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Characterizing Forest Fragments in Boreal, Temperate, and Tropical Ecosystems

An increased ability to analyze landscapes in a spatial manner through the use of remote sensing leads to improved capabilities for quantifying human-induced forest fragmentation. Developments of spatially explicit methods in landscape analyses are emerging. In this paper, the image delineation software program eCognition and the spatial pattern analysis program FRAGSTATS were used to quantify patterns of forest fragments on six landscapes across three different climatic regions characterized by different moisture regimes and different influences of human pressure. Our results support the idea that landscapes with higher road and population density are more fragmented; however, there are other, equally influential factors contributing to fragmentation, such as moisture regime, historic land use, and fire dynamics. Our method provided an objective means to characterize landscapes and assess patterns of forest fragments across different forested ecosystems by addressing the limitations of pixel-based classification and incorporating image objects.

INTRODUCTION

Forest fragmentation is induced by human activities and natural processes. Human-induced fragmentation increases ecosystem vulnerability toward fire, the threat of invasive species, and habitat decline (1). Forest fragmentation can be defined as the breaking up of a forested unit, where the number of patches and the amount of exposed edge increase while the amount of core area decreases (2), whereby core area is defined as a forested area free of edge effects (3). The size and shape of forest fragments are strongly dependent on terrain characteristics. For instance, roads in mountainous landscapes tend to follow topographic contours and resemble stream networks, while in flat terrain, road networks often exhibit systematic gridded patterns. Anthropogenic factors that have been well-described in recent literature and that affect forest fragmentation include roads (4), agriculture (5), forest logging practices (6), and urbanization (7).

Although forest fragmentation has serious implications for biodiversity loss and habitat decline (8, 9), another serious issue involves fire. The effects of fragmentation and fire dynamics are often intertwined. High densities of roads increase fire danger by drying forests along edges, altering fuel loads, and providing access to humans who ignite fires (10). Forest logging is often accompanied with increased road density, influencing both moisture regimes and the initiation of repeating fire cycles in formerly unburned forests (11).

Recently, developments in the field of remote sensing have increased the use of spatially explicit landscape analyses. Moderate-resolution satellite imagery, primarily Landsat, can be broadly applied for analyses of landscape patterns (12). Studies of the process of landscape fragmentation rely predominantly on land-cover classification derived from Landsat imagery (13). Landsat images are often preferred over other moderate-resolution multispectral satellite imagery because they have been available globally since 1972, and they also possess a 30 m pixel size that can resolve most changes in land use or land cover.

Traditional image classification algorithms operate at the level of a single pixel, ignoring the surrounding pixels; this results in classification units of only one pixel in size, which constitute noise for an analyst interested in landscape pattern or a manager desiring management units of a useful minimum size. Object-oriented methods for landscape classification and analyses have been found to exceed accuracies of traditional spectral classification methods that treat each pixel independently (14–16). Object-oriented image segmentation algorithms such as Fractal Net Evolution (17), available in the software eCognition (18), consider both spectral and contextual information to partition pixels into discrete image objects more representative of landscape pattern. Image segmentation aims to minimize variability within image objects while maximizing variability between image objects. This effectively describes the means by which an aerial photo interpreter delineates forest stands into management units. As such, automated object-oriented image segmentation, or the partitioning of similar image pixels into landscape units (polygons), has potential to replace slower and more subjective manual aerial photo interpretation and stand delineation techniques.

Software programs such as FRAGSTATS have been widely applied to calculate patch, class, and landscape metrics from classified data layers (19). Landscape metrics have been used to compare different landscape patterns (20) and to establish relationships between ecological processes and individual species (21). Appropriate caution must be exercised not to use too many metrics (which number in the hundreds) without recognizing and accounting for the high degree of redundancy among them (4, 22).

The aforementioned developments in satellite remote sensing (e.g., Landsat), digital image processing (e.g., eCognition), and geographic analysis techniques (e.g., FRAGSTATS) are facilitating spatially explicit consideration of landscape patterns and processes. A single image represents a mere snapshot of fragmentation (or any landscape process) in time, but much about a landscape process may be inferred by landscape pattern (1). Fragmentation can proceed slowly, or over longer time scales than the available images record. A comparison of several landscapes representing various stages of fragmentation along a spatial chronosequence provides a useful means to quantify and better understand fragmentation effects on landscapes in general.

In this paper, we assess forest fragmentation in six forested landscapes representing varying degrees of fragmentation located in boreal, temperate, and tropical forests in North America and the Caribbean. We hypothesize that landscapes that have higher population density and more roads are more fragmented. Our goal is to demonstrate that remotely sensed data, image segmentation, and landscape analysis tools can be a used in a consistent manner to characterize and compare fragmented forest landscapes across boreal, temperate, and tropical forest ecosystems in North America and the Caribbean.

