Article

Spatial Analysis of the Drivers, Characteristics, and Effects of Forest Fragmentation

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Abstract: Building on the existing literature, this study examines whether specific drivers of forest fragmentation cause particular fragmentation characteristics, and how these characteristics can be linked to their effects on forest-dwelling species. This research uses Landsat remote imaging to examine the changing patterns of forests. It focuses on areas which have undergone a high level of a specific fragmentation driver, in particular either agricultural expansion or commodity-driven deforestation. Seven municipalities in the states of Rondônia and Mato Grosso in Brazil are selected as case study areas, as these states experienced a high level of commodity-driven deforestation and agricultural expansion respectively. Land cover maps of each municipality are created using the Geographical Information System software ArcGIS Spatial Analyst extension. The resulting categorical maps are input into Fragstats fragmentation software to calculate quantifiable fragmentation metrics for each municipality. To determine the effects that these characteristics are likely to cause, this study uses a literature review to determine how species traits affect their responses to forest fragmentation. Results indicate that, in areas that underwent agricultural expansion, the remaining forest patches became more complex in shape with longer edges and lost a large amount of core area. This negatively affects species which are either highly dispersive or specialist to core forest habitat. In areas that underwent commodity-driven deforestation, it was more likely that forest patches would become less aggregated and create disjunct core areas. This negatively affects smaller, sedentary animals which do not naturally travel long distances. This study is significant in that it links individual fragmentation drivers to their landscape characteristics, and in turn uses these to predict effects on species with particular traits. This information will prove useful for forest managers, particularly in the case study municipalities examined in this study, in deciding which species require further protection measures. The methodology could be applied to other drivers of forest fragmentation such as forest fires.

Keywords: forest fragmentation; deforestation; GIS; remote imaging; Fragstats

1. Introduction

Fragmentation occurs when "a large expanse of habitat is transformed into a number of smaller patches of smaller total area, isolated from each other by a matrix of habitats unlike the original" [1] (for an example of this process, see Figure S1 which demonstrates a time-lapse of forest fragmentation in Northern Alberta over 42 years).

An increase in forest fragmentation threatens the existence of intact forest landscapes, which are defined as untouched natural areas of forest. These forest landscapes are recognised as "some of the most important ecosystems in the world", providing critical benefits to innumerable species [2]. They are the "greatest terrestrial carbon stores" [3], and are able to store a disproportionately higher amount of carbon than non-intact landscapes, making them a key natural solution in any climate change mitigation strategy [4]. In addition, risks of decreased biodiversity and local extinctions are disproportionately higher from

removing relatively intact landscapes as compared to already fragmented ones [5]. They also provide other vital services such as water supply and erosion control, and are the main source of livelihood for 1.6 billion people, particularly in indigenous communities [6].

However, around the world, large swathes of intact forest are under threat, particularly the Amazon and Atlantic forests in South America [7]. 7.2% of global remaining intact forest area, or 919,000 km^2, an area almost four times the size of the UK, was lost between 2000 and 2013 [3]. In Amazonia, there has been a shift from large to small scale deforestation across the region, with 34% of forest loss patches in Brazil being smaller than 6.24 hectares, making these areas difficult to monitor. Big new deforestation hotspots are opening up in Peru and Bolivia, which are likely caused by industrial agriculture. In Colombia, deforestation has increased from around 300 km^2 in 2001–2007 to 9560 km^2 between 2008–2014 [8].

Forests become fragmented due to a number of different causes, which are considered here as "drivers" of fragmentation. Although these drivers can be natural causes, for example wildfires, they are mainly anthropogenic. These include commodity-driven deforestation, timber logging, agricultural expansion, and urbanisation [9]. Such anthropogenic drivers have increased in recent years due to increases in population, food consumption, and commercial practices. The fragmentation patterns caused by each driver are termed fragmentation characteristics. These characteristics can be quantitatively measured using metrics such as the area, edge length, connectivity, aggregation, and shape complexity of remaining forest patches.

Although there is a wealth of knowledge on where specific drivers of forest fragmentation, such as agricultural expansion, are occurring globally, very little research links specific drivers to the patterns of fragmentation that they cause.

This paper examines if specific drivers of forest fragmentation cause specific fragmentation characteristics, and how these fragmentation characteristics can be linked to their effects on forest-dwelling species. This information is particularly useful to predict which species are likely to experience the most negative impacts following forest fragmentation caused by different means.

2. Background and Previous Studies

Since the early 1900s, researchers have investigated how the spatial structure of landscapes affects their ecological functions [10]. There have also been major developments over the past century in approaches to quantify landscape structure and measure forest fragmentation. These approaches have drawn on evolving knowledge in a diverse variety of fields, including classical ecology, network theory and fractal geometry [11]. However, there are differences in the ways that fragmentation is measured, making direct comparisons between studies difficult. The main contentions between fragmentation experts arise from the choice of the initial landscape model, and the types of metric collected (for information on the types of landscape models, see Supplementary Information SI1; for information on the levels of fragmentation metrics, see Supplementary Information SI2; for information on the difference between structural and functional fragmentation characteristics, see Supplementary Information SI3).

2.1. Fragmentation Characteristics

There are several different categories of fragmentation characteristics, which are described below and illustrated in Figure 1.

2.1.1. Area

The area of different land class types in a given landscape will have a significant impact on the types of species the landscape can support. Fragmentation can affect a landscape area in several ways, such as reduction in total forest area and reduction in mean forest patch size (Figure 1A).

Fragmentation Characteristic	Description
A AREA (a) (b)	A pictorial representation of two effects of fragmentation on area, where light green represents a grassland matrix and dark green represents forest patches. (a) shows a constant mean patch size but reduction in total forest area. (b) shows a constant total forest area but a reduction in mean patch size.
B EDGE	A pictorial representation of forest fragments of different shapes, edge lengths and core area, where light green represents a grassland matrix, dark green represents core forest area and mid-green represents edge-affected areas.
C CONTRAST	A pictorial representation of edge contrasts, where light green represents a grassland matrix, dark green represents forest patches and grey represents an urban matrix. The solid line represents a barrier through which an organism would not pass, and the dashed line a permeable barrier.
D AGGREGATION	A pictorial representation of high and low aggregation, with the first picture showing highly aggregated forest patches, and the second showing sparsely aggregated forest patches.
E DIVERSITY (a) (b)	A pictorial representation of diversity metrics. (a) represents on the left a highly diverse landscape of many different land class types, and on the right a landscape of lower diversity with only 3 class types. (b) represents two landscapes of the same number of land classes, but each has a different area distribution.

Figure 1. Pictorial representation of fragmentation characteristics. Fragmentation characteristics described in each subfigure are **A**—Area, **B**—Edge, **C**—Contrast, **D**—Aggregation and **E**—Diversity.

2.1.2. Edge, Core Area and Shape

Edge effects in forests describe the changes in forest environment which occur close to forest boundaries, such as changes in wind conditions, sunlight, and temperature. Core area of a forest refers to any area not affected by these edge effects, defined as all area which is a specified distance away from the forest edge. Figure 1B shows one circular forest fragment with a large core area and little edge-affected forest on the left. On the right it illustrates a complex shaped fragment of the same total area, but with a smaller core area and a larger area of edge-affected forest. This is relevant to species which show preference to live, hunt or mate in one of either edge-affected or core forest areas.

2.1.3. Contrast

Contrast refers to the "difference between adjacent patch types with respect to ecological attributes relevant to an organism" [12]. This is important as a single species can have

different reactions to different edge types. Figure 1C represents the view of an organism which perceives a forest-urban edge as a barrier, but a forest-grassland edge as a permeable membrane which it can move through.

2.1.4. Aggregation

Aggregation metrics, which are related to proximity or isolation metrics, are those that measure the likelihood of patches of the same land class being close to each other, (Figure 1D). Closer patches can enable subpopulation survival by allowing easier movements between habitat patches, whilst a greater distance between patches can decrease the likelihood of metapopulations meeting. Measures of aggregation can be extended to include not just Euclidean distance between patches but functional weighted distance, representing the difficulty a particular species would have in moving between patches.

