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Landscape metric performance in analyzing two decades of deforestation in the Amazon Basin of Rondonia, Brazil

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Abstract

Sixteen landscape metrics were evaluated with respect to the effects of spatial aggregation on six different years of Landsat data for a deforested area in Rondonia, Brazil. Spatial aggregation was performed by two methods. The first method involved varying the window size in texture mean co-occurrence filtering prior to classification. The second method involved aggregating the data post-classification by resampling with a majority filter. The *Landscape Shape Index* (*LSI*) and *Square Pixel* (*SqP*) metric showed the most predictable behavior of the shape complexity metrics having strong decreases with each increase in aggregation. The *Edge Density* (*ED*) and *Patch Density* (*PD*) metrics showed the most predictable behavior among the edge and patch metrics, decreasing with increasing aggregation. The *Mean Nearest Neighbor* (*MNN*) metric also behaved as expected but its results were less consistent than those of *ED and PD*. Many of the remaining metrics gave inconsistent and unpredictable results with respect to spatial aggregation.

Keywords: Landscape metrics; Spatial aggregation; Spatial resolution; Scale; Grain size; Texture filtering; Majority filtering

1. Introduction

Landscape pattern metrics are used to quantify landscape composition and configuration on a map or remotely sensed image. There are numerous examples of the development and application of landscape metrics for ecological analysis (eg. Ares et al., 2001; Brown et al., 2000; Frohn, 1998; Fuller, 2001; Hargis et al., 1998; Heggem et al., 2000; Herzog & Lausch, 2001; Imbernon & Branthomme, 2001; Jorge & Garcia, 1997; Leitao & Ahern, 2002; Li et al., 2001; Liu & Cameron, 2001; McGarigal & Marks, 1994; Pan et al., 2001; Peralta & Mather, 2000; Ravan & Roy, 1997; Read & Lam, 2002; Trani et al., 1999; Walsh et al., 1998). Metrics can be easily calculated on classified map data using available software. The utility of a landscape metric is dependent on maintaining consistent response to observed phenomena. There are many characteristics that affect the quality of map and image data including spatial aggregation and resolution, spatial extent, texture, geometric registration, classification level, and classification accuracy. An effective landscape metric is one that is relatively insensitive or predictably sensitive to arbitrary sampling characteristics while being very sensitive to the actual spatial patterns of the landscape (Frohn, 1998). Since remote sensing and map data are captured in a wide variety of geometric representations, landscape metrics should be formulated to compensate for specific sampling geometries in order to facilitate comparison across scales and among different studies.

Many landscape metrics are highly correlated. Ritters et al. (1995) investigated 55 metrics and found that their information could be reduced to 6 general measures of landscape pattern and structure: *Average Perimeter-Area Ratio*, *Contagion*, *Standardized Patch Shape*, *Patch Perimeter-Area Scaling*, *Number of Attribute Classes*, *and Large-Patch Density-Area Scaling*. Hargis et al. (1998) examined correlation between landscape metrics using simulated landscapes and found that *Contagion* and *Edge Density* had a high inverse correlation. They also found that *Mean Nearest Neighbor Distance* and

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Mean Proximity Index have comparatively lower correlation to other metrics. Imbernon and Branthomme (2001) statistically screened various landscape indices before applying them to a Landsat TM image. They found 6 statistically independent indices: *Number of Crop Land Patches*, *Fractal Dimension of All Patches*, *Mean Distance between Patches and Their Nearest Neighbor*, *Percentage Forest Area*, *Mean Proximity between Forest Patches* and *Mean Crop Land Patch Size*. Generally, metrics can be divided into three groups: patch based metrics (e.g., *Mean Patch Size*), edge based metrics e.g., *Edge Density*) and metrics based on both patch and edge (e.g., *Perimeter-to-Area Ratio*, *Shape Index*).

Most landscape metrics have been shown to be sensitive to scale (McGarigal & Marks, 1994; Walsh et al., 1998). Several studies have focused on the effects of spatial resolution and spatial extent on the performance of metrics (Frohn, 1998; Frohn et al., 1996; Saura, 2002, 2004; Saura & Martines-Millan, 2001; Shen et al., 2004; Wu, 2004; Wu et al., 2000, 2002). Spatial resolution or grain size refers the smallest unit of measurement in the data (e.g. pixel size) while spatial extent refers to the total area measured (e.g., size of the study area). In a recent study, Wu (2004) evaluated scale effects on seventeen landscape metrics and found that class level metric responses fell into one of two categories: predictable scaling functions and unpredictable behavior. Landscape level metric responses had a third category, a staircase pattern response (Wu, 2004). Frohn (1998) analyzed two commonly used metrics, *Contagion* and *Fractal Dimension*, and concluded that both metrics were unstable or predictable with respect to varying spatial resolution. Saura (2004) examined the performances of six indices with varying aggregation using remote sensing data and found that *Landscape Division* and *Largest Patch Index* were the most stable in both aggregated and actual sensor patterns. *Number Patches*, *Mean Patch Size*, and *Edge Length* were the most sensitive indices not suitable for direct comparison across different spatial resolutions. Wu et al. (2002) grouped landscape metrics into three classes: Type I—predictable responses with simple scaling relations; Type II—staircase like responses with no simple scaling relations; and Type III—erratic response exhibiting no general scaling relations. Saura and Martines-Millan (2001) studied the sensitivity of eight landscape metrics to changing spatial extent. They found *Edge Density* was the least sensitive to varying spatial extent while *Mean Shape Index*, *Area Weighted Mean Shape Index*, and *Perimeter-Area Fractal Dimension* were the most sensitive. Saura (2002) determined that changes in minimum mapping unit (MMU) resulted in different responses among ten different landscape metrics. Moody (1998) has also shown that changes in scale can affect the accuracy of proportion estimates for land-cover types (see also Moody & Woodcock, 1994, 1995, 1996).

The most common method of comparing landscape spatial patterns with respect to spatial aggregation is by scaling landscape maps to coarser resolutions using a majority rule filter. But landscape maps derived using a majority rule filter often produce more fragmented landscapes than the actual sensor produces at the same resolution (Saura, 2004). Texture analysis can provide a useful alternative to majority filtering in the analysis of spatial aggregation. Texture in the image is determined by the brightness variation, which is characterized by uniformity, coarseness, regularity, frequency, and linearity (Musick & Grove, 1991). Local neighborhood intensity variance and other statistics (e.g., mean, skewness) derived from frequency distributions are used as statistical texture measures. Haralick (1979) described eight basic statistical texture measures including autocorrelation functions, optical transforms, digital transforms, textural edgeness, structural element filtering, spatial intensity-value co-occurrence probabilities, intensity-value run length, and autoregressive models.

The purpose of this research was to analyze the effects of spatial aggregation on sixteen commonly used landscape metrics. Landsat images of a deforested area in Ariquemes, Rondonia, Brazil (path 232 row 67), for six different years were used in the analysis. A subset of a deforested area of 1024×1024 pixels (30.72×30.72 km) was used for testing the effectiveness of landscape metrics in capturing spatial patterns at different spatial aggregations by two types of methods. The first method varied the window size in texture analysis used to obtain local statistics (e.g., mean, variance, skewness, etc.) before conducting classification. By doing so, local mean instead of the original digital value was used to determine the amount of aggregation in the output landscape maps. The second method used the more common approach of spatial aggregation by means of majority filtering.

This research builds on prior research concerning the effects of scale on landscape metrics in several ways. First, Wu (2004) has emphasized the need for empirical analysis of the scale effects on landscape metrics for real landscapes not just simulated landscapes. The area in this study is a real landscape that has shown significant change over the past two decades due to deforestation. Second, Shen et al. (2004) have shown that changes in the number of classes can affect scaling relations of most landscape metrics. This study uses a simple binary classification of forest/non-forest so that metrics will be unaffected by the number of classes as images are aggregated. Third, this study evaluates scale effects on a series of multi-temporal images instead of a single time frame so that scale effects can be determined for different degrees of landscape change in multiple years. Finally, this study uses two different spatial aggregation methods so that sensitivity of landscape metrics to different types of aggregations can be assessed.

