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Scale-dependent patterns of deforestation in the Brazilian Amazon

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SUMMARY

Tropical forests of the Amazon Basin are being rapidly converted to agricultural land uses and fallow land, resulting in accelerating rates of forest loss in one of the world's most biodiverse ecoregions. This process has been extensively described and modelled, but as yet there has been no formal test of how the spatial patterns of deforested and fragmented areas change with the spatial scale of forest clearings. It was hypothesised that different land-use practices are driving small and large clearings, with small-scale cultivators often creating small, irregularly shaped clearings and large-scale ranchers and soy farmers creating larger, more regular-shaped clearings. To quantitatively test this hypothesis, Mandelbrot's theory of fractals was applied to deforested areas in the Brazilian Amazon to test for scale-invariance in deforestation patterns. The spatial pattern of deforestation differed between small and large clearings, with the former creating more complex landscapes and with a threshold occurring at *c.* 1200 ha in area. As a consequence, the sizes and shapes of forest clearings, and hence the relative vulnerability of the remaining forest to edge, area and isolation effects, may differ systematically between landscapes with different deforestation drivers. Further tests of this hypothesis are needed to assess its efficacy in other tropical landscapes and geographical locations.

Keywords: Amazon, deforestation, fractal dimension, landscape, scale, shape index, spatial pattern

INTRODUCTION

Tropical deforestation is a diverse phenomenon and is caused by a wide variety of processes that vary in space and time (Mertens & Lambin 1997; Geist & Lambin 2001; Rudel 2005). Deforestation varies considerably among (Rudel 2005) and within (Mertens & Lambin 1997) regions. In locations where deforestation is caused by a particular process, such as part of a deliberate resettlement scheme or for large-scale agriculture, distinctive spatial patterns can be seen in the landscape (Fig. 1*a*, *b*; Dale *et al.* 1994; Mertens & Lambin 1997; Geist & Lambin 2001). These differing patterns can be included in a single spatial model of deforestation by 'regionalizing' the model, so that different processes are modelled for different sections of the study area (Mertens & Lambin 2001).

However, such a region-specific approach has two shortcomings that restrict its applicability to real-world landscapes. First, deforested areas will accumulate in a landscape through time, resulting in a blurring of distinct spatial deforestation patterns as more and more cleared land begins to connect with itself (Fig. 1*c*). Second, in many areas multiple processes act on the same landscape (Geist & Lambin 2001; Rudel 2005), and hence their individual patterns can combine and mask each other, leaving behind a hybrid pattern of forest clearings (Fig. 1*d*). The net result of these two phenomena is a landscape with deforestation patterns that become less distinctive in space and time.

To realistically predict future deforestation patterns, modellers must be able to (1) accurately decompose the aggregated spatial pattern of a landscape into the component sub-patterns that comprise it, and (2) ascertain the underlying processes that generate each sub-pattern. One possible beginning point for determining the number and types of processes driving land-use change within a given landscape is to assess the degree to which spatial patterns are recreated at different scales, and to determine the spatial scales over which each process is dominating the landscape pattern. Probably the simplest way to test for scale-invariance in spatial patterns that arise from different deforestation processes is to use Mandelbrot's (1977) theory of fractals, to investigate the area-perimeter (*A*:*P*) relationship of deforested areas. Fractals can be described as patterns that are the same, or self-similar, at a range of spatial scales, meaning they will appear the same regardless of the magnification, or scale, at which they are observed. Mathematically, they are described as a power relationship (i.e. a linear fit when both axes are log-transformed) between the area and perimeter of a set of patches (Ferrarini *et al.* 2005).

The area-perimeter relationship characterizes a given set of shapes by the formula $P \sim \sqrt{A^D}$, where D (the slope of the log area versus log perimeter relationship) is a dimension reflecting the complexity of the shapes (Lovejoy 1982). The dimension D is bounded between the values of 1 (the dimension of a line) and 2 (the dimension of a plane). For regular sets of shapes such as circles and squares of varying area, D approaches 1, but for more complex shapes where the perimeter becomes contorted and doubles back on itself, D approaches a value of 2. If the value for D is constant across all scales, then the patterns of deforestation in the landscape

