Size Coefficient Variation; ED = Edge Density; SHAPE_AM = Area-Weighted Mean Shape Index; NP = Number of Patches; PD = Patch Density; LSI = Landscape Shape Index; COHESION = Patch Cohesion Index; CLUMPY = Clumpiness Index; PR = Patch Richness; SHDI = Shannon's Diversity Index; PAFRACMN = Perimeter Area Fractal Dimension Index and GYRATE_AM = Radius of Gyration Area Weighted Mean. (B) Qualitative factor map illustrating the best LULC categories shown on the plane (Forest; Shrubland; Grassland; Non-Vegetation; Waterbodies and Built-up areas).

An examination of the contribution values for the landscape metrics suggests that AREA_CV, AREA_MN, PLAND, LPI, ED, COHESION, CLUMPY and SHAPE_AM were positively correlated to Component 1 (DIM1). Therefore, metrics related to the percentage of landscape (PLAND), size/area/edge of the patches, either their mean patch size (AREA_MN) or their variability (AREA_CV), the largest path index (LPI), shape (SHAPE_AM) and the aggregation metrics of COHESION and CLUMPY shared high values for this axis. While PD, NP, ED and LSI positively contributed to Component 2 (DIM2). In Component 1, AREA_CV (0.96), PLAND (0.94) and LPI (0.90) were the strongest correlated landscape metrics, whereas PD (0.91) and NP (0.91) were found to be the strongest correlated landscape metrics for Component 2. On the other hand, Discriminant analysis of the three landscapes using the values of the metrics and stepwise method resulted in one axis accounting 95% of the variance with edge density and landscape shape index being the most significant for the landscape differentiation (**Figure 5**).

The eigenvalue of (2.028) showed a strong canonical correlation. The Wilks' Lambda's statistical significance of 0.302, with the Chi-square statistic (17.367), confirmed this result. The probability value $p < 0.05$ at four (4) degrees of freedom showed that group discrimination is highly significant. The analysis indicated that the first discriminant function is significant but not the second. Edge density (ED) and Landscape shape index (LSI) were the metrics variables with the highest correlation (**Figure 5**). The landscape metric Edge Density (ED) is

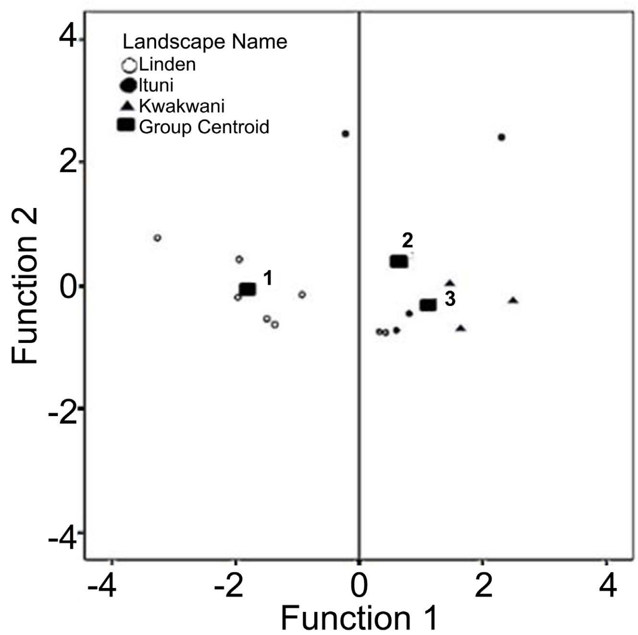

Figure 5. Analysis of the discriminant classification of the landscapes classes with the resulting metrics of the landscapes (1, 2, 3 = Group centroid). The eigenvalue of (2.028) showed a strong canonical correlation. The Wilks' Lambda's statistical significance of 0.302, with the Chi-square statistic (17.367), and a probability value $p < 0.05$ at four (4) degrees of freedom (df).

larger for Linden than for Ituni and Kwakwani, the Largest Patch Shape (LSI) was greater in Ituni and Kwakwani than in Linden.

4. Discussion

4.1. Land Cover Classification

A landscape approach interpretation from the land use history of each landscape during the last thirty years was used to explain these results: 1) forest regeneration Ituni > Linden > Kwakwani, 2) shrubland regeneration Kwakwani > Ituni > Linden and 3) grassland regeneration Ituni > Kwakwani > Linden. Furthermore, the highest secondary shrubland regeneration in Kwakwani could indicate extensive intermediate successional dynamics associated with the community forestry, while the lowest early successional grassland communities are in Linden, where mining is responsible for active early stages of regeneration.