2. Study area

The Brazilian state of Rondonia provides a unique study area to investigate the effects of human disturbance on the spatial patterns of a natural landscape. Rondonia has undergone massive land-use change over the past three decades as a result of road building, colonization, and the subsequent settlement of farmers who slash and burn the forest (Frohn et al., 1990). The main highway through Rondonia, BR-364, was completed in

1984 and has facilitated immigration into the state (Dale et al., 1993a,b). Agricultural expansion has been the primary force behind deforestation in the legal Amazon (Lucas et al., 2000, 2002). Unlike deforestation in other Brazilian Amazonian states to the north and the east where the major cause of deforestation is large-scale industrial cattle ranching, deforestation in Rondonia is limited to small farmer settlements and the clearing of tropical forest for agriculture and cattle raising (Frohn et al., 1990). Farmers settle on 100-hectare rectangular lots along feeder roads that are spaced every 4–5 km. Rondonia has experienced tremendous landscape changes since the 1970s, and is likely to continue this trend under the pressure of population growth and migration. In this research the colonization area of Ariquemes was selected for analysis (Fig. 1).

3. Methodology

Six Landsat TM images (Path 232 Row 67) of the northern part of the Brazilian state of Rondonia were used in the

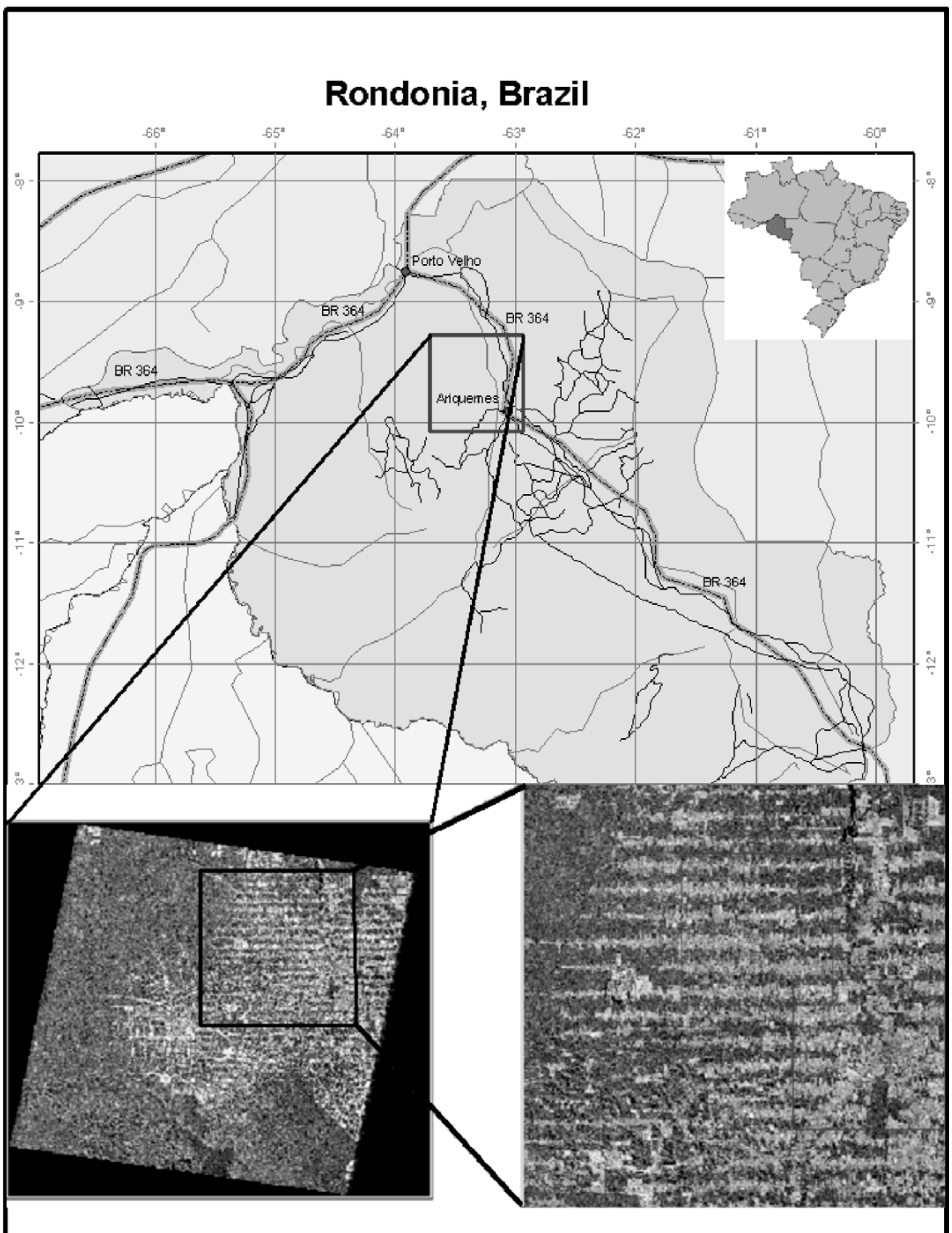

Fig. 1. Location of the study area in Ariquemes, Rondonia, Brazil.

analysis. The dates of the imagery are 1984, 1989, 1993, 1995, 1998, and 2000. Images were co-registered to each other. A relatively homogenous square of 1024×1024 pixels was used for metrics testing. This testing area is 94 371.84 ha and located in the northwestern part of the image. The test area is approximately 13% of the entire image.

3.1. Image classifications

A simple unsupervised K-means classifier was used to classify deforested areas and give consistent results between years for metrics testing. K-means classification uses statistical techniques to group n-dimensional data into their natural spectral classes The K-means unsupervised classifier requires the analyst to select the number of clusters to be located in the data, arbitrarily locates this number of cluster centers, then iteratively repositions them until optimal spectral separability is achieved. All classifications were initialized with 15 classes and 20 maximum iterations based on visual inspection of the imagery.

For testing the effects of varying resolution by textural filtering, the K-means classifier was applied to each mean co-occurrence image after textural filtering. The classification results were then grouped into forest and non-forest classes by visual inspection of the imagery. There were 17 texture window sizes for each of 6 years resulting in 102 different classifications. For testing the effects of changing spatial resolution by means of majority filtering, the classifier was applied to the image before aggregation. Thus there were a total of 6 classifications for majority filter testing.

3.2. Landscape metric calculations

Sixteen landscape metrics were calculated in this study using Patch Analyst 2.2 (Grid) in ArcView (Elkie et al., 1999). A brief description for each of them follows McGarigal and Marks (1994).

(1) *Class Area* (*CA*): The sum of areas of all deforested patches in hectares.

(2) *Percent LAND* (*%LAND*): It equals the percentage of the landscape deforested.

(3) *Patch Density* (*PD*): *PD* measures the number of deforested patches per square kilometer.

(4) *Largest Patch Index* (*LPI*): It equals the percentage of the landscape comprised by the largest patch.

(5) *Mean Patch Size* (*MPS*): Average patch size. $MPS = CA/$ number of patches in hectares.

(6) *Patch Size Standard Deviation* (*PSSD*): The standard deviation of patch sizes in hectares. $PSSD = 0$ when all patches in the class are the same size or when there is only 1 patch.

(7) *Patch Size Coefficient of Variation* (*PSCoV*): It measures the variability (as a percentage) in patch size relative to the mean patch size. $PSCoV = (PSSD/MPS) * 100$. $PSCoV = 0$ when all patches in the class are the same size or when there is only one patch.

(8) *Edge Density* (*ED*): The amount of edge relative to total landscape area in meters/hectare.

(9) *Mean Nearest Neighbor Distance* (*MNN*): It is the average distance in meters to the nearest neighboring patch of the same type, based on shortest edge-to-edge distance.

$$\mathrm{MNN} = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n'} h_{ij}}{N'}$$

Where, h_{ij} is the distance to the nearest patch of the same type for each patch in the landscape with a neighbor. It is based on nearest edge-to-edge distance, N is the number of patches with a neighbor.

(10) *Landscape Shape Index* (*LSI*): *LSI* measures shape complexity of patches. It is given as $\mathrm{LSI} = P/(4 * A^{1/2})$ where P is the total perimeter edges in the landscape and A is the total area of the landscape.

(11) *Square Pixel* (*SqP*): *SqP* is a modified *Perimeter to Area Ratio* scaled to that of a square pixel and normalized from 0–1.

$$\mathrm{SqP} = 1 - \left(4{*}A^{1/2}\right)/P$$

Where, P is *TE*, A is *CA* at class level. No unit. ($\mathrm{SqP} = 0$ when all patches are square and approaches 1 as patches become more complex in shape). SqP is correlated with LSI and measures patch shape complexity (Frohn, 1998).

(12) *Mean Shape Index* (*MSI*): *MSI* is the average *Perimeter to Area Ratio*. It is given as:

$$\mathrm{MSI} = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} \left(\frac{.25 p_{ij}}{\sqrt{a_{ij}}}\right)}{N}$$

Where, P_{ij} is the perimeter for each patch, a_{ij} is the area for the corresponding patch, and N is the number of patches. No unit. $\mathrm{MSI} = 1$ if when all patches are square and increases as the shape complexity of patches increases.