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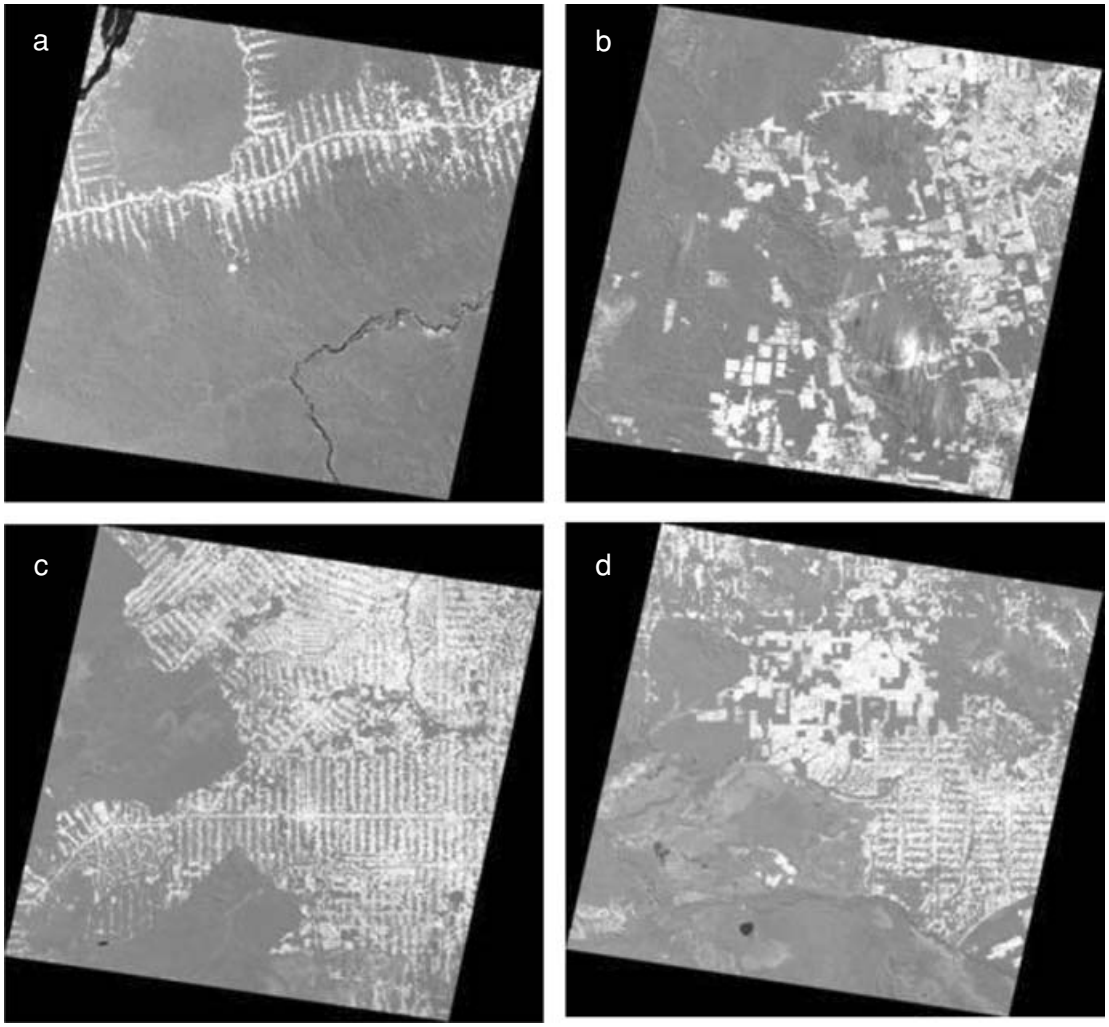


Figure 1 Spatial patterns of forest clearings in the Brazilian Amazon. Deforested areas are white, forest is shown in grey. (*a*) Fishbone pattern typical of deliberate colonization schemes composed of many very small clearings; (*b*) clearings for cattle ranching, which are much larger and more regularly shaped than those in (*a*); (*c*) the agglomeration of many small-scale clearings in a colonization scheme that occurs over time; and (*d*) a hybrid landscape, with clearings for cattle shown top-centre and a colonization scheme shown right-centre. All images are a single Landsat scene taken between 1999 and 2001, encompassing an area of 200 × 220 km.

are scale-invariant; that is, they are fractals. In contrast, if there are differing A:P relationships for clearings in different size ranges, then we can infer that there is a meaningful distinction between small- and large-scale patterns (Lovejoy 1982; Krummel *et al.* 1987).

Fractals are frequently used to assess the scaling features of landscape processes. Because they describe a scale-free, self-similar phenomenon (Mandelbrot 1983; DiBari 2004), observed changes in the fractal pattern suggest a reorganization of the processes that determine spatial patterns (Jorge & Garcia 1997; DiBari 2004; Grossi *et al.* 2004; Ferrarini *et al.* 2005). In other words, if a single process or set of processes was responsible for generating landscape patterns at all scales, we would expect to find scale-invariance in those patterns. This has been observed for many natural phenomena (Bolliger 2006), including natural patterns in forested landscapes (Sprott *et al.* 2002).