2.1.5. Diversity

Diversity metrics, which are sometimes referred to as "contagion metrics", represent the diversity of different land classes in a single landscape. This is measured in several ways. Two common ones are demonstrated in Figure 1E, those of measuring the number of different types of land class in a landscape and measuring the distribution of different land class types in a landscape.

The main issue encountered in almost all fragmentation studies is in understanding the ecological impacts caused by differing levels of fragmentation in a forest. Although there is a temptation in the literature to view forest fragmentation as a purely negative phenomenon akin to habitat loss and degradation, it is far more nuanced than this. The reality is that forest fragmentation has completely different effects, both positive and negative, which are dependent on the specific preferences of each species (for a generalised view of the species responses of forest fragmentation see Figure S3). Several examples exist of studies which cite the positive effects of forest fragmentation on particular species or on biodiversity [13,14]. These positive responses are attributed to "increased functional connectivity, habitat diversity, positive edge effects, stability of predator-prey/host-parasitoid systems, reduced competition, spreading of risk, and landscape complementation" [14].

Each of the manifestations of forest fragmentation provided in Figure 1 have been shown in various studies to correlate with loss of some species. For example, supporting the idea that small fragment areas cause species loss, one study demonstrated the "near-complete extinction of native small mammal fauna" in a nature reserve in Thailand over 25 years following severe forest fragmentation, citing the decreasing size of forest fragment areas as a key cause [15]. Several studies show that the increased edge effects from a fragmented forest cause increased predator density [16] and nest parasitism in birds [17]. One example found that a particular bird species experienced up to three times its normal level of nest predation when its forest habitat became fragmented, forcing it to nest closer to forest edges [18]. Shape complexity also plays its part, with one study finding that the shape of remaining forest fragments was more important than total fragment area in predicting bird species loss in Mexican cloud forest [19]. Increased isolation of fragments limits the ability of different species to traverse their habitat, negatively impacting the survival of metapopulations [20], as studies of animal movements in fragmented landscapes have shown that some species "strongly avoided crossing stretches of non-forest matrix" [21]. The quality of non-forest matrix also has a crucial effect on species dispersal, with some matrix types providing far better cover and food prospects than others for traversing species [22]. These negative impacts from forest fragmentation are species-specific.

However, until fairly recently, an abundance of edge-affected habitat in a forest was viewed as a sensible, positive aim in landscape management, and "guided management practices for most of the twentieth century" [12]. This understanding of fragmentation can be seen in some circumstances as a positive process where edge habitats may maximise species diversity. Some species, such as brown-headed cowbirds, thrive in an edge habitat due to their increased access to nests of other bird species in which they lay their eggs [23].

Raccoons, foxes, opossums, and other smaller predators often perform very well in fragmented regions due to the increased access to their natural prey. The variation in habitats afforded by increased fragmentation can also have positive effects, with one study finding that the "increased access to both foraging and roosting sites for bat species", which roost in deeper forest but prefer to hunt in more open grassland, can support a higher diversity of bat species in eastern Ontario, Canada [13].

2.2. Overview of Forest Fragmentation Effects

Debates around the effects of fragmentation continue to exist (e.g., on whether biodiversity is better conserved by preserving one large or several smaller habitats) and is still unresolved [24] A major difficulty in understanding fragmentation effects has arisen from attempts to separate species in a binary manner to "edge-tolerant" or "edge-averse". This categorisation would greatly simplify studies, but risks ignoring crucial differences between types of edges, which can express a wide range of structural differences between adjoining habitats [25]. A more advanced idea is to recognise that there is a "sensitivity spectrum" along which different species fall regarding how they will react to different edge types. This gradient of edge tolerance "is bounded by forest-interior species on one end and edge and open-habitat species on the other" [26]. Even this gradient is fluid, with some species showing individual or seasonal variation in edge tolerance [27].

Developments to this sensitivity spectrum have led to research on whether species' fragmentation responses can be predicted by their traits, as demonstrated in Figure 2. Studies have found relationships between reactions to fragmentation and species traits such as body size [28,29], trophic level [30], rarity [31] and habitat specialisation [32].
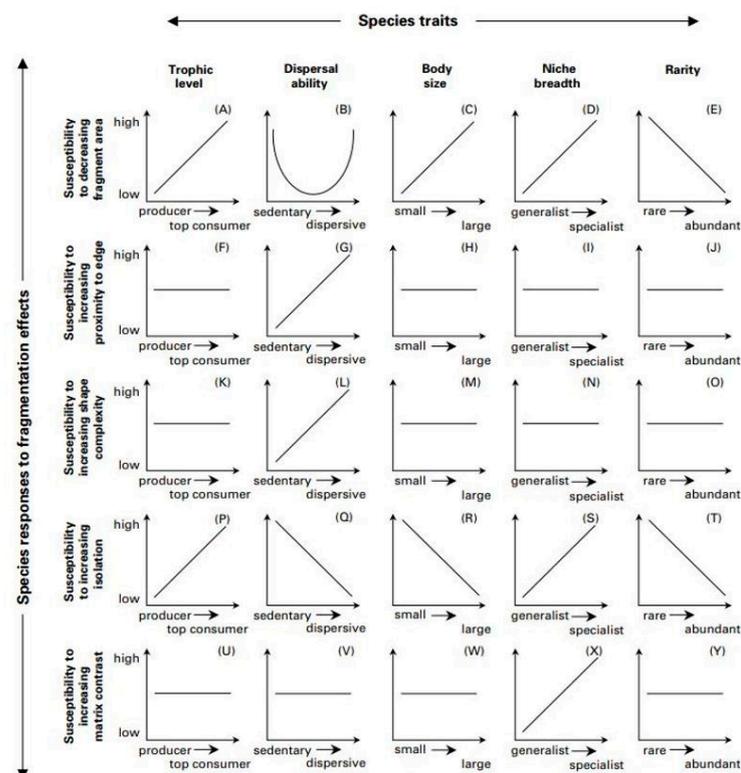

Figure 2. Graphs categorising species fragmentation responses by five species traits [32].

Figure 2 shows species responses to fragmentation characteristics such as decreasing fragment area, and how these change according to species traits such as trophic level. This figure demonstrates the variability in species response clearly. One example shown by the second row of graphs is that trophic level, body size, niche breadth and rarity do not affect species' response to increasing proximity to edges, as each of these are horizontal lines.

The only trait identified which affects this is the dispersal ability of the species in question, with highly dispersive species exhibiting a more negative response.

It is worth noting that one important relation not demonstrated in Figure 2 is that of how different species traits affect their responses to overall habitat loss. There is evidence that overall habitat loss more negatively affects larger species at higher trophic levels [30], and also those which are more specialist [33].

2.3. Studies of Forest Fragmentation

Many fragmentation studies are performed to understand the types and drivers of fragmentation occurring in a particular forest. Examples of drivers include commodity-driven deforestation, shifting agriculture, forestry, wildfire and urbanisation [9] (for the global distribution of percentage of tree cover lost permanently through these different drivers from the period of 2001 to 2015 see Figure S4).

Arguably the most complex fragmentation studies are those that attempt to directly measure ecological impacts of forest fragmentation on biodiversity and resident species. This can be done either through explicit ground-truth studies, where researchers obtain information pertinent to ecological processes such as biodiversity on site, or through models of species behaviour.

In one study [34], ground-truth studies of the Ecuadorian Tapaculo, a ground- dwelling, dispersal-limited bird, were used to understand the impact of habitat fragment size on their mobility. It was found that the level of habitat fragmentation in the bird's native cloud forests had a significant impact on the birds' wing morphology, with birds living in smaller patches often having narrower wings and thus better flight capacity.

Another study [35] recognised the importance of combining information on landscape spatial configuration with information on species in their use of the "metapopulation capacity" measure, which ranks fragmented landscapes in their ability to support species metapopulations. Using this information, they were able to identify fragmentation impacts on 34 biodiversity hotspots to test the potential of metapopulation capacity as a measure of fragmentation impact at a global scale.