(13) *Area Weighted Mean Shape Index* (*AWMSI*): *AWMSI* is the *Perimeter to Area Ratio*, weighted by patch area so that larger patches weigh more than smaller ones.

$$\mathrm{AWMSI} = \sum_{i=1}^{m} \sum_{j=1}^{n} \left[\left(\frac{.25 p_{ij}}{\sqrt{a_{ij}}}\right)\left(\frac{a_{ij}}{A}\right)\right]$$

$\mathrm{AWMSI} = 1$ if when all patches are square and increases as shape complexity of patches increases.

(14) Mean *Patch Fractal Dimension* (*MPFD*): Measures the average fractal dimension of patches:

$$\mathrm{MPFD} = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} \left(\frac{2 \ln(.25 p_{ij})}{\ln a_{ij}}\right)}{N}$$

$1 \leq \mathrm{MPFD} \leq 2$. It measures the irregularity or complexity of patch shape.

(15) *Area Weighted Mean Patch Fractal Dimension* (*AWMPFD*): *AWMPFD* equals the average patch *Fractal Dimension* (*FRACT*) of patches in the landscape, weighted by patch area.

$$\mathrm{AWMPFD} = \sum_{i=1}^{m} \sum_{j=1}^{n} \left[\left(\frac{2 \ln(.25 p_{ij})}{\ln a_{ij}}\right)\left(\frac{a_{ij}}{A}\right)\right]$$

$1 \leq$ AWMPFD ≤ 2. It measures the irregularity or complexity of patch shape.

(16) *Double Log Fractal Dimension* (*DLFD*): *DLFD* equals 2 divided by the slope of the regression line obtained by regressing the logarithm of patch area (m^2) against the logarithm of patch perimeter (m).

$$\mathrm{DLFD} = \frac{2}{\dfrac{\left[N \sum_{i=1}^{m} \sum_{j=1}^{n} \left(\ln p_{ij} \ln a_{ij}\right)\right] - \left[\left(\sum_{i=1}^{m} \sum_{j=1}^{n} \ln p_{ij}\right)\left(\sum_{i=1}^{m} \sum_{j=1}^{n} \ln a_{ij}\right)\right]}{\left(N \sum_{i=1}^{m} \sum_{j=1}^{n} \ln p_{ij}^{2}\right) - \left(\sum_{i=1}^{m} \sum_{j=1}^{n} \ln p_{ij}\right)^{2}}}$$

$1 \leq$ DLFD ≤ 2. It measures the irregularity or complexity of patch shape. Theoretically, *DLFD* approaches 1 for shapes with very simple perimeters such as circles or squares, and approaches 2 for shapes with highly convoluted, plane-filling perimeters. *DLFD* employs regression techniques and is subject to small sample problems and requires patches to vary in size.

3.3. Effects of spatial aggregation by texture filtering (Pre-classification)

For each of the images from 1984 to 2000, the window size for texture filtering was varied by using 3×3, 5×5, 7×7, ..., 31×31, 33×33, and 35×35 pixels. Co-occurrence measures use a spatial dependence matrix to calculate texture values. The matrix records the frequency with which pixel values occur in two neighboring processing windows of

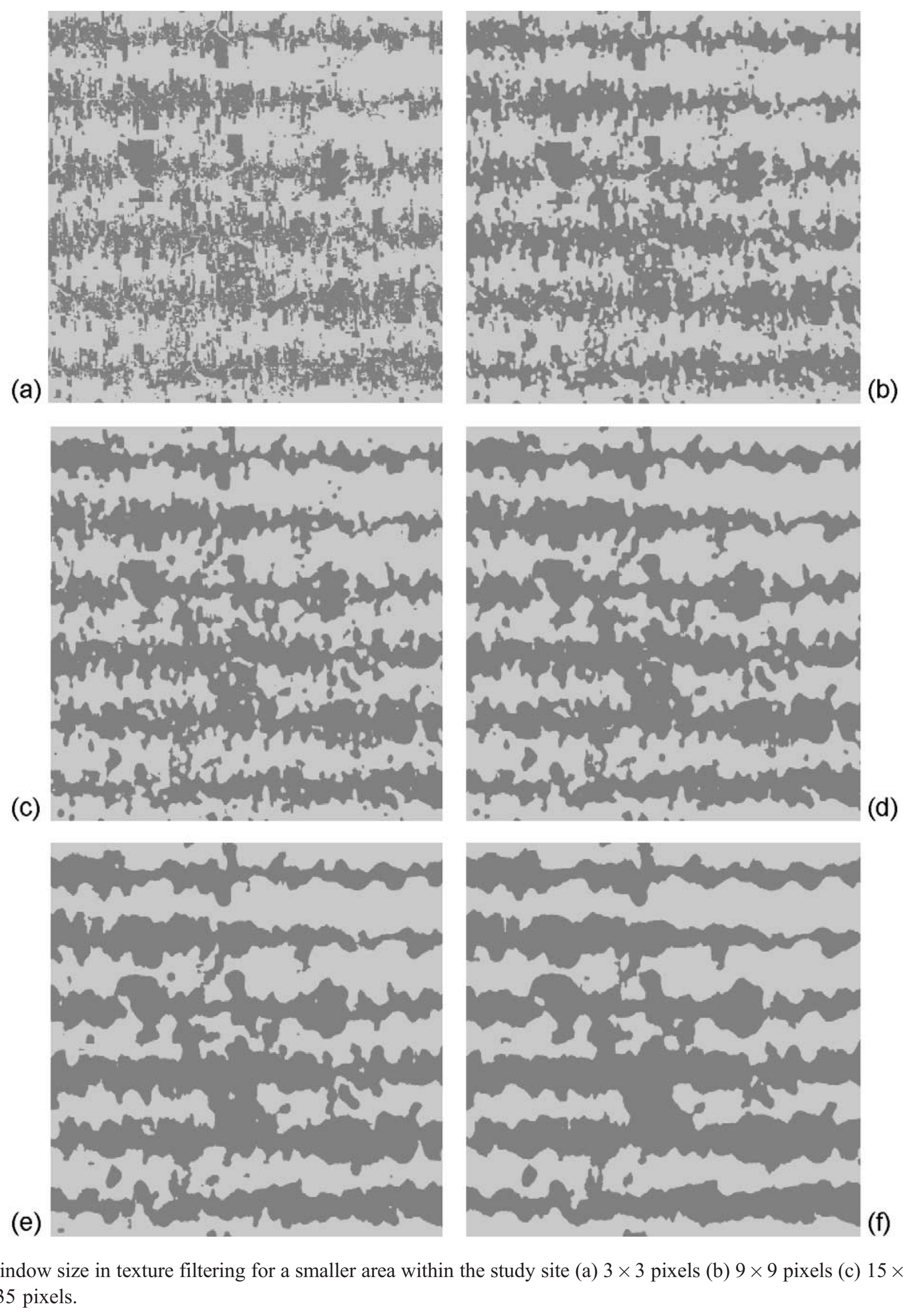

Fig. 2. Effects of varying window size in texture filtering for a smaller area within the study site (a) 3×3 pixels (b) 9×9 pixels (c) 15×15 pixels (d) 21×21 pixels (e) 27×27 pixels (f) 35×35 pixels.

a specified size and distance (Haralick et al., 1973). The mean co-occurrence image was obtained from the results of texture filtering. The K-means classifier was then applied to each of the mean co-occurrence images and the landscape metrics were calculated.

Despite their similarities in terms of spatial generalization, there are some significant differences between texture filtering and majority filtering for spatial aggregation. Majority filtering is applied after image classification, where the results are resampled according to a majority rule. Texture filtering resulted in spatial aggregation with varying window sizes before classification. The output spatial resolution is unchanged in texture filtering although the pixels are averaged over changing window sizes. With majority filtering the spatial resolution actually changes with each aggregation at varying window sizes. Fig. 2 shows the results of texture filtering for a small area within the study at some selected window sizes.