It follows, then, that a direct comparison of the fractal properties between predicted and observed landscapes will provide insights into the validity of a model of landscape change, in two ways. First, the comparison will suggest whether the generated patterns match the observed patterns in the landscape. Second, and even more importantly, it provides a clue as to whether differences between the model and reality are the result of scaling issues. For instance, some models of land-use change in the Brazilian Amazon have focused on small-scale landscape changes by individual landowners (for example Walker *et al.* 2004 modelled deforestation across a 6000 km^2 area), whereas others have focused on land-use change at very large spatial scales in response to government policies (for example Laurance *et al.* 2001 modelled deforestation across the entire Brazilian Amazon, which is approximately 4 million km^2 in area). If different processes operate at these two very different spatial scales,

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then simple extrapolation of one land-use-change model to the spatial scale of the other would not produce similar results. In this situation, a comparison of fractal patterns would allow us to determine over which range of scales each of these models provides realistic predictions, and hence would help pave the way for combining the two modelling approaches to provide a multi-scale prediction of land-cover changes.

It is important to also recognize that there are several potential limitations of using the fractal dimension to characterize scale in landscape patterns and processes. First, analyses of landscape patterns can be sensitive to the spatial resolution of the data being used (Costanza & Maxwell 1994), with decreases in resolution (larger pixel size) having little effect on clumped land-cover features but resulting in the gradual loss of dispersed landscape features (Turner *et al*. 1989*a*). Analysis of land-cover data in Kansas showed that data varying in resolution from 30–1000 m retained the same underlying features of the landscape, including the fractal dimension (Griffith *et al*. 2000). However, it is still desirable to conduct any analysis of landscape patterns with comparable data at different spatial resolutions (Turner *et al*. 1989*b*) and different spatial scales (Turner *et al*. 1989*a*), to confirm that the scale of measurement is not driving the observed patterns.

Second, the fractal dimension is just one of many indices that have been used to describe the shape of landscape features (Riitters *et al*. 1995; Moser *et al*. 2002; Saura & Carballal 2004). Most of these indices are highly intercorrelated (Riitters *et al*. 1995; Saura & Carballal 2004), but they nonetheless can provide significantly different information about the landscape. For example, Saura and Carballal (2004) showed that the shape of native versus exotic forests differed in Spanish landscapes, but that the ability to detect this difference depended sensitively on the particular shape index being used. Similarly, Moser *et al*. (2002) showed that the relationship between plant species richness and fragment shape could be positive, negative or absent for the same dataset, depending on which shape index was chosen. Thus, for any analysis of landscape patterns it is not prudent to rely on a single landscape metric.

In this paper, we conduct what we believe is the first-ever investigation into the scaling properties of tropical deforestation patterns and processes. We apply Mandelbrot's theory of fractals to the Brazilian Amazon, test for non-linearities in the A:P relationship, and compare the result with a similar analysis based on a more general shape index. The results are interpreted based on knowledge of forest-clearance methods, and the types, sizes and production efficiency of different farming systems. The results of this study contribute an empirical base and insights needed for constructing and validating tropical deforestation models that seek to predict patterns of deforestation across multiple spatial scales.

METHODS

We assessed the fractal dimension of deforested areas using satellite-derived data for the entire Brazilian Amazon (after Laurance *et al*. 2002). Data on forest cover were primarily obtained from a forest/non-forest map of the Amazon, prepared from Landsat TM data taken in 1990–1991 as part of the NASA Landsat Pathfinder Project (Chomentowski *et al*. 1994). In locations where Landsat imagery were not available, the forest/non-forest map was supplemented with land-cover data from the Global Land 1-km AVHRR Project (Elvidge *et al*. 2001), which classified land cover from satellite imagery obtained in 1992–1993 (URL http://edcdaac.usgs.gov/1KM/1kmhomepage.asp; Hansen *et al*. 2000). Non-forested areas included both deforested lands and open vegetation (mostly *cerrado* savannah and open woodland; Laurance *et al*. 2002), which were discriminated by overlaying non-forested areas on a digital vegetation map based on the RADAMBRASIL project (derived from data obtained between 1970 and 1985, and discussed by Veloso *et al*. 1991), which was made available in digital format at a 1:2 500 000 scale (Instituto Brasileiro de Geografia e Estatística 1997). The digital vegetation map was converted to raster format and areas of open vegetation were subtracted from non-forested areas, leaving a Brazilian Amazon-wide map of deforested areas based on 1-km pixels (Laurance *et al*. 2002). It should be noted that deforested areas in these data represent cumulative, rather than instantaneous, deforestation. In other words, clearings are not necessarily created by a single deforestation event, but rather are the result of the accumulation of multiple events through the deforestation history of the Brazilian Amazon.