It is crucial to note that the effects of fragmentation will vary widely between different plant and animal species and even sometimes be beneficial to some. Although indicator species have been used successfully to represent responses of many species to fragmentation, such as in a study of the Fundy Model forest [5], it is still important to recognise that these species can never be fully representative of the reaction of all forest species to fragmentation. This realisation shows that impact studies are difficult without accurate models of each species' behaviour or ground truth studies, hence their complexity and relative scarcity.

The rest of this paper focuses on the links between forest fragmentation drivers, characteristics, and impacts and explores if drivers of fragmentation can produce predictable, measurable spatial patterns. These patterns may then be linked to their impacts on species, using information from empirical studies.
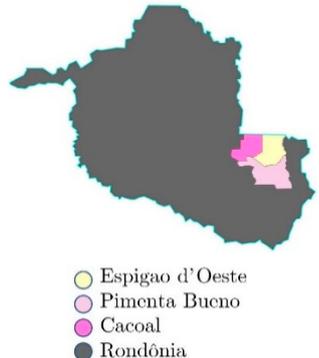
3. Materials and Methods

Agricultural expansion and commodity-driven deforestation were selected as key drivers of forest loss (for details of the steps uses to obtain information on the characteristics and effects of these drivers, see the flow diagram in Figure S5, which also indicates the relevant software used to achieve them).

3.1. Location Selection

The "Global Forest Watch" [36] was used to identify Brazil as a deforestation hotspot (for tree cover loss by dominant driver in central South America, see Figure S6). The Brazilian state of Mato Grosso, the name of which can literally be translated as "thick woods", has been described as "uniquely biodiverse, as it is the only Brazilian state to encompass significant parts of three different biomes"—the Amazon, the Cerrado and

the Pantanal [37]. Between 2000 to 2019, the state lost 11.2 Mha of tree cover, which is equivalent to 20% of its total forested area largely caused by agricultural expansion. The main crops grown in Mato Grosso are corn, soybean, rice and sugar cane [38]. Four of the 141 municipalities were studied (Table 1). The elevation of each municipality is similar to ensure this has minimal effect on observed fragmentation.

Table 1. Area and elevation of each selected Mato Grosso and Rondônia municipalities.

State		Area (km^2)	Elevation (m)	
Mato Grosso	Itanhang'a	2898	350	
	Tapurah	4489	393	
	Ipiranga do Norte	3467	470	
	Lucas de Rio Verde	3645	390	
Rondônia	Espigao d'Oeste	4518	280	
	Pimenta Bueno	6241	195	
	Cacoal	3793	206	

The Brazilian State of Rondônia has experienced a high amount of commodity-driven deforestation in recent years, which is defined as "permanent conversion of forest for the expansion of commodities" which can include products such as beef, minerals and oil and gas [39]. Rondônia in particular experiences a high level of cattle ranching, and in 2013 supplied 20% of exported beef from Brazil [40]. Between 2000 and 2019, the state lost 4.8 Mha of tree cover, which is equivalent to 23% of its total forested area. Three of the 52 municipalities were studied (Table 1). The elevation of each municipality is similar to ensure this has minimal effect on observed fragmentation. Figure 3 demonstrates a map of the forest cover types of both Mato Grosso and Rondônia [41].

3.2. Remotely Sensed Imagery

In order to identify forest fragmentation, this study uses satellite imagery from the USGS' "EarthExplorer" website, which contains freely downloadable Landsat satellite imagery [42]. Each image from the Landsat-8 satellite, which is referred to as a "scene", covers 180 × 185 km, meaning the satellite images the entire Earth every 16 days. Scenes were chosen from the years 2000 and 2019, so that the change in forest fragmentation over these 19 years could be examined. The scenes were chosen for their image quality and minimal scene cloud cover of less than 10%.
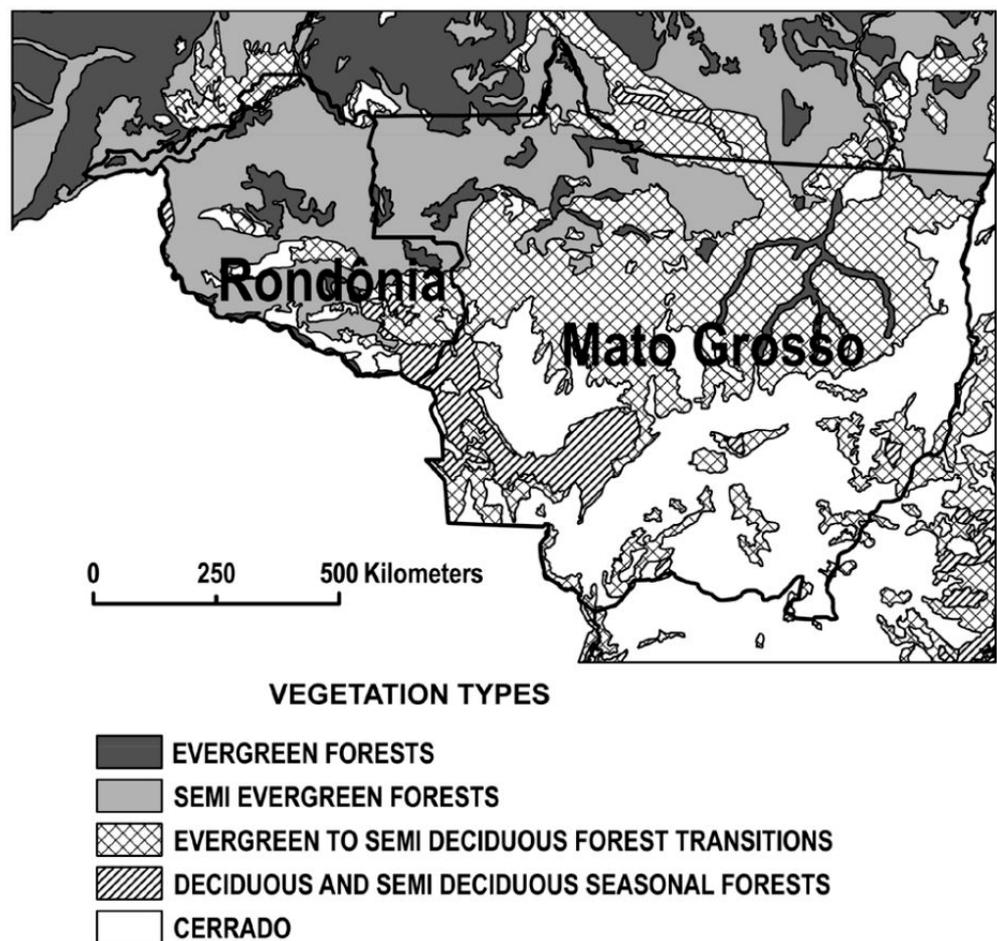
VEGETATION TYPES

EVERGREEN FORESTS

SEMI EVERGREEN FORESTS

EVERGREEN TO SEMI DECIDUOUS FOREST TRANSITIONS

DECIDUOUS AND SEMI DECIDUOUS SEASONAL FORESTS

CERRADO

Figure 3. Map of different forest types in Rondônia and Mato [41].

3.3. Image Manipulation

Quantifying fragmentation in each municipality involves clipping each scene to municipality boundaries (for an example for the municipality of Tapurah in the state of Mato Grosso, see Figure S7). Although Landsat raw imagery can require a large amount of pre-processing "to account for sensor, solar, atmospheric, and topographic effects" [43], this study makes use of Landsat Level 1 products which "consist of quantized and calibrated scaled Digital Numbers" [44] which for the purpose of this study do not require correction. In addition, the chosen images were taken during the daytime in the months between June and September to avoid a high level of seasonal variation in image colouring. Each scene was awarded an "image quality" mark by Landsat of 9 or higher and has scene cloud cover of less than 10%.