3.4. Effects of spatial aggregation by majority filtering (Post-classification)

Six image classifications, one for each year, were resampled using a majority filter at successively coarser intervals of 60 m up to a nominal resolution of 1 km. This 1 km maximum level of aggregation was selected to correspond generally with AVHRR

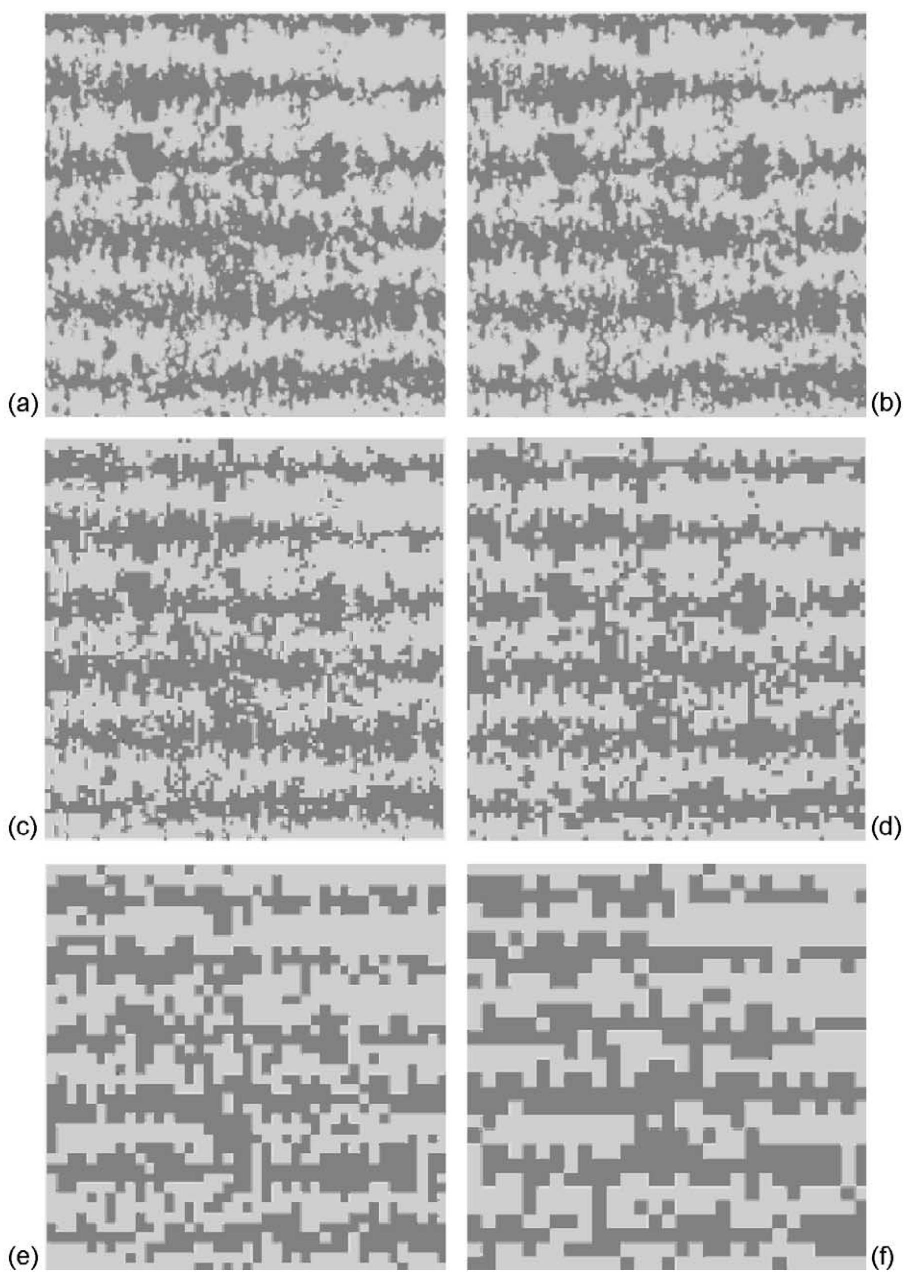

Fig. 3. Effects of varying window size in majority filtering for a smaller area within the study site (a) 3×3 pixels (b) 9×9 pixels (c) 15×15 pixels (d) 21×21 pixels (e) 27×27 pixels (f) 35×35 pixels.

LAC data, which is often used in studies of tropical deforestation. Aggregation involved using an increasing size window for the majority filter on the original classified image. A total of 210 images (6 years × 35 spatial resolutions) were obtained. Landscape metrics were calculated on each aggregated image to determine the effects of varying spatial resolution. Fig. 3 shows a portion of the study area with different spatial resolutions from majority filtering. The difference between texture filtering is obvious from comparing Figs. 2 and 3. Texture filtering creates a more natural looking landscape where the overall landscape pattern is maintained at the coarser resolutions. Majority filtering, on the other hand creates a more blocky type aggregation, which can sometimes result in a change in the overall landscape pattern at the coarsest resolutions.

4. Results and discussion

Sixteen landscape metrics were calculated and evaluated with respect to the effects of changing spatial resolution by two methods: texture filtering and majority filtering. The metrics were grouped into one of four categories.

4.1. Class metrics

Class metrics measure the deforested class area and proportion and consist of *Class Area* (*CA*) and *Percent LAND* (*%LAND*).

4.2. Shape metrics

Shape metrics have been used to measure shape complexity of patches on the landscape. There are seven metrics in this category. They consist of the *Landscape Shape Index* (*LSI*), *Square Pixel Metric* (*SqP*), *Mean Shape Index* (*MSI*), *Area Weighted Mean Shape Index* (*AWMSI*), *Mean Patch Fractal Dimension* (*MPFD*), *Area Weighted Mean Patch Fractal Dimension* (*AWMPFD*), and *Double Log Fractal Dimension* (*DLFD*).

4.3. Patch metrics

Patch metrics quantify information regarding patch size and distribution. There are five metrics based on patch statistics. They are the *Patch Density* (*PD*), *Largest Patch Index* (*LPI*); *Mean Patch Size* (*MPS*), *Patch Size Standard Deviation* (*PSSD*), and *Patch Size Coefficient of Variation* (*PSCoV*).

4.4. Edge metrics

Edge metrics quantify length and distribution of the amount of edge between patches. Two metrics are based on edge statistics: *Edge Density* (*ED*), and *Mean Nearest Neighbor Distance* (*MNN*).

When evaluating the effects of spatial resolution changes, we are mainly considering whether a metric has either a predictable change or exhibits erratic behavior. A metric should be insensitive or predictably sensitive to changing elements of remotelysensed images, such as spatial resolution, and most sensitive to the landscape component that it was designed to measure. If a metric is insensitive or predictably sensitive to spatial resolution then measurements across scales and across studies can be made without compromising the landscape element that is being measured. If a metric is not predictably sensitive to sampling geometries and we use it to measure landscape change over time, we will not know if it is measuring actual change in the landscape or simply measuring changes in the sampling geometry or both. It also should be noted that the spatial pattern of land cover in the study area is a function of land ownership; feeder road location and spacing; and the size and shape of lots. These factors will influence the metric responses to spatial aggregation. As the data are aggregated the landscape has a relatively higher connectivity and larger patch size mainly as a function of land-cover change and distance from feeder roads. Metrics calculated for a similar analysis in a location with a grid or irregular network of roads may exhibit a different response to aggregation than that found from an analysis of the fishbone-characterized landscape of this study area. The following sections summarize the results of the effects of varying spatial resolution by texture filtering and majority filtering on landscape metrics applied in this study.

4.5. Results of spatial aggregation by texture filtering (Pre-classification)

The effects of varying the window size in textural filtering on the class and shape metrics are shown in Fig. 4. Texture filtering has a small but predictable effect on both class metrics, *CA* and *%Land*. Increasing the window size results in aggregating larger cleared areas and eliminating smaller non-cleared areas. The overall result is a slight increase in the estimated area and percent area that was deforested. The increase is small, linear, and predictable. Moody (1998) and Moody and Woodcock (1996) demonstrated the potential for using a posteriori calibration methods to improve land-cover area and proportion estimates at coarser scales. A calibration method that considers the linear relationship between land-cover proportion and spatial aggregation would be applicable in this study.