To ensure the rigour of our results, we conducted two sensitivity analyses. First, we repeated our analysis using an independent dataset derived from Landsat imagery to rule out the possibility that our results were an artefact of satellite resolution (Turner *et al*. 1989*b*; Costanza & Maxwell 1994). Data from AVHRR satellites have a 1-km resolution, whereas Landsat satellites have a much higher spatial resolution of just 30 m. Landsat-derived deforestation maps were not available for the entire basin, so we used 75 scenes covering an approximate 2 140 000 km^2 (42% of the Legal Amazon; Fig. 2) that are available through the Brazilian Space Agency's PRODES project (URL http://www.obt.inpe.br/prodes; Valeriano *et al*. 2004). The PRODES project resampled Landsat images to a 60-m resolution and classified land cover into five categories (Câmara *et al*. 2005; da Motta *et al*. 2005): total deforestation, recent deforestation (1 August 2002–1 August 2003), forest, water and cloud (areas that could not be classified owing to cloud cover). We used the total deforestation category, which is equivalent to the cumulative deforestation class of the AVHRR data. Importantly, the satellite images used in the PRODES project were interpreted digitally, removing any potential bias that may have existed in the 1-km dataset where the input images (*a*) differed in resolution and (*b*) were interpreted manually (Valeriano *et al*. 2004).

Second, we investigated the possibility that the scale or spatial extent (Turner *et al*. 1989*a*) of our study influenced

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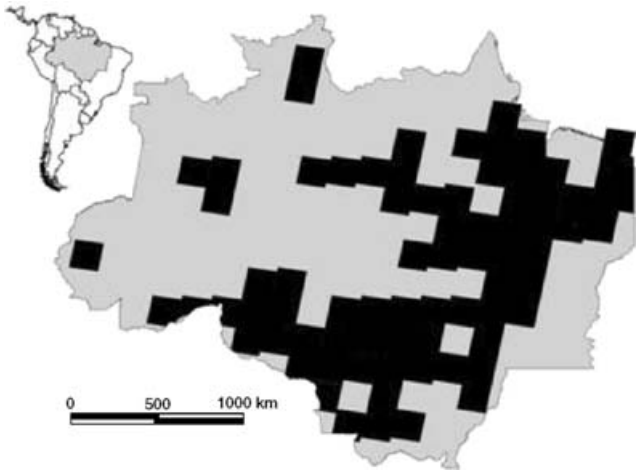


Figure 2 Availability of 2003 deforestation data (black areas) for the Brazilian Amazon (grey) from the PRODES project. The project encompasses 42% of the Legal Amazon region.

our results by repeating the analysis independently for each of the nine states within the Brazilian Amazon, which differ significantly in their deforestation histories. Furthermore, we repeated the analysis for a randomly selected sample of 30 municipalities (selected from a total of 762) from across the Basin, that also vary widely in extent, timing and causes of deforestation. Because deforested areas often crossed state and municipality boundaries, we analysed the full area and perimeter of all clearings that intersected the chosen political units. We did this to avoid the alteration of A:P ratio of cleared areas that would have occurred if the cleared areas were arbitrarily truncated at political boundaries.

For all deforested areas, the logarithm (base 10) of perimeter (m) was graphed against the logarithm of area (m^2), with the slope of the line representing D. Three models were fitted to these data and the Akaikie Information Criterion (AIC) was used to choose among them (Johnson & Omland 2004). First, we fitted a simple linear model, which is what would be predicted if deforestation patterns were scale-invariant. Second, we fitted a logarithmic model to test for gradual changes in D across scales. Finally, we fitted a piecewise regression model, which tests for abrupt changes in D that would represent thresholds between small- and large-scale patterns (after Grossi *et al.* 2004 and Ferrarini *et al.* 2005). All models were fitted in the non-linear regression module of Statistica 6.0 (StatSoft 2001).

Because the fractal dimension is just one of many indices available for quantifying the shape of landscape features (Saura & Carballal 2004), we also calculated the shape index (SI) of all clearings using the formula $SI = P/(200(\pi A)^{0.5})$ (after Patton 1975). The shape index measures deviation from circularity, with circles having values of 1.0 and more complex shapes (with higher P:A ratios) having progressively higher values. We assessed how the shape index varies with fragment area using piecewise regression.

RESULTS

All models were highly statistically significant because of the large sample sizes in this analysis ($p < 0.001$; $n = 91\,531$). Fractal dimension was best fitted by the piecewise regression model, with the Akaikie Information Criterion indicating that this model was over 99% likely to be the correct model out of the three tested (Table 1). The model showed a threshold in D at 12.04 km^2 (95% confidence interval [CI]: 11.82–12.27 km^2); D was highest for clearings less than this size ($n = 87\,050$) and lowest for larger clearings ($n = 4181$; Fig. 3). By comparison, there was also a clear non-linearity in the relationship between shape index and fragment area, but the threshold occurred at slightly smaller clearing sizes (11.06 km^2, 95% CI: 10.91–11.21 km^2).

The detected threshold in fractal dimension was robust to the potential confounding effects of satellite resolution, with the Landsat-derived PRODES data giving similar values to the AVHRR data ($n = 72\,644$; Table 2). Furthermore, estimates of D for all models were consistently around the values 1.2 and 1.8 for deforested areas above and below the threshold, respectively, regardless of whether the analysis was conducted at the scale of entire basin, state or municipality (Table 2). However, piecewise regression models could not be fitted to eight of the thirty randomly selected municipalities because of low sample sizes in the number of clearings (mean $n = 9$). For the 22 municipality models that were fitted, there was greater variation in the location of the threshold, with estimates ranging from 3.61–62.44 km^2 (Table 2). While this is a considerable amount of variation in absolute terms, it is still small relative to the range of sizes of deforested areas in the dataset (0.64–45 000 km^2).