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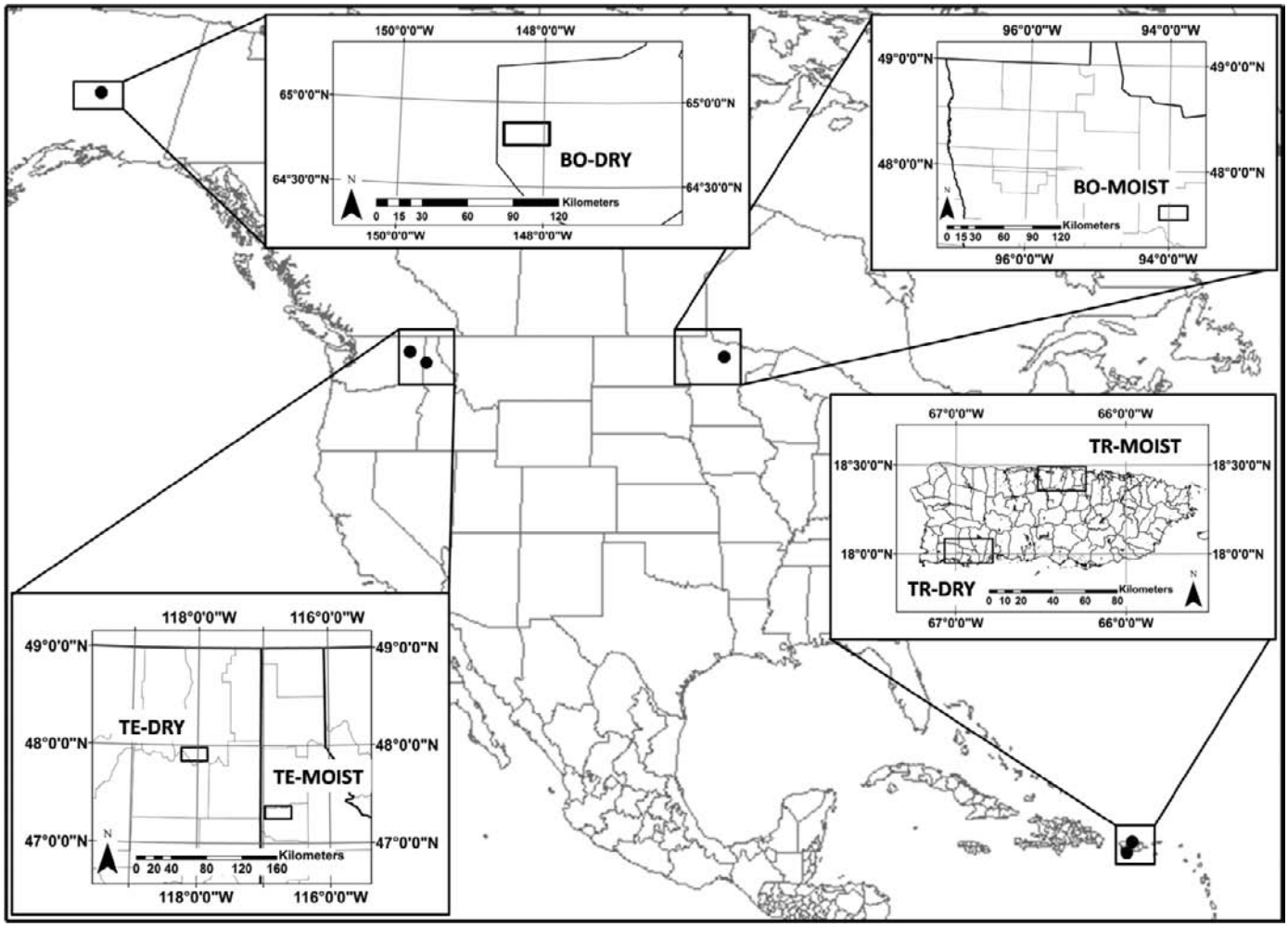

Figure 1. Study area locations (rectangles); BO-DRY in Alaska, BO-MOIST in Minnesota, TE-DRY in Washington, TE-MOIST in Idaho, and TR-DRY and TR-MOIST in Puerto Rico.

METHODS

Study Area Descriptions

The six study areas (Fig. 1) analyzed in this study contrast high population densities in tropical forest with much lower population densities in temperate and boreal forests (Table 1). The six selected study areas were selected to be approximately the same size (~45 000 ha) and to represent dry and moist boreal (Alaska and Minnesota), temperate (Washington and Idaho), and tropical (Puerto Rico) forest types. These study areas were selected for permission and practicality of access as well as the availability of field data to validate the edge location of forest fragments. For purposes of this study, we assumed them to be representative of the six forest types sampled.