The effect of textural filtering is to generalize the overall shapes of patches on the landscape. The larger the window size, the greater the generalization. Thus, we would expect a predictable decrease in the value of shape complexity metrics with each increase in window size. However, the shape metrics were affected differently with respect to textural filtering. *SqP* showed a strong linear decrease as predicted with each increase in the size of the texture window filter. *SqP* also showed the same trend and results for each year of deforestation. *LSI* behaved as predicted and showed a strong logarithmic decrease with each increase in the filtering window size. *LSI* showed similar results for each year of deforestation analyzed. Wu et al. (2002) found similar results in evaluating *SqP* and *LSI* and described them as Type I

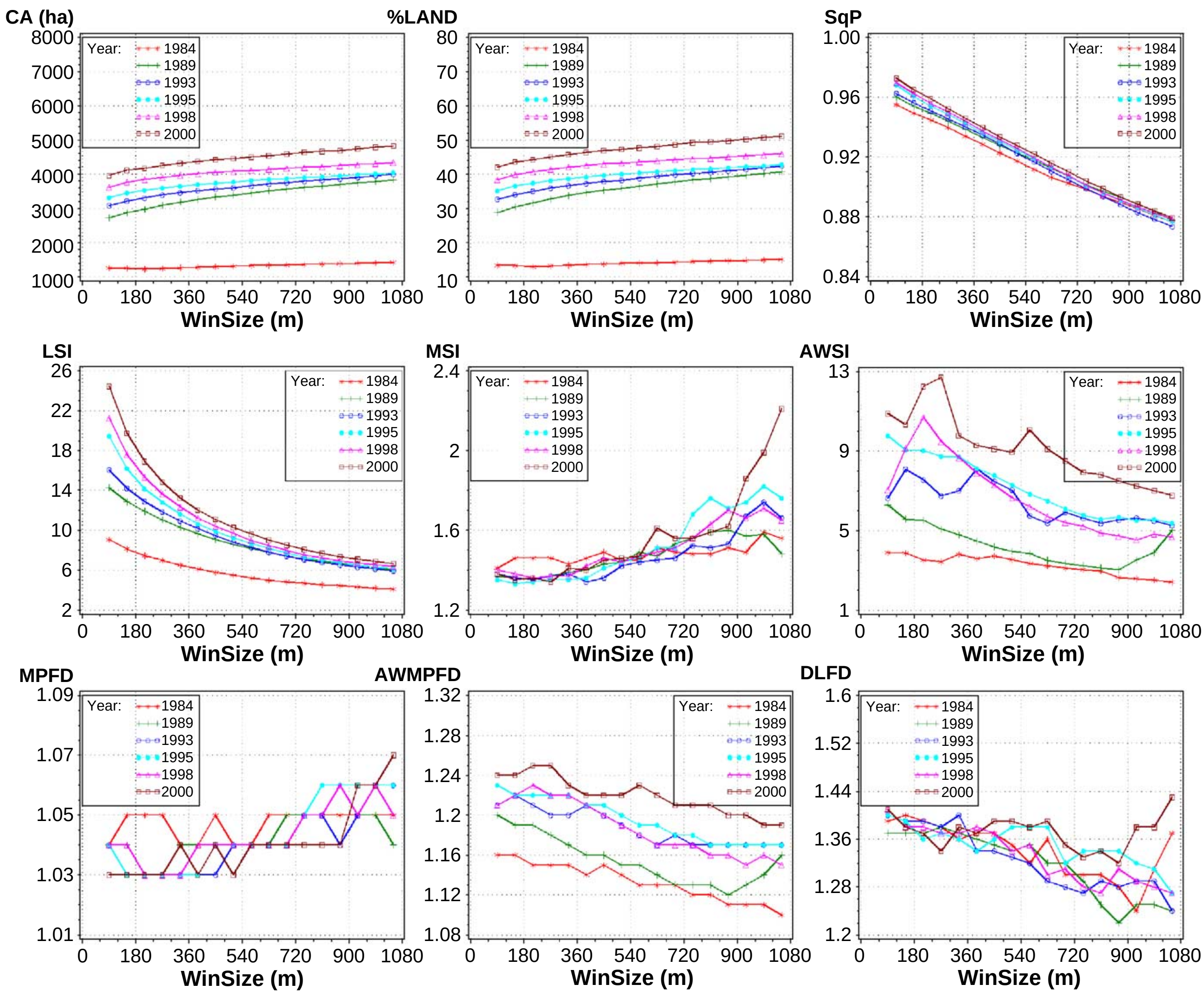

Fig. 4. Responses of class and shape metrics to varying window size in texture filtering.

metrics (predictable responses with simple scaling relations) with respect to grain size. The shape metrics *AWMSI* and *AWMPFD* showed an overall decrease in shape complexity, which is expected. However, both metrics showed no predictable trend for this decrease and had different results for each year analyzed. These results conflict with other research on the performance of these two metrics with respect to changes in spatial resolution. For example, several researchers have found that these two metrics exhibit Type I behavior with respect to changes in grain size (Shen et al., 2004; Wu, 2004; Wu et al., 2002). A closer examination of the results for multiple years shows that these two metrics are affected differently depending on the amount and degree of deforestation. The fact that some years are affected more than others by changes in spatial aggregation may explain the differences between this and other studies with respect to *AWMSI* and *AWMPFD*. These two metrics may behave differently depending on class proportions. *DLFD* varied in results by year. Some years had an increase in *DLFD* and some had a decrease. Responses for *DLFD* were erratic and not predictable. *MSI* and *MPFD* behaved counterintuitively and showed an overall increase in shape complexity with increased textural filtering. Since the effects of texture filtering include a generalization of the shape complexity of the landscape, these two metrics should have increased. The behaviour of *DLFD*, *MSI*, and *MPFD* in this study is in agreement with that also reported by several other researchers (Saura, 2002; Wu, 2004; Wu et al., 2002). Saura (2002) have recommended that *MSI* not be used in landscape studies if land-cover data have different spatial resolutions or patch size frequencies. *SqP and LSI* appear to be the most predictable of the shape complexity metrics to the effects of spatial aggregation by texture.

Pearson correlation coefficients were calculated to show the degree of correlation between metric values and the window size of texture filtering. Table 1 shows the correlation coefficients for the shape metrics. *SqP* showed a high degree of correlation with window size for all years. *SqP* values range from −0.9982 to −0.9997 with a mean value of −0.9989, standard deviation of 0.0006, and a p value <0.0001. Pearson

Table 1
Correlation coefficients for shape complexity metrics and texture window size

	SqP	LogLSI	LSI	AWPFD	AWMSI	DLFD	MSFD	MSI
1984	−0.9983	−0.9930	−0.9474	−0.9791	−0.9464	−0.7493	0.4216	0.7993
1989	−0.9996	−0.9871	−0.9596	−0.8327	−0.7193	−0.9297	0.6896	0.8930
1993	−0.9997	−0.9879	−0.9520	−0.9243	−0.8104	−0.9350	0.8420	0.8964
1995	−0.9990	−0.9955	−0.9240	−0.9739	−0.9765	−0.8002	0.8915	0.9476
1998	−0.9982	−0.9957	−0.9185	−0.9507	−0.8813	−0.9375	0.8076	0.9414
2000	−0.9988	−0.9975	−0.9058	−0.9382	−0.8918	−0.1038	0.8269	0.8694
Mean	−0.9989	−0.9928	−0.9345	−0.9332	−0.8710	−0.7426	0.7465	0.8912
StdDev	0.0006	0.0044	0.0214	0.0534	0.0939	0.3229	0.1727	0.0541

coefficients were also calculated for the log transform of *LSI* since it showed a logarithmic decrease with increasing window size. *LogLSI* also had high correlation coefficients ranging from −0.9871 to −0.9975 with a mean of −0.9928, standard deviation of 0.0044 and a p value <0.0001. The Pearson coefficients for the rest of the shape metrics were much lower.

The effects of textural filtering on the patch and edge metrics are shown in Fig. 5. Texture filtering results in fewer patches, decreased patch density (*PD*), an increase in the average size of patches (*MPS*), and a decrease in the amount and density of edges (*ED*). Most of the patch and edge metrics behaved as predicted with respect to the effects of increasing window size. *PD* measures the density of patches on the landscape per a specified unit area. As the landscape becomes more aggregated due to textural filtering, patch density decreases. *ED* measures the density of edges on the