For the municipal analyses, confidence intervals around the fractal-dimension threshold were reasonably consistent (*c.* 5–30 km^2 wide) for all but four municipalities (Conceicao da Lago-Acu, Guarai, Novo Jardim and Presidente Medici), which each had confidence intervals of >50 km^2 that probably resulted from relatively small sample sizes ($n = 45$, 73, 30 and 31 clearings, respectively, compared to an overall average n of 179 for all municipalities). Confidence intervals were notably lower around the threshold estimates at the whole-basin and state levels (1–2 km^2), reflecting the much higher precision associated with the larger sample sizes at these scales.

Table 1 Results of selection by Akaikie Information Criterion (AIC) among the three tested models of the area-perimeter relationship for deforested areas. SS_{res} represents the residual sums of squares for the models, ΔAIC the difference between a model's AIC value and the best AIC value of the three models, and W the probability of that particular model being the correct model from the three that were tested.

Model	SS_{res}	*AIC*	Δ *AIC*	*W*
Linear	539	−469 985	48 008	<0.01
Logarithmic	344	−511 091	6902	<0.01
Piecewise	319	−517 993	0	>0.99

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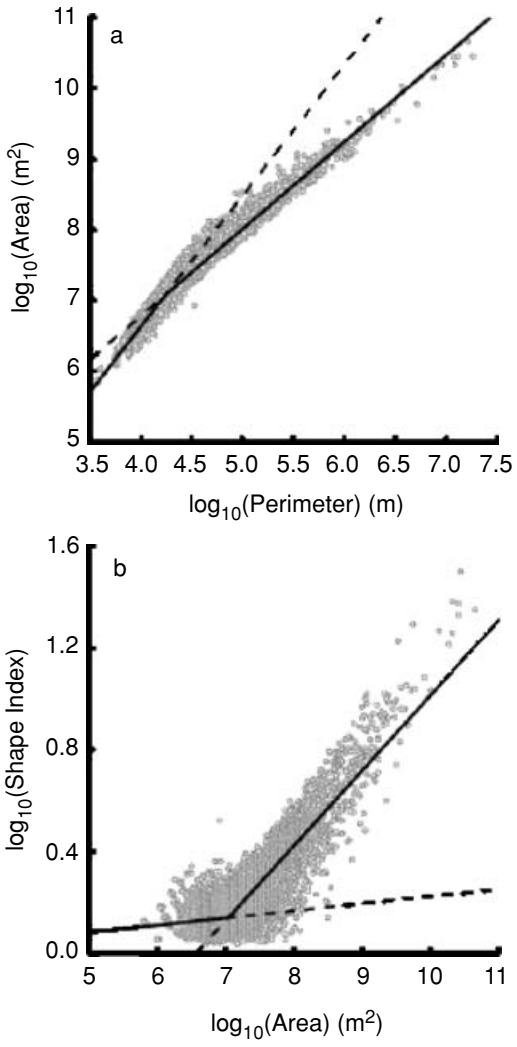


Figure 3 Area versus perimeter and shape-index values of deforested sites in the Brazilian Amazon. (*a*) The difference in fractal dimension between small and large clearings. The fitted curve (solid line) was selected using the Akaikie Information Criterion from three models and shows a significant change in slope at area = 12.04 km^2 (model parameters in Table 2). (*b*) Relationship between the area and shape index of deforested sites, showing a significant change in slope at area = 11.06 km^2. Dashed lines show continuations of the separate regression lines from above and below the threshold.

DISCUSSION

The AVHRR dataset used in this analysis shows that many more small than large forest clearings have been created in the Brazilian Amazon, but that the latter have destroyed much more forest (65 000 versus 3.61 million km^2). The direct effects of habitat loss evidently outweigh those of habitat fragmentation and edge creation (Fahrig 2003), indicating that large-scale deforestation poses a larger and more direct challenge to the long-term conservation of Brazilian species and ecosystems than small-scale clearings. Across the Brazilian Amazon, large-scale clearings are almost unanimously attributed to the dramatic expansion of cattle ranching (Mertens *et al.* 2002; Fearnside 2005), which is sometimes displaced and pushed further into the Amazonian frontier by the burgeoning soybean industry (Fearnside 2001; Brown *et al.* 2005). Although large clearings are the main cause of large-scale deforestation, one findings suggest that small clearings can also have important ecological impacts as they can cause severe forest fragmentation and create disproportionately large amounts of edge-affected habitat.