3.4. Classification

The measurement of fragmentation metrics is performed using a land cover map of each state, which maps the land cover classes such as forest, agriculture, and water. In order to create these land cover maps, ArcGIS Spatial Analyst's built-in unsupervised classification tool was used, which groups image cells into a pre-specified number of spectrally similar classes using maximum likelihood classification. There is debate over the ideal number of classes to specify as too few will lose image information but too many requires a long time to reclassify and may give unnecessary information. In this case, thirty classes were used. This number was chosen through experimentation, as it was found that numbers less than thirty did not provide a high degree of accuracy, but more than thirty was unnecessarily high and provided extraneous information. In areas which underwent

agricultural expansion, these thirty classes were then manually reclassified manually using visual data into the three classes of forest, agriculture, and water, as shown in Figure 4.
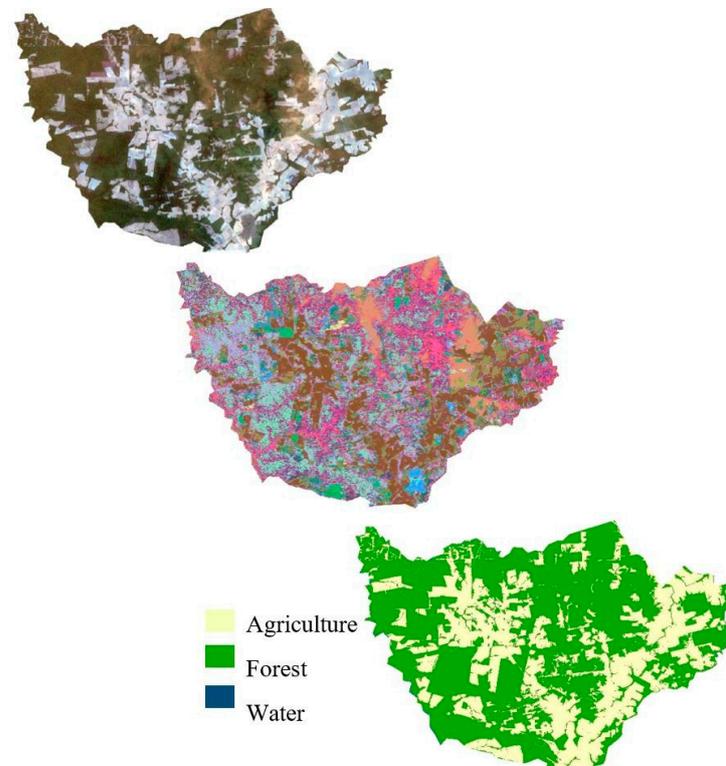

Figure 4. An illustration of the classification of Tapurah municipality. The first image shows the natural composite image, the second shows the unsupervised classification into 30 spectrally similar classes, and the final image is the manually reclassified municipality.

3.5. Accuracy Assessment

To ensure accuracy of the image classification, a set of random points were generated and individually checked against Google Earth Historical Imagery of the locations. Using these 110 random accuracy assessment points, an error matrix is calculated to demonstrate the likelihood of misclassification for each image. In this matrix, each cell a_{ij} represents the likelihood of a cell which is in reality land class i being classified as land class j (for an example matrix for the municipality of Tapurah in 2019, see Table S1).

Using this error matrix, Kappa's error coefficient is calculated for each, which measures the reliability of classification systems through the equation below [45].

$$\kappa = \frac{p_0 - p_e}{1 - p_e}$$

κ = Kappa coefficient
p_o = relative observed agreement between rating systems
p_e = hypothetical probability of chance agreement

Although there is no definite rule for an acceptable value of the kappa coefficient, it is generally agreed that above 0.7 is acceptable, where a value of 0.7 means that the image classification is 70% better than if each cell had been assigned randomly. The error matrix in Table S1 gives a Kappa value of 0.85, meaning that the classification is more than accurate enough to be used to calculate fragmentation metrics.

3.6. Land Cover Change Assessment

As habitat loss is recognised to have a huge impact on the survival viability of forest dwelling species, it is useful to calculate the total land cover change over the time duration. This evaluation is performed using ArcGIS, which can create land cover change maps, such as shown in Figure S8.

Using these maps, land cover transition matrices are created to show the total area which changes land cover category in a comparison between two images (for an example of a land cover transition matrix for Tapurah from 2000 to 2019 see Table S2).

3.7. Fragmentation Analysis

To quantify the spatial changes to forest pattern that agricultural expansion and commodity-driven deforestation have caused in the case study areas the fragmentation metrics catalogued in Table 2 were computed.

Table 2. Fragmentation metrics [12].

Category	Metric	Description
Area related	Total Class Area	The sum area of all patches of a particular class
	% of Landscape	The proportion of the total landscape taken up by a particular class
	Mean Patch Area	The average area of all patches of a particular class
	Standard Deviation of Mean Patch Area	The standard deviation away from the mean forest patch area
Edge related	Area-weighted edge length	Total edge length of the forest divided by forest area
Contrast related	Contrast-weighted edge density	The sum of the lengths of all edge segments of a particular patch type multi- plied by their corresponding contrast weights divided by the area for a particular class.
Shape related	Mean Radius of Gyration	The mean distance between each cell in the patch and the patch centroid
	Perimeter-Area Fractal Dimension	An indication of the departure of each patch from Euclidean geometry rep- resenting an increase in patch shape complexity
	Mean Contiguity Index	An indication of the spatial connectedness of cells within a grid-cell patch
Core-area related	Total Core Area	The sum of the total core area of all patches of a particular class
	Number of disjunct core areas	The total number of core areas which are disjunct and contained within each patch of a particular class
	Mean Core Area	The average size over all core area patches for a particular class
Aggregation related	Mean Euclidean Nearest Neighbour Distance	The average distance between nearest neighbouring patches of the same land class
	Proximity Index	The mean of the sum of patch areas for a particular land class divided by the closest edge-to-edge distance between a patch and the focal area of all patches of the same class within a specified distance.
	Clumpiness	The proportional deviation of the proportion of like adjacencies of forest cells from that expected under a completely random spatial distribution

4. Results

4.1. Land Cover Change

Land cover changes from 2000–2019 in the case study states are shown in Figure 5.