4.2. Class-Level Vegetated Land Cover Structure

The study illustrated the use of landscape structure and connectivity analysis as a means of quantitatively evaluating the spatial patterns of the three-forested landscapes with different land use histories in the last thirty years. The PCA results confirmed that from the six LULC classes, forest and shrubland regeneration dominated the studied landscapes. PLAND (percentage of landscape) and LPI (largest patch index) were the main landscape metrics explaining the main axis of spatial variation so they can be considered as useful indicators to describe the current landscape fragmentation. EDGE DENSITY is an important indicator of the rate of forest recovery and the metric showed that forest (540 m/ha) and shrubland (501 m/ha) classes for Ituni having the highest value. This is an important finding related to the land use history of this landscape as after the initial closing of mining operations the community did not continue mining operations but a community forest industry developed and involved timber extraction activities.

The lower LPI values for Linden (23.7%) which is the landscape where the mining activities continued after initial closing of mining operations suggested that the patches were more scattered, resulting in a spread throughout the landscape, whilst higher LPI values for Ituni (31.2%) and Kwakwani (60.9%) indicated that the patches were more compact. The LSI for the forest and shrubland classes fluctuated amongst landscapes, which suggests high levels of fragmentation due to low patch compactness [34]. LSI, COHESION and CLUMPY are measures of the degree of complexity of classes and it can apply to the whole landscape. These aggregation metrics are of particular importance in the analysis of land cover changes; such changes reflect the alteration in the structural and functional characteristics of the landscapes [35]. The results found a significant increase of the physical connection of forest patches, the COHESION index was above 1 for the three landscapes which implies that over the period of thirty years, the small isolated patches of forest fragments gradually clumped into irregular patches of compact woody vegetation.

4.3. Landscape-Level Connectivity

Concerning the landscape level metrics, the results for the SDI (Shannon Diversity Index) are between 0.90 and 1.0 for the three landscapes indicating uniformity and low diversity given the dominance of the forest class.

The results of the study showed a similar perimeter fractal dimension (PAFRAC) for the three landscapes indicating similarities in the processes of fragmentation and forest regeneration within the landscapes [36]. The PAFRAC results obtained for this study means that the differences in land use histories were the main factors explaining the landscape patterns of natural forest regeneration.

Furthermore, after thirty years natural forest regeneration, new forest and shrubland classes together at the three studied landscapes occupied a large proportion of each landscape. These results were similar to those highlighted in a study by [36] for some abandoned bauxite residue storage areas in Linden where high rainfall facilitated the development of vegetation cover overtime [37]. Natural forest regeneration is higher in Ituni, while in Kwakwani, the secondary forest succession was mainly comprised of grasslands and shrublands.

The high reduction in connectivity observed from Kwakwani (1823.72 m) and Ituni (1732.29 m) in relation to Linden (1503.40 m) indicated that Linden had a reduction of potential habitats for forest species conservation. The continuation of mining as an exclusive land use leads to increased alteration of the landscape. This was demonstrated in several case studies by [37]. Future restoration activities will need to design corridors to increase connectivity.

In terms of landscape configuration and connectivity, the landscape metrics of GYRATE_AM and PAFRAC indicated that these landscapes are highly fragmented, especially Linden that experienced a continuous mining operation and it is possible to describe the current landscape matrix as a complex system consisting of a number of smaller disconnected forest regeneration patches that are isolated from each other.

5. Conclusion

The study aimed at detecting the land use/land cover change during 30 years of land use history in the Upper Demerara Berbice River Basin of Guyana by employing a combination of a Landscape ecology approach and Remote Sensing technology. This analysis reveals the development of different mosaics of early, intermediate and late successional sequences as a result of community forestry, community forestry and bauxite mining and predominantly continuous mining. This study confirmed that vegetation occupied a large proportion of each landscape as was pointed out by Santini and Fey in 2013 for some abandoned bauxite residues storage facilities in Linden. In Kwakwani, the vegetation covers are mainly comprised of grass than woody vegetation, however, in Ituni the highest proportion of the landscape was occupied by woody vegetation. The investigation goes further with the identification of potential drivers which are essential to the process of changes emerged from various land uses. Regardless of the large areas of forest cover, the build-up class occupied the third level of importance in relation to the class level metrics, however, these forest areas are seeming to be suitable for edge species. The results obtained from this preliminary study demonstrate that there is some degree of fragmentation within the landscapes and is similar to the results obtained by studies done by Wang *et al.* (2014) [36]. The landscape metrics indicated that these sites are highly fragmented and it is possible to describe the current landscape matrix as a complex system. The decline in bauxite mining after thirty years of land use histories has identified three distinct land use configurations that suggest a mosaic of the primary succession of vegetation which needs to be examined through experimentation in the field and testing of primary successional theories. Each of the studied metrics independently offers information that allows explanations for the vegetation cover differences in the three landscapes. The approach used in this study can be replicated in other areas within the Guiana Shield where similar commercial deposits of bauxite are found.

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Conflicts of Interest

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

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