Significant non-linearities exist in the spatial patterns of deforestation in the Brazilian Amazon. The fractal dimension of cleared areas below *c.* 12 km^2 is higher than for larger clearings, indicating that small clearings result in a more complex landscape, with more-irregular edge and fragment shapes. By contrast, the slope of the relationship between the shape index and clearing area is positive, indicating that large clearings have more convoluted shapes. Superficially, these results appear contradictory, but can be reconciled by considering the difference between the two metrics. The shape index is a measure of the shape complexity of individual forest clearings, whereas the fractal dimension assesses the slope of the *P*:*A* ratio across many clearings. Hence, the fractal dimension is an index of landscape, rather than patch, complexity. Thus, the two metrics provide different, yet complementary, information. They indicate that the shape complexity of individual clearings increases with the size of clearings, and that this relationship is most pronounced for large clearings. However, at the landscape scale, large clearings create a more uniform landscape that is dominated by long, straight lines, unlike landscapes with small clearings. Overall, many small and relatively compact-shaped clearings within a given region combine to create a landscape that is more spatially complex than one that is dominated by a few large irregularly-shaped clearings.

Different deforestation processes have been shown to leave distinctive footprints in the spatial structure of cleared areas (Fig. 1; Geist & Lambin 2001; Cochrane & Laurance 2002), so differences in the *P*:*A* ratios between large and small cleared areas strongly suggest that the methods of deforestation differ at these scales, for which we offer two possible explanations. First, small clearings are most likely to be deforested by hand or by using simple cheap technology, such as chainsaws. As a result, these clearings are likely to reflect small-scale variations in topography and soil conditions as the farmer tries simultaneously to reduce the effort required to clear the land, while selectively clearing forest on soils that will provide the best possible agricultural returns. Small-scale farmers also tend to clear land incrementally, slashing and burning 1–2 hectares of primary forest each year as previously cultivated areas become fallow owing to the poor nutrient status of most Amazonian soils (Brown 1987; Chauvel *et al.* 1987). In contrast, large clearings, which are generally associated with large cattle ranches and industrial soybean farms, are more likely to be created using heavy machinery such as bulldozers. The large-scale clearing process is probably less affected by

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Table 2 Model parameters (with 95% confidence intervals) for piecewise regressions on the area-perimeter relationship for deforested areas in Brazilian Amazonia. Models were tested at two data resolutions (AVHRR with 1-km resolution and Landsat-derived PRODES data with 60-m resolution) and three spatial scales (whole basin, state and municipality). The Landsat PRODES data covers a non-contiguous subset of 42% of the Amazon Basin only. D_1 and D_2 represent the fractal dimension of deforested areas above and below the threshold, which is the clearing size (km^2) that divides small- from large-scale patterns. Models could not be fitted to eight Amazonian municipalities because of small sample sizes (Benevides, Castanhal, Igarape do Meio, Jurua, Lago da Pedra, Mirassol D'Oeste, Sao Joao do Soter and Sao Jose do Povo).