4.2. Fragmentation Metrics

Figure 6 shows percentage changes in fragmentation metrics in each municipality between 2000 and 2019. The values for Lucas de Rio Verde municipality do not appear to follow a trend with the other three, as very little forested land was lost overall in this municipality over the time period under study. This municipality can be taken as a control value to show that there is very little change expected in fragmentation metrics if land cover change is minimal.
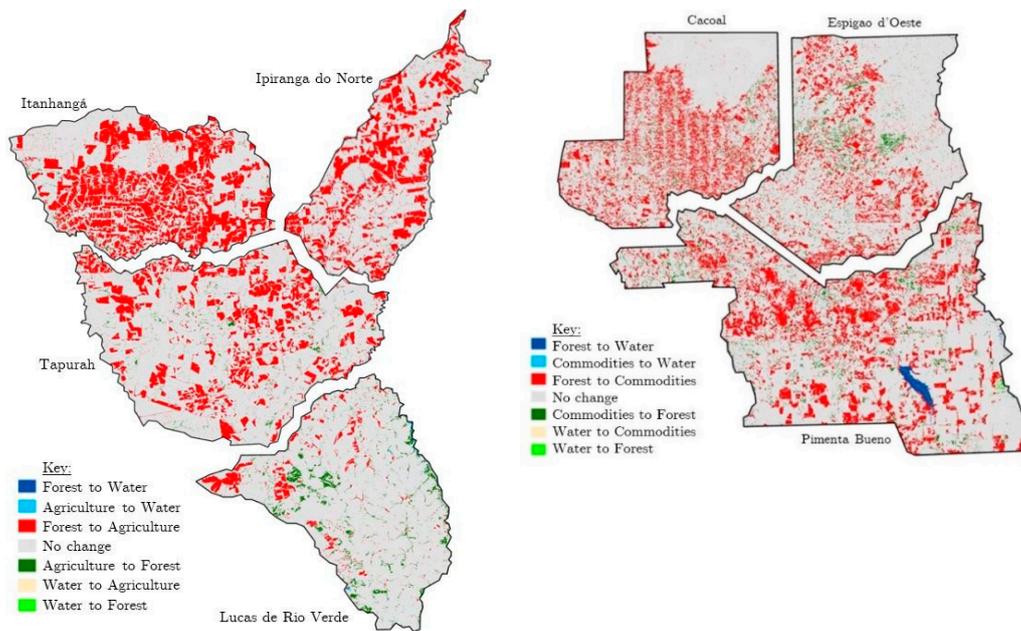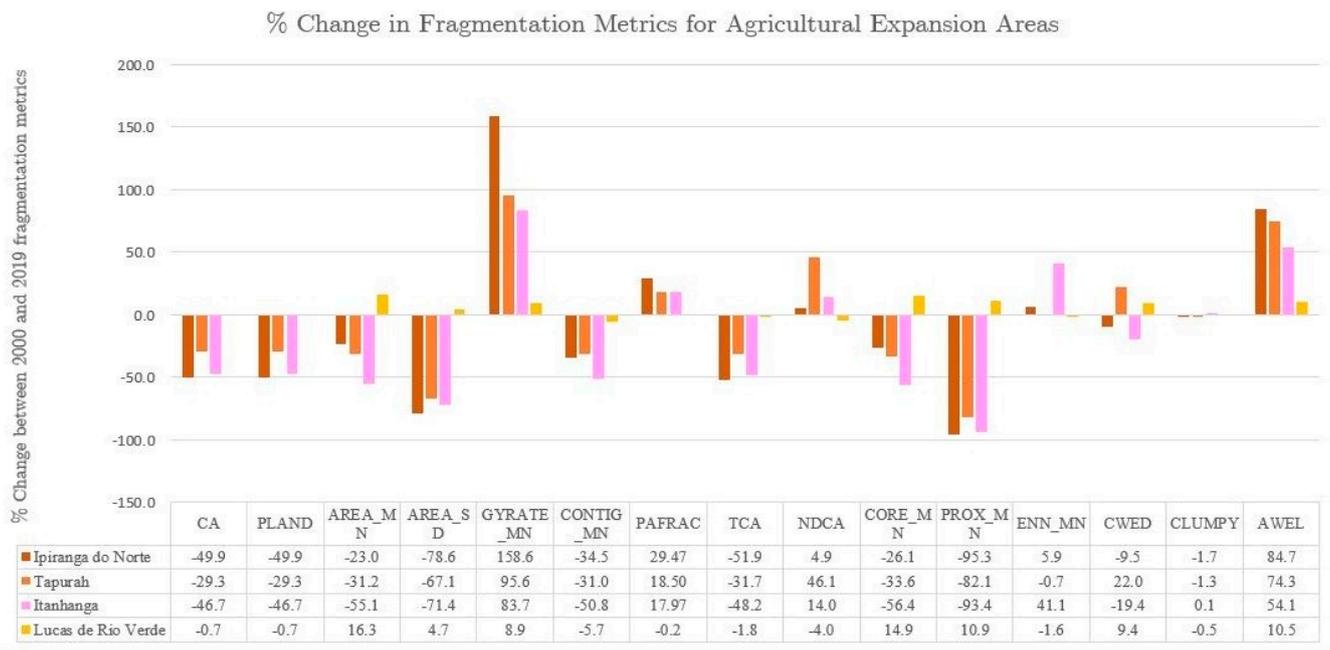
Figure 5. Land cover change 2000–2019 in seven municipalities—4 in Mato Grosso and 3 in Rondônia.

% Change in Fragmentation Metrics for Agricultural Expansion Areas

	CA	PLAND	AREA_MN	AREA_SD	GYRATE_MN	CONTIG_MN	PAFRAC	TCA	NDCA	CORE_MN	PROX_MN	ENN_MN	CWED	CLUMPY	AWEL
Ipiranga do Norte	-49.9	-49.9	-23.0	-78.6	158.6	-34.5	29.47	-51.9	4.9	-26.1	-95.3	5.9	-9.5	-1.7	84.7
Tapurah	-29.3	-29.3	-31.2	-67.1	95.6	-31.0	18.50	-31.7	46.1	-33.6	-82.1	-0.7	22.0	-1.3	74.3
Itanhanga	-46.7	-46.7	-55.1	-71.4	83.7	-50.8	17.97	-48.2	14.0	-56.4	-93.4	41.1	-19.4	0.1	54.1
Lucas de Rio Verde	-0.7	-0.7	16.3	4.7	8.9	-5.7	-0.2	-1.8	-4.0	14.9	10.9	-1.6	9.4	-0.5	10.5

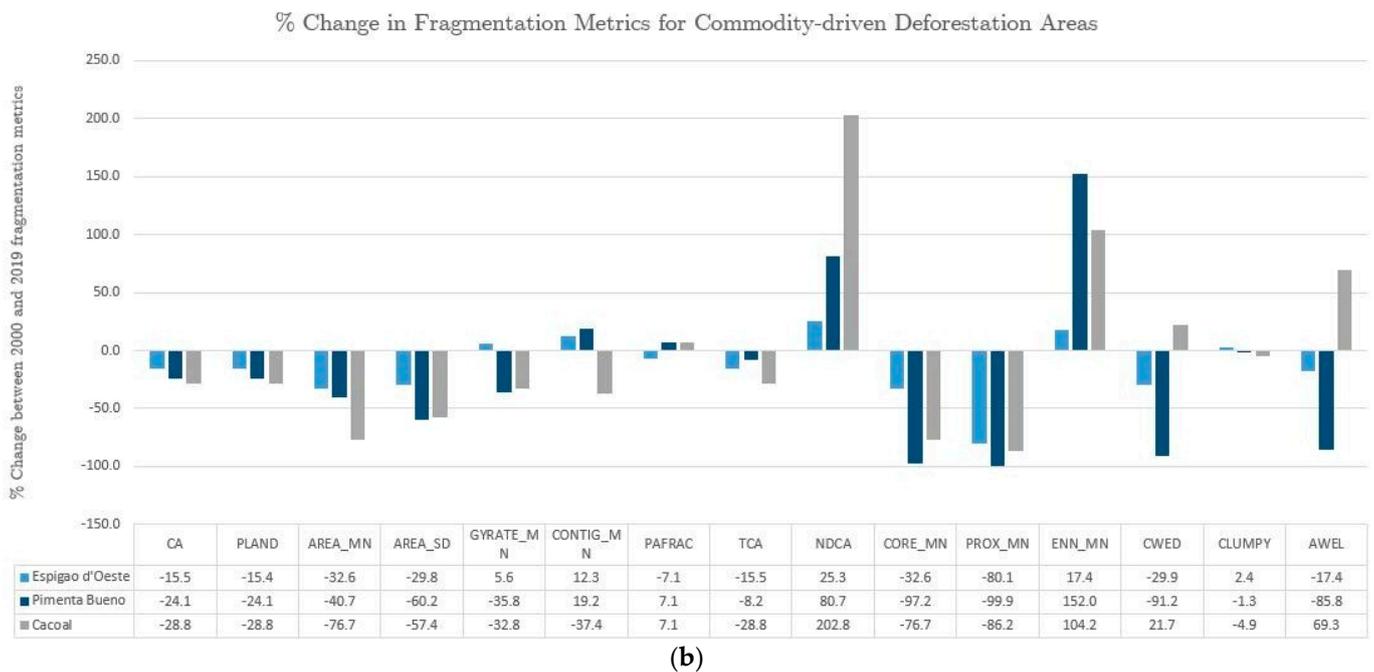(**a**)

Figure 6. *Cont.*

(**b**)

Figure 6. (**a**) A bar chart showing the percentage change in fragmentation metrics for agricultural expansion areas, with the following abbreviations: Total (Class) Area: CA, Percentage of Landscape: PLAND, Mean Patch Area: Area_MN, Standard Deviation of Patch Area: AREA_SD, Mean Radius of Gyration: GYRATE_MN, Mean Contiguity Index: CONTIG_MN, Perimeter-Area Fractal Dimension: PAFRAC, Total Core Area: TCA, Number of Disjunct Core Areas: NDCA, Mean Patch Core Area: CORE_MN, Mean Proximity Index: PROX_MN, Mean Euclidean Nearest Neighbour Distance: ENN_MN, Contrast-Weighted Edge Density: CWED, Clumpiness Index: CLUMPY, Area-Weighted Edge Length: AWEL. (**b**) A bar chart showing the percentage change in fragmentation metrics for commodity-driven deforestation areas.