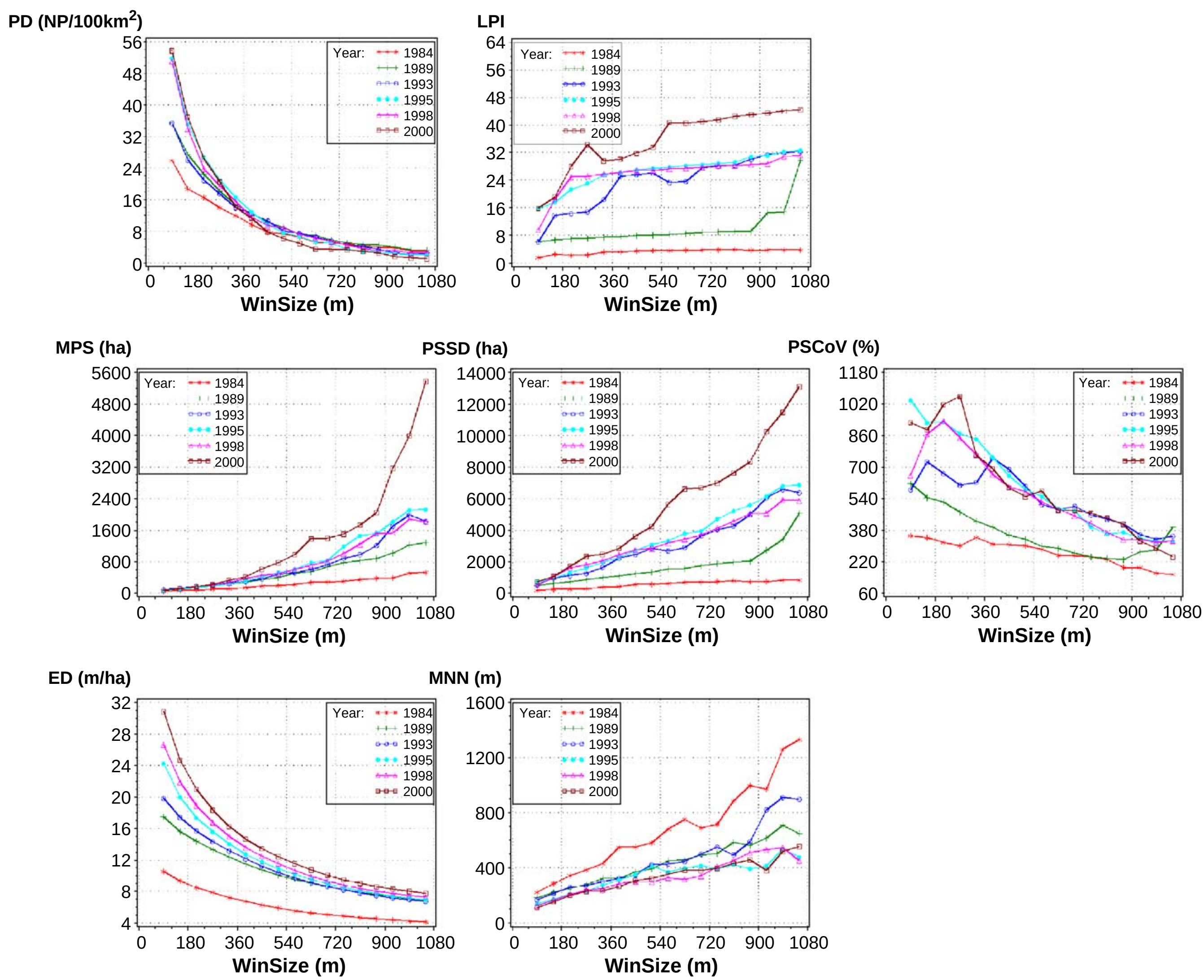

Fig. 5. Responses of patch and edge metrics to varying window size in texture filtering.

landscape. As the filtering effect increases there is a greater aggregation of patches and less edge. *ED* appears to quantify this decrease in edge well. Both *PD* and *ED* show strong logarithmic decreases with each increase in filtering window size. Also, *PD* and *ED* have very similar results for each year analyzed. *MPS* behaved as expected with an overall increase in the average size of patches. However, the effect was not the same for each year analyzed. The behaviour of *PD*, *ED*, and *MPS* with respect to spatial resolution in this study is similar to that found in other studies (Shen et al., 2004; Wu, 2004; Wu et al., 2000, 2002). Saura and Martines-Millan (2001) also found both *PD* and *ED* to be insensitive to changes in spatial extent.

PSSD measures the standard deviation of patch sizes. *PSSD* showed an overall increase with textural filtering. However, *PSSD* was not consistent between years analyzed. *PSSD* appears to be affected by the proportion deforested in the study area. When there is a low amount of deforestation (1984) there is a lower standard deviation between patch sizes as spatial aggregation changes. With increasing deforestation such as in 2000 the deforested patches have greater standard deviation between patch sizes as the data is aggregated. *PSCoV* measures the variability in patch size relative to the mean patch size. *PSCoV* had an overall decreasing trend but was irregular and not consistent between years. *LPI*, which measures the largest patch on the landscape showed a slight overall increase but was very inconsistent. *PSSD*, *PSCoV*, and *LPI* have been reported to be stable metrics with respect to spatial resolution by other researchers contrary to the results of this study (Saura, 2002, 2004; Shen et al., 2004; Wu, 2004; Wu et al., 2000, 2002). The difference between the behaviour of these three metrics in this study and that in other studies may be due to differences in land-cover proportions. In some years, these metrics behaved as predicted. However, for other years they behaved more erratically. Future studies should consider the number of classes and proportion land-cover when examining these metrics as they may be affected by spatial resolution changes. Finally, *MNN* measures the mean distance to the patches nearest neighboring patch. As patches coalesce through texture filtering, the distance between patches increases and *MNN* increases. *MNN* is not consistent, however, in how it is affected among different years and different window sizes and appears to be affected by the proportion deforested in the study area. For example, notice the high variation in MNN for 1984 where deforestation is very low compared to other years. When deforestation is low, large forest patches dominate the landscape and texture filtering tends to eliminate the smaller island patch clearings causing an increase in the distance between these patches.

Pearson coefficients were calculated for the patch and edge metrics including log transforms of *ED* and *PD* (Table 2). *LogED* had the highest correlation coefficients of the edge metrics ranging from −0.9853 to −0.9968 with a mean value of −0.9914, standard deviation of 0.0048, and p value <0.0001. *LogPD* had the highest correlation values of the patch metrics ranging from −0.9635 to −0.9860 with a mean of −0.9784, standard deviation of 0.0082 and p value <0.0001. The correlation values for the rest of the patch and edge metrics are shown in Table 2.

Fig. 6 demonstrates the predictability of *LSI*, *PD*, and *ED* with respect to the window size used in textural filtering when log transforms are applied. All three graphs are log plots of each metric versus the window size. All three metrics in the log plots have a strong negative linear correlation with window size in texture filtering.

4.6. Results of spatial aggregation by majority filtering (Post-classification)

The second method used to evaluate the performance of the metrics with respect to changing spatial aggregation is more common and performed by simply resampling the data after classification using a majority filter. Unlike texture filtering, majority filtering actually changes the spatial resolution of the data. The spatial resolution ranges from 30 to 1050 m, with an interval of 30 m. The result of post-classification spatial aggregation is a blockier appearance of data than with texture filtering. Saura (2004) has noted that this type of aggregation produces a more fragmented landscape than the actual sensor does at the same resolution. The results for each landscape metric can be similar to those found from texture filtering. However, if spatial aggregation causes actual changes in the pattern of the landscape then the metric behavior may become less predictable than that found from texture filtering.

Fig. 7 shows the effects of majority filtering on the class and shape metrics. Spatial aggregation had very little effect on the class metrics, CA and %LAND. Both the area of deforestation and the proportion of deforestation in the images have little or no change from spatial resolutions ranging from

Table 2
Correlation coefficients for patch and edge metrics and texture window size

	LogED	LogPD	PSSD	MNN	MPS	ED	PSCoV	PD	LPI
1984	−0.9910	−0.9832	0.9632	0.9699	0.9819	−0.9471	−0.9632	−0.9007	0.8470
1989	−0.9853	−0.9830	0.8787	0.9904	0.9813	−0.9600	−0.8143	−0.8955	0.6941
1993	−0.9863	−0.9635	0.9796	0.9474	0.9364	−0.9518	−0.8894	−0.9046	0.9259
1995	−0.9943	−0.9797	0.9947	0.9314	0.9634	−0.9237	−0.9782	−0.8531	0.9337
1998	−0.9948	−0.9860	0.9942	0.9631	0.9686	−0.9180	−0.9289	−0.8376	0.7761
2000	−0.9968	−0.9749	0.9804	0.9717	0.8909	−0.9054	−0.9471	−0.8300	0.9176
Mean	−0.9914	−0.9784	0.9651	0.9623	0.9537	−0.9343	−0.9202	−0.8702	0.8491
StdDev	0.0048	0.0082	0.0439	0.0205	0.0350	0.0216	0.0603	0.0338	0.0971