	Intercept	*D_1*	*Threshold (km^2)*	*D_2*
Whole basin				
AVHHR	−0.76 (−0.77, −0.75)	1.85 (1.85, 1.85)	12.05 (11.83, 12.42)	1.23 (1.22, 1.23)
Landsat PRODES	0.01 (−0.01, 0.02)	1.58 (1.57, 1.58)	10.82 (9.82, 12.86)	1.21 (1.19, 1.22)
State				
Acre	−0.70 (−0.75, −0.64)	1.83 (1.81, 1.84)	17.38 (15.25, 21.54)	1.17 (1.13, 1.21)
Amapa	−0.76 (−0.80, −0.71)	1.85 (1.83, 1.86)	15.17 (13.64, 18.10)	1.22 (1.20, 1.25)
Amazonas	−0.79 (−0.82, −0.77)	1.86 (1.85, 1.87)	7.62 (7.26, 8.27)	1.28 (1.27, 1.30)
Maranhao	−0.79 (−0.82, −0.76)	1.86 (1.85, 1.86)	10.18 (9.64, 11.14)	1.23 (1.21, 1.24)
Mato Grosso	−0.77 (−0.79, −0.76)	1.85 (1.85, 1.86)	17.97 (17.32, 19.08)	1.19 (1.18, 1.19)
Para	−0.74 (−0.76, −0.72)	1.84 (1.84, 1.85)	12.29 (11.87, 13.01)	1.19 (1.19, 1.20)
Rondonia	−0.72 (−0.75, −0.68)	1.83 (1.83, 1.84)	11.49 (10.83, 12.67)	1.19 (1.18, 1.21)
Roraima	−0.85 (−0.89, −0.80)	1.87 (1.86, 1.88)	7.89 (7.25, 9.12)	1.31 (1.30, 1.33)
Tocantins	−0.76 (−0.79, −0.73)	1.85 (1.84, 1.86)	11.73 (11.02, 13.02)	1.22 (1.21, 1.24)
Municipality				
Alvaraes	−1.11 (−1.49, −0.72)	1.95 (1.84, 2.05)	7.53 (3.27, 31.40)	1.39 (1.01, 1.77)
Careiro	−0.99 (−1.25, −0.72)	1.92 (1.84, 1.99)	5.41 (3.94, 9.10)	1.25 (1.18, 1.32)
Claudia	−1.05 (−1.32, −0.77)	1.93 (1.85, 2.00)	15.83 (10.21, 31.96)	1.17 (0.92, 1.41)
Conceicao do Lago-Acu	−0.26 (−0.88, 0.36)	1.72 (1.55, 1.88)	10.50 (3.62, 64.91)	1.22 (1.16, 1.28)
Divinopolis do Tocantins	−1.05 (−1.69, −0.40)	1.93 (1.75, 2.11)	4.03 (2.36, 9.70)	1.25 (1.21, 1.30)
Grajau	−0.89 (−1.04, −0.75)	1.89 (1.85, 1.92)	9.59 (7.65, 13.96)	1.24 (1.18, 1.30)
Guarai	−0.78 (−0.97, −0.60)	1.85 (1.80, 1.90)	47.76 (25.12, 132.51)	1.09 (1.03, 1.15)
Normandia	−1.16 (−1.37, −0.94)	1.95 (1.89, 2.01)	8.07 (5.44, 15.53)	1.28 (1.18, 1.38)
Novo Jardim	−1.16 (−1.84, −0.49)	1.96 (1.77, 2.14)	62.44 (20.96, 328.55)	1.02 (0.88, 1.16)
Paranatinga	−0.80 (−0.87, −0.72)	1.86 (1.84, 1.88)	26.07 (21.69, 34.97)	1.10 (1.07, 1.14)
Pindorama do Tocantins	−0.63 (−0.90, −0.36)	1.81 (1.74, 1.88)	14.97 (7.89, 43.51)	1.20 (1.13, 1.27)
Pium	−0.54 (−0.68, −0.40)	1.79 (1.75, 1.83)	16.71 (12.26, 27.94)	1.18 (1.14, 1.22)
Presidente Medici	−0.71 (−1.19, −0.23)	1.84 (1.71, 1.97)	16.82 (1.14, 1162.62)	1.06 (0.81, 1.30)
Santana	−0.42 (−0.72, −0.12)	1.76 (1.68, 1.84)	21.58 (10.76, 67.95)	1.14 (0.97, 1.30)
Sao Miguel do Tocantins	−0.74 (−1.40, −0.08)	1.85 (1.67, 2.02)	10.77 (4.34, 47.22)	1.16 (1.08, 1.23)
Sao Salvador do Tocantins	−0.75 (−1.03, −0.47)	1.85 (1.77, 1.92)	8.79 (6.04, 16.28)	1.19 (1.12, 1.25)
Sao Sebastiao do Uatuma	−1.12 (−1.58, −0.67)	1.96 (1.83, 2.08)	3.61 (2.17, 8.40)	1.29 (1.15, 1.43)
Sena Madureira	−0.56 (−0.71, −0.42)	1.79 (1.75, 1.83)	8.69 (4.94, 23.28)	1.34 (1.24, 1.43)
Taituba	−0.88 (−0.97, −0.79)	1.88 (1.85, 1.90)	9.64 (8.03, 13.03)	1.23 (1.18, 1.27)
Terra Santa	−0.69 (−1.13, −0.25)	1.83 (1.71, 1.95)	7.70 (4.43, 19.20)	1.19 (1.10, 1.28)
Vargem Grande	−0.75 (−1.40, −0.10)	1.84 (1.67, 2.02)	6.72 (2.81, 28.67)	1.23 (1.14, 1.31)
Vera	−0.75 (−0.92, −0.57)	1.84 (1.80, 1.89)	15.18 (10.44, 28.15)	1.20 (1.11, 1.29)

small-scale variations in topography and soil conditions and more affected by long, linear boundaries between adjacent, large-scale properties. In essence, then, a difference in the availability or affordability of technology between small- and large-scale farming operations may explain much of the difference in spatial patterns.

This hypothesis is, in part, supported by recent models indicating that farms in the Brazilian Amazon are least efficient at sizes of *c.* 10 km^2 (Helfand & Levine 2005). Below this threshold, more human labour is needed to increase the production efficiency of farming operations (calculated as actual production relative to 'best-practice' production; Helfand & Levine 2005), whereas the same gains in efficiency are obtained on larger farms by obtaining machinery that substitutes for human labour. Similarly, in a meta-analysis of tropical deforestation processes, Geist and Lambin (2001) argued that large-scale forest clearings are usually the result of mechanized large-scale commercial farming operations that make effective use of modern technology.