5. Species Impacts from Different Fragmentation Drivers

5.1. Analysis of Agricultural Expansion Metrics

Several of the metrics appeared to show very little trend, such as "perimeter-area fractal dimension", "non-disjunct core area", "mean Euclidean nearest- neighbour distance", "contrast-weighted edge density", "clumpiness" and "connectivity".

There were nine, however, which appeared to show correlation. Of these nine metrics, the type of fragmentation characteristic they represent, and their direction of change are shown in Table 3. Of the groups of fragmentation characteristic types only "Contrast" is not represented in the list of correlated metrics even though contrast metrics were measured. This is because there was insufficient variety of large-area land cover types to merit any great impact, as almost the entire area is taken up by forest and agricultural land.

5.2. Analysis of Commodity-Driven Deforestation Metrics

Several of the metrics for areas which underwent commodity-driven deforestation appeared to show very little trend, such as "perimeter-area fractal dimension", "clumpiness" and "connectivity". There were seven metrics, however, which appeared to show correlation. Of these, the type of fragmentation characteristic they represent and their direction of change are shown in Table 3. "Edge", "Shape" and "Contrast" are not represented.

5.3. Comparison of Metrics Associated with Different Drivers

5.3.1. Area Metrics

In terms of "total area" and "percentage of landscape", all agricultural expansion (AE) and commodity-driven deforestation (CDD) municipalities lost a substantial amount of area. The area which experienced the highest level of total forest area change was Ipiranga do Norte, which lost 49.9% of forest cover over the 19 years of study (for a land cover

map of Ipiranga do Norte showing forest loss over 19 years of study see Figure S9). This area also experienced the greatest decrease in "standard deviation of mean patch area" in forests. This signifies that, over the 19 years, patches tended towards having smaller variation in size, so becoming more similar in area.

Table 3. Correlated metrics of change for different fragmentation drivers.

Fragmentation Driver	Metric	Group	Direction of Change
Agricultural Expansion	Total Area	Area	Decreasing
	Mean Patch Area	Area	Decreasing
	Standard Deviation of Patch Area	Area	Decreasing
	Mean Radius of Gyration	Shape	Increasing
	Mean Contiguity Index	Shape	Increasing
	Total Core Area	Core Area	Decreasing
	Mean Patch Core Area	Core Area	Decreasing
	Mean Proximity Index	Aggregation	Decreasing
	Weighted Edge Length	Edge	Increasing
Commodity-driven Deforestation	Total Area	Area	Decreasing
	Mean Patch Area	Area	Decreasing
	Standard Deviation of Patch Area	Area	Decreasing
	Number of disjunct core areas	Core Area	Increasing
	Mean Patch Core Area	Core Area	Decreasing
	Mean Proximity Index	Aggregation	Decreasing
	Euclidean Nearest Neighbour Distance	Aggregation	Increasing

The "mean forest patch area" also decreased drastically for both AE and CDD areas, with Cacoal being the municipality which experienced the greatest reduction (for an example of this reduction in mean forest area in the municipality of Cacoal, see Figure S10).

5.3.2. Edge Metrics

The "area-weighted edge length" changed quite dramatically for AE areas, but far less so for CDD municipalities. This means that, even accounting for the reduction in area in CDD states, the total amount of edge did not increase drastically. The municipality which experienced the greatest increase in "area-weighted edge length" was Ipiranga do Norte, at 84.7%. Whilst the total edge length was less in 2019 due to the drastic reduction in area, a relatively long edge length remained compared to the remaining area due to the long, thin shapes of forest left in the municipality (for a close-up land cover map of the municipality, see Figure S11).

5.3.3. Shape Metrics

As with "area-weighted edge length", the "mean radius of gyration" and "mean contiguity index" changed far more for AE areas than CDD areas. This can be explained as some edge and shape metrics are closely related. In AE areas, the "mean radius of gyration" increased greatly, which signifies that the mean distance between every cell in a forest patch and the patch centroid is increasing. This may at first seem confusing, as it could signify that the forest patches are getting larger. However, as the "mean forest patch area" in each municipality decreases whilst the "mean radius of gyration" increases, this is not the case. Instead, the patch shapes are becoming more complex. This coincides with the "area-weighted edge length" increase for AE municipalities, which also suggests that the forest patch shapes are deforming further from regular shape. Although the "perimeter area fractal dimension" did not change drastically, it is worth noting that it did increase more for AE areas, which demonstrates that forest patches in AE areas departed further from Euclidean geometry such as squares or circles.

The "mean contiguity index" also changed far more drastically in AE areas than in CDD areas. It decreased in each AE municipality, meaning that the spatial connected-

ness of cells within a moving window grid-cell patch decreased. This signifies increased encroachment of agricultural areas into forest patches.

5.3.4. Core Area Metrics

Although the "mean core area" of each forest patch decreased for both AE and CDD areas, the "total core area" of AE municipalities decreased far more than CDD ones. This coincides with the fact that AE municipalities experienced a greater change in edge and shape metrics (for an example of the decreasing total core and mean core area within forest patches in a close-up region of Itanhang´a, see Figure S12).

In contrast, in states which experienced commodity-driven deforestation, the "number of disjunct core areas" increased far more, but the "total core area" lost was not as large as in AE municipalities (for an example of the increase in the "number of disjunct core areas", see Figure S13).

5.3.5. Aggregation Metrics

The "mean proximity index", which considers how many neighbouring forest patches a focal patch has within a search radius, decreased significantly with both drivers. However, the "Euclidean nearest neighbour distance", which indicates the average distance between a forest patch and its closest neighbour, increased far more drastically for CDD areas than for AE areas (for an example of this in a close-up image of Pimenta Bueno, see Figure S14). This indicates that several forest patches disappeared entirely for each driver, but that in CDD areas it was more likely that forest patches would lose their close neighbours. The search radius used for the mean proximity index was 100 m. A similar pattern was displayed at search radii of 20, 50, 100, 500, 1000 and 10,000 m, but 100 m was chosen as the most useful distance to represent a species crossing between two patches.

The "clumpiness" metric did not change drastically with either driver. "Clumpiness" indicates the level of aggregation of a class. It does so by using the adjacency matrix, which demonstrates the frequency with which different pairs of patch types appear side-by-side on the map. In the case study areas the majority of the landscape is either forest or agriculture in AE areas, or forest or commodity-driven deforested land in CDD areas, so it would have been very surprising if this metric had changed drastically.

5.3.6. Contrast Metrics

The "contrast weighted edge density" did not change greatly for either AE or CDD areas, as there was not a wide enough variety of large-area land cover types in any municipality to merit any great impact. This may not have been the case in other municipalities or if a greater number of land use types, such as different types of forests, wetlands, grasslands, etc., had been used, so demonstrates a shortcoming in the selected areas.

As neither AE nor CDD areas were strongly affected by contrast metrics, there is little that can be deduced here about the effects of changing contrast on forest species in AE and CDD areas.

5.4. Fragmentation Effects on Species

Although there is no comprehensive set of traits which can fully describe the likelihood of species' survival upon fragmentation of its habitat, several studies have pointed to characteristics which experience noticeable effects. The five traits which are most likely to impact a species' response to habitat fragmentation are trophic level, dispersal ability, body size, niche breadth and rarity [32].

The International Union for Conservation of Nature (IUCN) Red List, [46]. has been filtered to show animals which are forest-dwelling and classified as either "endangered", "vulnerable" or "near threatened" in the states of Mato Grosso and Rondônia. Table 4 classifies each of these IUCN Red List species for Mato Grosso and Rondônia according to these traits.

Table 4. Classification of IUCN Red List species in case study areas according to key species traits which affect fragmentation response. ("MG"—Mato Grosso, "R"—Rondônia, "M"—Mammal, "I"—Insect, "V"—Vulnerable, "E"—Endangered, "NT"—Near threatened) Sources: [47–56].