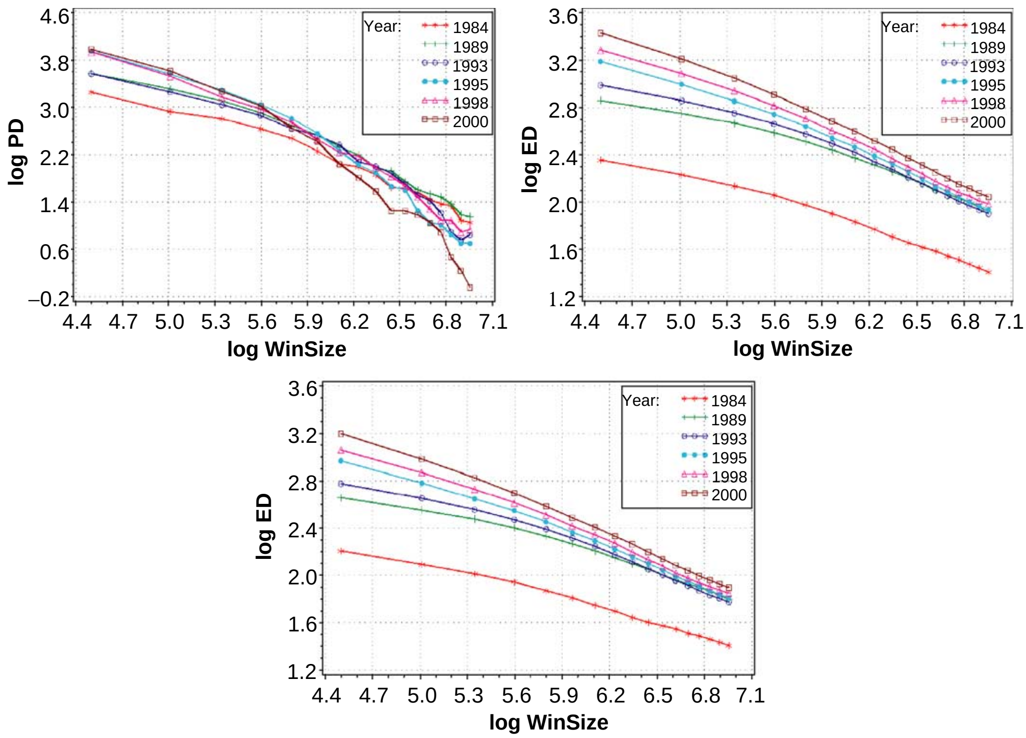

Fig. 6. Log transforms of *PD*, *ED*, and *LSI* and window size in texture filtering.

30 to 1050 m. The spatial aggregation causes the landscape to become more clumped and generalized so its complexity decreases. Both *LSI* and *SqP* show a predictable decrease in shape complexity with each increase in spatial resolution. *LSI* and *SqP* behavior with majority filtering is similar to that with texture filtering. The other five shape complexity metrics however show erratic and unpredictable patterns with respect to changing spatial resolution and in some cases the behavior was different from that found with texture filtering. *AWMSI* and *AWMPFD* show an overall decrease but the response is inconsistent and different for each year and each resolution change. *MSI* shows an overall increase for most years but a decrease for 1984. This behavior is different from texture filtering where *MSI* has an increase with each aggregation for all years including 1984. *MSI* behavior is very erratic with respect to spatial resolution. *MPFD* and *DLFD* exhibit counterintuitive increases in shape complexity with increasing spatial resolution. Since the effects of majority filtering include a generalization of the complexity of shapes on the landscape, MPFD and DLFD should increase with each aggregation. However, both of these metrics increase with majority filtering. *DLFD* shows the opposite pattern with respect to majority filtering than it does with texture filtering. With majority filtering *DLFD* showed increases for all years with each spatial aggregation while with texture filtering *DLFD* showed decreases for all years. The responses are very inconsistent with respect to each year analyzed and each resolution change.

Pearson coefficients for the shape metrics with respect to spatial resolution changes from majority filtering are shown in Table 3. *SqP* had the highest degree of correlation ranging from −0.9845 to −0.9944 with a mean of −0.9914, standard deviation of 0.0036, and p value <0.001. LSI had the second highest correlation with values ranging from −0.9830 to −0.9860, mean of −0.9845, and standard deviation of 0.0012. The rest of the shape complexity metrics had correlations less than 0.90.

Fig. 8 shows the effects of majority filtering on the patch and edge metrics. Majority filtering had similar results to that of texture filtering with less patches, decreased patch density (*PD*), an increase in the average size of patches (*MPS*), an increase in the average distance between patches *(MNN*), and a decrease in the amount and density of edges (*ED*). Once again *PD* and *ED* showed strong decreasing predictable trends with respect to increases in spatial resolution. The trends are not as definitive as those found from texture filtering because the spatial aggregation results in a blockier landscape that changes the spatial pattern slightly. The effects of spatial resolution changes on *PD* and *ED* were also consistent for each year analyzed. *MNN* also behaved as predicted showing increases with increasing spatial resolution. As spatial resolution increases, more patches coalesce and the distance between patches increases causing *MNN* to increase. *MPS* also showed an overall increase with increasing spatial resolution but the changes were erratic and inconsistent among different years. *PSSD*, *PSCoV*, and *LPI* showed the same trends as that found from textural filtering but the changes were much more irregular among years.

Correlation coefficients for the patch and edge metrics with respect to spatial resolution changes were also calculated (Table 4). *ED* had the highest correlation coefficients of the edge metrics ranging from −0.9830 to −0.9850 with a mean

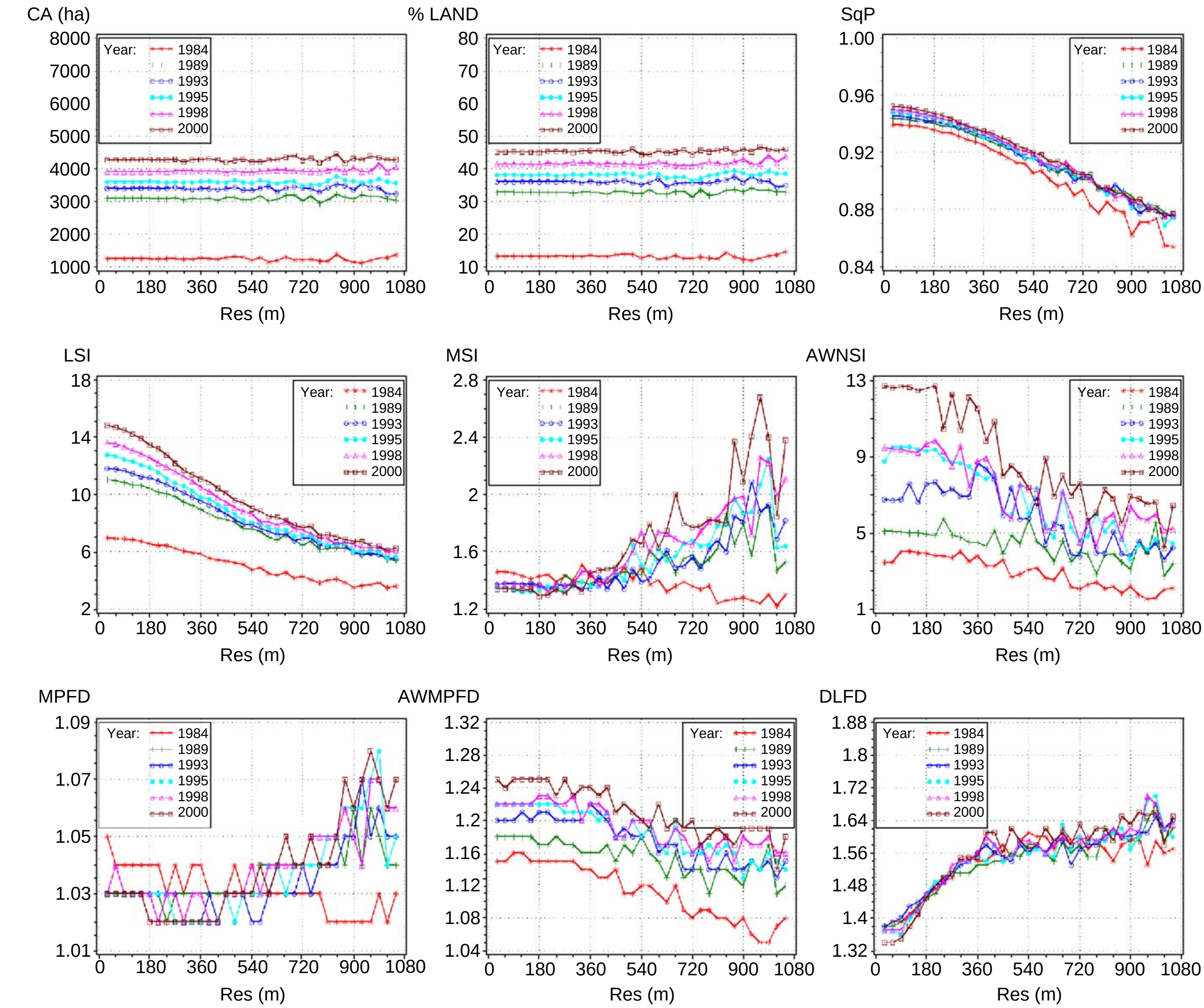

Fig. 7. Responses of class and shape metrics to varying window size in majority filtering.

value of -0.9841, standard deviation of 0.0010, and p value <0.0001. *MNN* also had high correlation values, ranging from 0.9665 to 0.9865 with a mean of 0.9751, standard deviation of 0.0095, and p value <0.0001. PD correlation coefficients were also high, with a mean of -0.9239, standard deviation of 0.0222, and p value <0.0001. The correlation values for the rest of the patch and edge metrics are shown in Table 4.