A second reason for landscapes with small clearings to have relatively complex shapes results from the cumulative nature of deforestation data in the AVHHR imagery, which combines separate deforestation events through time into single clearings. The cumulative effect of large numbers of small farms creates inherently more-complex boundaries, because the property boundaries are juxtaposed in a more haphazard manner than are the more regular geometries of larger properties (Mertens & Lambin 1997; Geist & Lambin

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2001). Thus, the spatial patterns of cleared areas on adjacent small properties are also necessarily convoluted, leading, for example, to the spatially complex 'fishbone' pattern of deforestation that arises from government-sponsored colonization projects, in which hundreds of small-scale farmers are settled in forests along a series of parallel and transverse roads (Fig. 1*a*; Dale & Pearson 1997; Laurance *et al.* 1998; Geist & Lambin 2001). As a consequence, the accumulation of multiple small-scale deforestation events will lead to more complex spatial patterns than does the accumulation of multiple large-scale events.

Meta-analyses of tropical deforestation have shown that the specific processes driving deforestation vary widely among tropical regions (Geist & Lambin 2001; Rudel 2005). However, the spatial patterns that result from these processes are much less varied, with just six major patterns identified (geometric, corridor, fishbone, diffuse, patchy and island; Mertens & Lambin 1997). We suggest that these six patterns can be further simplified to those that are caused by small- or large-scale processes. This is because, at the heart of deforestation issues, two groups of land-users are consistently identified: (1) smallholder cultivators, including settlers and traditional farmers (Myers 1991), and (2) industrial farmers or plantation owners. These two groups differ in terms of their specific characteristics among regions, but their impacts are similar. For instance, many small-scale agriculturalists in Central America farm coffee, but in West Africa the dominant crop is cocoa. Similarly, industrial agriculture in the Brazilian Amazon consists largely of soybean farms and cattle ranches, but in Indonesia it is dominated by oil-palm plantations (Rudel 2005). Despite these regional variations in crop types, there remains a crucial distinction between the mechanized and non-mechanized forms of agriculture that we believe transcends regional differences in crops, and gives rise to a similar distinction between small- and large-scale clearings that should be detectable across the tropics. Future studies could consider this question explicitly by comparing the patterns observed in this study with those from other tropical landscapes and in other geographical locations where deforestation is ongoing.

Fractals are commonly used to assess the spatial development of landscape patterns (see Sprott *et al.* 2002; Bolliger *et al.* 2003; DiBari 2004; Martin & Church 2004; Bolliger 2006). Furthermore, they are also used to compare the results of landscape simulations against observed landscapes, to assess the extent to which the simulations have reproduced reality (see Jorge & Garcia 1997; Sprott *et al.* 2002; Bolliger 2006). In Brazilian Amazonia, the presence of obvious scaling phenomena in the pattern of deforestation provides a simple method for helping to validate predictive models of Amazonian deforestation (for example, Laurance *et al.* 2001; Soares-Filho *et al.* 2004, 2006; Walker *et al.* 2004). If the relative importance of the current deforestation drivers continues into the future, it is likely that the observed spatial patterns will also persist, regardless of the total amount of forest that is cleared (assuming that previously deforested land remains cleared and does not regenerate within the time scale being investigated). This is especially true at the scale of the whole Basin or individual states in Brazilian Amazonia, given that the spatial patterns described here are the result of cumulative deforestation events through time, and, moreover, that the pattern holds for states that vary widely in deforestation extent, age of deforestation frontier and underlying causes of deforestation. Thus, by calculating a simple $A{:}P$ metric for predicted landscapes, a modeller can obtain instant feedback as to whether their model results are consistent with known landscape-scale patterns (for example, Soares-Filho *et al.* 2002). By contrast, changes in the underlying processes causing deforestation may result in temporal changes to the landscape patterns described here. For example, changes in the enforcement of legislation requiring forest reserves on private land have the potential to greatly alter spatial patterns of deforestation (Soares-Filho *et al.* 2006).

Although the fractal dimension is just one of many available metrics that can be used for assessing spatial patterns of landscapes (Riitters *et al.* 1995), it has a distinct advantage in that it compares spatial patterns across scales within a landscape, rather than simplistically generating a single metric for the entire landscape. For example, if we are interested in understanding deforestation patterns within a municipality, the fractal dimension can highlight scale-related differences in the patterns and processes that both operate within the municipality and combine to create the pattern observed in the municipality as a whole. Thus, the fractal dimension allows one to detect scaling factors that have not been properly accounted for in a predictive model of deforestation patterns. This is particularly important for assessing the validity of spatially explicit deforestation models where it is assumed a priori that different processes operate at different scales, such as in the Amazon basin (Geist & Lambin 2002). The straightforward test proposed here will quickly highlight inconsistencies between real landscapes and models that attempt to account for the spatial patterning of deforestation. Moreover, future changes in observed $A{:}P$ metrics might indicate shifts in the importance of different land-use drivers, such as the growing role of large-scale cattle ranching and industrial soybean farming (Fearnside 2001; Laurance *et al.* 2004) as causes of Amazonian deforestation.

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