Species	Area	Class	Trophic Level	Dispersal Ability	Size (kg)	Niche Breadth	Rarity
Giant armadillo	MG, R	M	Omnivore, few predators	Slightly dispersive	<30	Generalist, diverse range of habitats	V
Giant anteater	MG, R	M	Omnivore, few predators	Highly dispersive	<63	Generalist, but requires forested areas	V
White-cheeked spider monkey	MG	M	Omnivore, several predators	Slightly dispersive	<6	Specialist, preferring upper levels of primary rainforest canopy	E
Black-faced black spider monkey	MG, R	M	Frugivore, several predators	Highly dispersive	<10	Specialist to primary rainforest, does not utilise edge habitats	E
Spix's red-handed howler monkey	MG	M	Folivore or frugivore, few predators	Slightly dispersive	<8	Specialist, preference for dense forest	V
Bearded capuchin	MG	M	Omnivore, few predators	Highly dispersive males	<3.5	Generalist	NT
Cerrado Rhino Katydid	MG	I	Omnivore, many predators	Sedentary	<0.3	Specialist, adapted to hide in forests	NT
Golden-backed squirrel monkey	MG, R	M	Omnivore, few predators	Highly dispersive males	<1.3	Generalist	NT
Goeldi's spider monkey	R	M	Omnivore, many predators	Highly dispersive males	<0.6	Slight preference for dense vegetation	V
Perissolestes aculeatus	R	I	Carnivore, many predators	Sedentary	<0.1	Habitat specialist, requires freshwater in rainforests	V
Rondon's marmoset	R	M	Omnivore, few predators	Sedentary	<0.3	Generalist	V
Black-and-gold howler monkey	R	M	Folivore, very few predators	Slightly sedentary	<7	Slight preference for dense vegetation	NT
Black-headed marmoset	R	M	Omnivore, many predators	Highly dispersive	<0.5	Generalist	NT

5.4.1. Area Metrics Effects

It is well known that changing the available habitat area for forest-dwelling species will affect their survival viability. Larger areas to live in generally provide greater feeding opportunities, more chance of finding shelter and raising young safely and wider hunting grounds. However, decreasing forest fragment area has a greater effect on some species than others, as shown in Figure 2. This demonstrates that animals which are either top consumers, highly sedentary or dispersive, large, specialist or rare will be impacted more greatly by a reduction in forest fragment area.

The reasons that these species traits affect survival viability are varied. Although some studies have found little correlation between body size and fragmentation risk [31], a larger number claim that the effects of body size on response to fragmentation effects is significant [28,29,57]. Due to the fact that body size is generally correlated with needing larger areas of habitat in which to roam, larger animals are more susceptible to decreasing fragment area. Rare and specialist animals are also likely to be strongly negatively affected by decreasing area as it may disproportionately affect their smaller, specialist hunting grounds and already slim survival margins. Food webs are complex mechanisms so it is difficult to predict with accuracy the effect that a species' position in the trophic hierarchy will have on its response to fragmentation as there will be many exceptions. In general, however, studies have found that "consumer species at high trophic positions go extinct faster than smaller species at lower trophic levels, despite being superior dispersers" [30]. This is attributed to a "combined effect of higher biomass loss during dispersal with increasing habitat isolation. and the associated energy limitation in highly fragmented landscapes" [30].

As all area metrics changed similarly for both AE and CDD areas, these species will be strongly affected by both of these drivers. An example of a species which fits the description of being particularly at-risk is the giant anteater. Although it is a generalist

and can survive in other habitats, it still requires forested areas, has a high trophic level, is highly dispersive, large, and fairly rare.

5.4.2. Edge Metrics Effects

The forest edges were only strongly affected in AE areas, rather than CDD areas, as AE areas gained a far longer forest edge length given the area of forest remaining. Some species are far more sensitive than others to edge effects, the changing climatic conditions at the edges of their habitats. Figure 2 demonstrates that, whilst many species show little response to increased edge proximity, highly dispersive species are likely to demonstrate a negative response. This is because they are prone to travel long distances, so crossing many forest edges and entering other habitats is likely to put them more at risk than sedentary animals which will remain in forest habitats. Examples of highly dispersive species in Mato Grosso, an AE area, are giant anteaters, black-faced black spider monkeys, bearded capuchins and golden-backed squirrel monkeys.

5.4.3. Shape Metrics Effects

The shape metrics which demonstrated the most change were "mean radius of gyration" and "mean contiguity index", both of which only changed drastically in AE areas. As with species which show a negative response to edge proximity, the species trait which predicts the most negative response to increasing shape complexity is dispersal ability (Figure 2), with the same species identified in Section 5.4.2 at risk from this effect.

5.4.4. Core Area Metrics Effects

A species response to changing core area depends on its specialisation. Habitat specialisation is perhaps the biggest predictor of a species' response to fragmentation [32]. For species which are forest specialists, their difficulty with dispersal through a non-habitat matrix or with proximity to a forest edge can significantly reduce their chances of survival. Some species are highly averse to leaving core forest areas as they would be unlikely to survive in other habitats. In AE areas, the sharp decrease both in "total core area" and "mean core patch area" is therefore likely to have a strong negative effect on specialist creatures which require core forest areas in which to survive. In CDD areas, this study found a far greater increase in the number of disjunct core areas. Although the literature is less well-researched on this metric, it is generally agreed that this increase can have a "significant effect on population density and rate of spread" [58]. Examples of species which require core forest area to live in are white-cheeked spider monkeys, black-faced black spider monkeys, Spix's red-handed howler monkeys, cerrado rhino katydids and perisollestes aculeatus.

5.4.5. Aggregation Metrics Effects

The aggregation metrics which changed drastically in CDD areas were "mean proximity index" for both drivers, and "mean Euclidean nearest neighbour distance". Figure 2 indicates that the species most likely to be affected by this increasing isolation are top consumers, sedentary, small, specialist or rare. Small ground-dwelling animals are more affected as they are generally less able to travel further distances so cannot react well to increased isolation of patches. They therefore struggle more with moving between distant, isolated habitat patches. More sedentary animals also struggle, as if resources in their habitat patch run out it is harder for them to move to find food. Rare species have difficulty too, as under fragmentation conditions they are "at greater risk of extinction" [31]. An example of a species which will be strongly negatively affected from CDD areas in Rondˆonia is the black-and-gold howler monkey, which has few predators, is slightly sedentary, fairly small, rare and prefers dense vegetation.

6. Discussion

6.1. Fragmentation Characteristic Changes and Impacts

Several types of fragmentation metric appear to be correlated with specific fragmentation drivers for the municipalities studied. In areas which underwent agricultural expansion, there was a tendency for the total forest area and mean forest patch area to decrease, whilst the remaining forest patch shapes became less aggregated and more complex in shape. A large amount of core forest area was also lost. In areas which underwent commodity-driven deforestation, there was a similar tendency for total forest area and mean forest patch area to decrease, but no obvious tendency for the forest patch shapes to become more complex. There was a stronger likelihood that forest patches would be further apart in areas which saw a high level of commodity-driven deforestation, and a higher chance that the core areas would become disjunct (Table 5).

Fragmentation is by no means the only factor which will affect species viability in a particular place. Changes in hunting practices, changes in prey populations, and climatic changes will also have some effect. However, for the purpose of solely considering forest fragmentation and its effects on species viability, the approach described here can be utilised by forest managers to identify and protect particularly vulnerable species in areas experiencing fragmentation caused by a particular driver. For example, some species seem more likely to suffer adverse effects of forest fragmentation from particular drivers. Two examples, the giant anteater and the black-faced black spider monkey, are identified as at risk from three different changing metrics in areas of agricultural expansion. If confirmed by further studies, this information could be used to place both species in a higher category of vulnerability on the IUCN Red List, or as a basis from which to implement measures such as increasing the size of protected areas for these animals. This information could also be particularly useful if it is discovered that agricultural expansion is occurring in many forests where these at-risk species are present, as this would indicate that these species are at particularly high risk of becoming endangered or extinct.