Table 3
Correlation coefficients for shape complexity metrics

	SqP	LSI	AWPFD	AWMSI	MSFD	MSI	DLFD
1984	−0.9845	−0.9842	−0.9562	−0.9258	−0.8187	−0.8252	0.7617
1989	−0.9931	−0.9859	−0.7996	−0.6545	0.6938	0.7749	0.9133
1993	−0.9908	−0.9860	−0.8944	−0.8207	0.7037	0.8420	0.9027
1995	−0.9920	−0.9843	−0.9356	−0.9337	0.7584	0.8577	0.8788
1998	−0.9935	−0.9834	−0.8739	−0.8677	0.8083	0.9230	0.8889
2000	−0.9944	−0.9830	−0.9134	−0.9206	0.8428	0.8918	0.8527
Mean	−0.9914	−0.9845	−0.8955	−0.8538	0.4981	0.5774	0.8663
StdDev	0.0036	0.0012	0.0553	0.1068	0.6476	0.6889	0.0554

5. Summary and conclusion

This study evaluated the behavior of sixteen metrics with respect to spatial aggregation by texture filtering and majority filtering. The *Square Pixel* (*SqP*) and *Landscape Shape Index* (*LSI*) metrics showed predictable decreases with increasing spatial aggregation and had the highest correlation values with increasing window size among the shape complexity metrics. *LSI* may require a log transform in order to predict its behavior across scales. The rest of the shape complexity metrics showed very little predictability and often behaved inconsistently. *Edge Density* (*ED*) showed the strongest predictable trend of the edge metrics and decreased with spatial resolution increases. The *Patch Density* (*PD*) metric showed the most predictable behavior among the patch metrics decreasing with increasing spatial resolution. Both *ED* and P*D* may require a log transform in order to predict its value across scales. The *Mean Nearest Neighbor* (*MNN*) metric also behaved as expected but its results were less

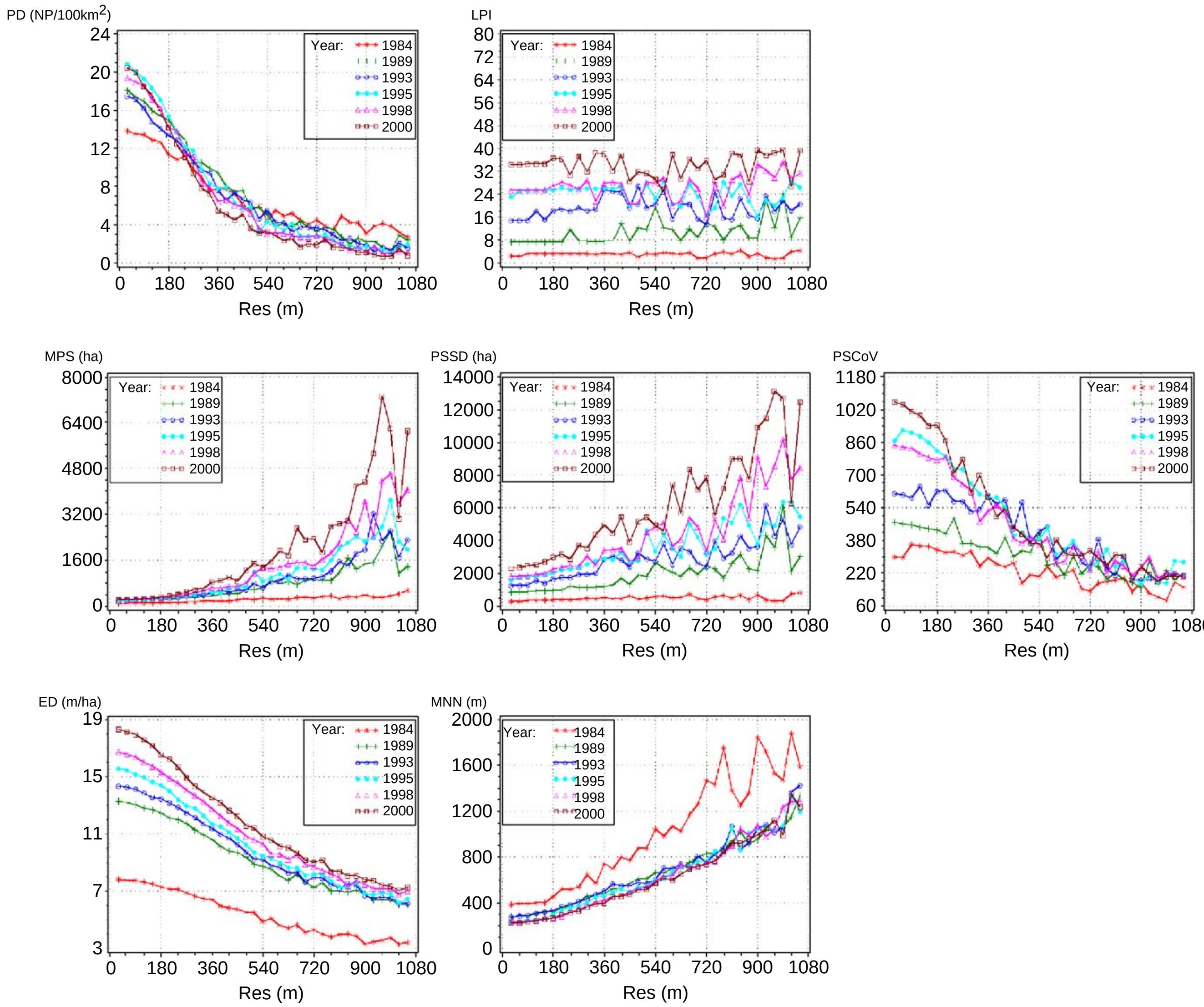

Fig. 8. Responses of patch and edge metrics to varying window size in majority filtering.

consistent than those of *ED*. Other patch metrics performed inconsistently and unpredictably. This analysis indicates that if different data with spatial resolutions are used, such as comparing Landsat classifications with MODIS or AVHRR classifications, then the effect on metrics such as *SqP*, *LSI*, *ED*, and *PD* can be predicted directly and measures across scales can be made.

It should be emphasized that the spatial patterns of deforestation in this study are unique to the area of Rondonia, Brazil and that metrics may behave differently to aggregation in areas with different spatial patterns. The fishbone pattern of deforestation in Rondonia may exhibit scale dependent relationships not found in other areas. Also, having predictable responses to changing spatial resolution does not necessarily make a metric robust for other types of analysis. There are also many other factors that affect the applicability and effectiveness of metrics as indicators of landscape pattern in addition to spatial resolution (Li & Wu, 2004). With these caveats in mind, we make the following conclusions from the results of this study:

- *SqP*, *LSI*, *ED*, and *PD* showed consistent and predictable behaviour with respect to spatial aggregation.
- Most of the remaining shape complexity, edge, and patch metrics gave unpredictable and inconsistent results with respect to spatial aggregations.
- The amount of deforestation (land-cover proportion) may have an effect on the response a metric will have with respect to changing spatial aggregation.

Table 4
Correlation coefficients for patch and edge metrics and majority filter size

	ED	MNN	PSCoV	PD	MPS	PSSD	LPI
1984	−0.9836	0.9610	−0.9095	−0.9326	0.9377	0.5220	−0.0509
1989	−0.9850	0.9865	−0.9063	−0.9436	0.8845	0.7939	0.5662
1993	−0.9857	0.9665	−0.9390	−0.9484	0.8939	0.8776	0.1408
1995	−0.9838	0.9812	−0.9511	−0.9159	0.9210	0.9062	−0.2701
1998	−0.9834	0.9787	−0.9423	−0.9145	0.9150	0.9046	0.3308
2000	−0.9830	0.9768	−0.9386	−0.8887	0.8859	0.8991	0.0519
Mean	−0.9841	0.9751	−0.9311	−0.9239	0.9063	0.8172	0.1281
StdDev	0.0010	0.0095	0.0186	0.0222	0.0216	0.1507	0.2931

- Both aggregation methods (texture filtering and majority filtering) showed similar responses for all metrics except *DLFD*, which gave opposite responses with respect to texture and majority filtering.
- A landscape metrics response to spatial aggregation and changes in spatial resolution should be one factor considered when applying the metric to quantify spatial patterns of the landscape.

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