The understanding of how different fragmentation drivers affect characteristics, which in turn affects different species types can have wide-ranging policy implications for governments. Examples of government incentives to maintain and enhance forests include schemes such as environmental taxation and Payment for Ecosystem Services (PES). There is already evidence from Mexico that PES schemes have helped to reduce forest fragmentation, where it was found that "low-PES areas increased twice as much the number of forest patches (and) forest edge" [59], which are both signs of fragmentation. One successful example of a PES scheme is the "Reducing Emissions from Deforestation and Degradation" (REDD+) scheme, in which entities including companies and forest owners in developing nations are rewarded financially for maintaining their forests [60]. An extension to such a scheme could result from research such as this, whereby governments could include payments to directly discourage forest fragmentation which would be harmful to critically endangered species. This knowledge can also inform government decisions on large-scale ecosystem management, by informing bans on logging or agricultural conversion in land which would have a strongly negative impact on critical species.

Table 5. Summary of the fragmentation effects, impacted metrics, influencing traits and example species impacted in areas which underwent agricultural expansion (AE) ad commodity driven deforestation (CDD).

	Driver—Agricultural Expansion			Driver—Commodity-Driven Deforestation		
Effects	Significant Fragmentation Metrics	Specific Traits Influenced	Examples of Impacted Species	Significant Fragmentation Metrics	Specific Traits Influenced	Examples of Impacted Species
Area	Total area, Mean patch area, Standard deviation of mean path area	Trophic level, Dispersal ability, Body size, Niche breadth, Rarity	Giant anteater	Total area, Mean patch area, Standard deviation of mean patch area	Trophic level, Dispersal ability, Body size, Niche breadth, Rarity	Giant anteater
Edge	Area-weighted edge length	Dispersal ability	Giant anteaters, Black-faced black spider monkey, Bearded capuchin, Golden-backed squirrel monkey	N/A	N/A	N/A
Shape	Mean radius of gyration, Mean contiguity index	Dispersal ability	Giant anteaters, Black-faced black spider monkey, Bearded capuchin, Golden-backed squirrel monkey	N/A	N/A	N/A
Isolation	Mean proximity index	N/A	N/A	Mean proximity index, Euclidean nearest neighbour distance	Trophic level, Dispersal ability, Body size, Niche breadth, Rarity	Black-and-gold howler monkey
Core area	Total core area, Mean patch core area	Niche breadth	White-cheeked spider monkey, Black-faced black spider monkeys, Spix's red-handed howler monkeys, Cerrado rhino katydid	Number of disjunct core areas, Mean patch core area	Niche breadth	Perisollestes aculeatus, Black-faced black spider monkey

6.2. Limitations

Whilst this does cover a relatively large geographical area in total, of approximately 30,000 km^2, it is still confined to two states within a single country. By controlling the location and elevation of each municipality, it was easier to attribute changes in forest shapes to the driver under study rather than other factors. However, it is not possible to say from this analysis that agricultural expansion creates the same geometric shape change in forests in Brazil as in any other country. It is also difficult to say whether this choice of scale has an important impact on results. It would also be useful to explore further which of the measured metrics are dependent on each other, as it has been shown that many fragmentation metrics are not independent [61].

Landsat-8 provides a spatial resolution of 30 metres. Other satellites vary in spatial resolution, with some such as Google Earth providing a higher resolution which may offer more nuanced analysis. To classify the satellite imagery into land cover categories, ArcGIS' the unsupervised classification tool was used but this has limitations in that it is difficult to know how many classes should be input for the software to split the image into. This was overcome by trial and error, setting several different levels and arriving at 30 as a number of classes which contained enough information to provide a high enough classification accuracy consistently. Supervised classification in which the user inputs specific areas for each class may have produced improved results but was rejected as being far more labour intensive and difficult to judge when enough information samples have been input.

In the accuracy assessments, very little information is available on an appropriate number of accuracy points to use, so the chosen number of 110 was a compromise as, although some of the literature recommends a higher number [62], this requires a more intensive time commitment.

Similar analysis of key drivers in other locations would help confirm the notion that specific fragmentation drivers cause specific characteristics, regardless of country location. Additionally, the methodology developed here could be applied to other fragmentation drivers such as wildfires and urbanisation, to understand if these too appear to cause specific fragmentation patterns. Further studies could be extended by using historical empirical species data and back-casting to see if the predicted effects of fragmentation characteristics are correct.

A final limitation of this study relates to the difference between habitat loss and fragmentation. It is suggested that "the term "fragmentation" should be reserved for the breaking apart of habitat, independent of habitat loss" [63]. This study [63] concludes that "the breaking apart of habitat, independent of habitat loss, has rather weak effects on biodiversity". The research in this paper considered the total forest habitat lost within each municipality, but did not separate it from other fragmentation effects. This is a limitation, and it is recommended that future studies attempt to separate the effects of the two.

7. Conclusions

The significance of this paper lies in the linking of fragmentation drivers, characteristics, and effects on species with different traits. The paper has shown two different fragmentation drivers did exhibit different characteristics for the case study municipalities, and that these could be linked to their effects on at risk forest-dwelling species. This provided a greater understanding of the links joining particular fragmentation drivers with their characteristics and their effects on forest species. The results demonstrate that agricultural expansion and commodity-driven deforestation cause different fragmentation characteristics and have different effects on resident forest species. This information can be used by a variety of different forest owners and those involved in forest management. In particular, if a forest is becoming fragmented by a single driver, such as agricultural expansion, this knowledge can be used to help forest managers predict how the shape of the forest will change before it happens, and therefore which animals will require protection and additional support to continue living there. It can also be used by governments in countries which are experiencing a high level of a particular driver to understand how their resident forest species are likely to be affected. This will inform the government which species may require measures such as protected areas or hunting bans.

Forest management can range from single- owner forests which may be impacted on a small-scale by fragmentation drivers, to national-level forests which require an overview of fragmentation. This type of study can be used in forest management plans as it can predict the type of fragmentation that a forest is likely to experience given certain drivers and therefore help forest owners to mitigate negative effects through replanting or creating protected areas in which deforestation is illegal.

Similarly, this approach may be useful for creators of endangered species lists such as the IUCN. It could be used to predict which species need to be put on a "watch" list, as they may be in danger of increasing threat due to fragmentation. This can in turn be used by forest managers to reintroduce or provide better protection for these species.

Supplementary Materials: The following are available online at https://www.mdpi.com/2071-1050/13/6/3246/s1, Figure S1: A time-lapse of forest fragmentation in northern Alberta, showing forest being slowly overtaken by agricultural and urban land in 1949, 1964, 1982 and 1991, Figure S2: A pictorial representation of the difference between the patch-matrix and gradient surface models, Figure S3. Graphs depicting common generalisations about species responses to fragmentation of their habitats, Figure S4. A map of regional tree cover loss by driver between 2001 and 2015, Figure S5. A flow diagram of the steps taken in this study to derive fragmentation information, with relevant software, Figure S6. Tree cover loss by dominant driver in Brazil, Figure S7. An example clip of the municipality of Tapurah from a Landsat scene Figure 2000, Figure S8. A difference map showing the land cover changes in Tapurah from years 2000 to 2019, Figure S9. A land cover map of the municipality of Ipiranga do Norte, which experienced the greatest loss of total forest area over the 19 years of study, Figure S10. A close-up land cover map of the municipality of Cacoal,

which experienced the greatest reduction in mean forest patch area. Figure S11. A close-up land cover map of the municipality of Ipiranga do Norte, which experienced the greatest in-crease in area-weighted edge length, Figure S12: A close-up land cover map of the municipality of Itanhang´a. The top two images Scheme 2000. to 2019, whilst the bottom two show the same but with core forest area highlighted in dark green, Figure S13. A close-up land cover map of the municipality of Cacoal, demonstrating an increasing number of disjunct core areas, Figure S14. A close-up land cover map of the municipality of Pimenta Bueno, demonstrating, Table S1. An error matrix demonstrating the likelihood of incorrect classification for the Tapurah 2000 image, Table S2. A Land Cover Transition Matrix for the state of Tapurah between the years 2000 and 2019 showing the total land cover change between land types in km2. Each cell aij represents the total area which was class type i in 2000, and had transitioned to class type j by 2019. Total areas of each class type for the years 2000 and 2019 are provided in the far right column and bottom row respectively, Landscape models, Fragmentation Metrics, Structure versus Function.

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