The dry boreal forest area (BO-DRY) is located in eastern interior Alaska on Bureau of Land Management (BLM) land, while the moist boreal forest (BO-MOIST) is located in north central Minnesota in the Chippewa National Forest. The BO-DRY area is more coniferous than deciduous and interspersed by rivers, while the BO-MOIST area is more deciduous than coniferous and more interspersed by lakes. Both temperate areas occurred in coniferous forests on Native American Tribal lands in the Interior Northwest: the TE-DRY area is located in the Spokane Indian reservation in eastern Washington, while the TE-MOIST area is located in the Coeur d'Alene Indian Reservation in northern Idaho. The TE-DRY area is dominated by *Pinus ponderosa* (ponderosa pine) and, on moister aspects, *Pseudotsuga menziesii* (Douglas fir), while the TE-MOIST area is a more species-rich mixed conifer forest. Both tropical forest areas in Puerto Rico, TR-DRY and TR-MOIST, occur mainly on private land. The TR-DRY area is located in southwestern Puerto Rico and encompasses the Guánica Dry Forest Reserve and has relatively high tree species diversity. The TR-MOIST area occurs in the heavily populated northern coastal plain of Puerto Rico, west of the San Juan Metropolitan area. Importantly, dry forests have a more open canopy structure than moist forests in all three climate regions (23). The terrain is mainly flat in the two boreal landscapes, while it is generally hilly in the two temperate and two tropical landscapes.

Forest patterns in the BO-DRY area have been fragmented mostly by historic fires and less by human activities, with relatively few settlements, roads, or logging. The BO-MOIST area has been more fragmented by settlements, roads, logging, and agriculture than by historic fires. Prescribed fires also have fragmented forests in the TE-DRY area, as have logging, roads, and settlements. The TE-MOIST area similarly has been impacted by logging, roads, and settlements, with agriculture an added factor. Both the TR-DRY and TR-MOIST areas have been heavily fragmented due to high population densities, contributing to widespread urbanization, dense road networks, and intensive agriculture.

Field Data

In 2002 and 2003, field campaigns were conducted in Puerto Rico, Washington, Idaho, Minnesota, and Alaska to measure canopy and ground fuels along forest edge gradients. Forest edges caused by roads, timber harvest, agriculture, or urban-

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Table 1. Study area description and corresponding ETM+ imagery used.

No.	Study area	Population density (no. km^{-2})*	Road length (km)†	Mean annual precipitation (mm)‡	No. of transects used to train classification	Path/Row of ETM+ scene	Acquisition date
1	BO-DRY	4.6	236.9	339	14	P69/R15	27 May 2002
2	BO-MOIST	7.5	521.3	700	18	P28/P27	15 July 2002
4	TE-DRY	6.8	525.4	442	18	P43/R27	24 July 2002
3	TE-MOIST	4.7	380.5	731	11	P43/R27	24 July 2002
5	TR-DRY	228.5	1097.0	995	44	P05/R48	13 November 2000
6	TR-MOIST	340.8	1397.3	1617	17	P05/R47	05 March 2001§
						P05/R47	22 January 2003

* Population densities were calculated for each study area from the 2000 TIGER census data (per county/municipality) (http://www.census.gov; accessed 23 June 2007). † Road length was calculated for each study area using the second edition of the TIGER/LINE 2006 data (released 06 March 2007) (http://www.census.gov/geo/www/tiger; accessed 03 September 2007). ‡ Precipitation was calculated for each study area from PRISM data layers (30 y average) (http://prism.oregonstate.edu; accessed 18-10-2006). § Cloud-masked image "on top" of the other image.

ization were sampled in the field across the full range of forest structure types observed in each study landscape. A forest edge was defined as a distinct nonforest-forest transition as observed in the field, rather than *a priori* in a Landsat image. Thus, edges were selected in the field somewhat subjectively but in a manner that could not have biased the ability to detect the edges from Landsat data. This was because the scale of a forest edge is finer than that of 30 m Landsat pixels, or 15 m in the case of fused pixels (i.e., fused by combining the 30 m multispectral bands with the 15 m panchromatic band), as were used in this study. Therefore, the position of a point along an irregular forest edge selected for sampling was necessarily independent of its position within the regular Landsat raster image grid encompassing that edge.

At each field site, forest canopy and ground fuels were measured using standard forestry techniques at five variable-radius plots systematically located along a 60 m linear transect oriented perpendicular to the forest edge (Fig. 2). Each transect consisted of a nonforest plot centered 5 m outside the forest edge, an edge plot centered 5 m inside the forest edge, and three forest (interior) plots 15, 35, and 55 m inside the forest edge (see Table 1 for the number of transects used for each study area). Horizontal distances between plots along a transect were measured with a laser rangefinder with slope correction. The centers of the outermost (nonforest) and innermost plots of each transect were geolocated by logging at least 100 static positions with a Trimble ProXR geographic positioning system (GPS), and these positions were subsequently differentially corrected using Pathfinder Office v2.9 with a geolocational error of <1 m. The canopy and ground fuel values were measured for other purposes and are inconsequential for this paper, but the plot location data were used to train the image classification of the landscapes into forested and nonforested classes, as will be described in a subsequent section.

Image Preprocessing

The TE-DRY and TE-MOIST areas were situated within the same Landsat Enhanced Thematic Mapper (ETM+) scene, while the BO-DRY area in Alaska and BO-MOIST area in Minnesota were necessarily in separate scenes. Therefore, it was necessary to correct for solar illumination angles and atmospheric conditions, which differ between scenes. For consistency, the same correction techniques were applied to all scenes (Table 1).

The authors developed code in ERDAS IMAGINE Spatial Modeler Language (SML) to atmospherically correct images using the cost-correction model developed by Chavez (24) with dark object subtraction, converting digital numbers into at-sensor reflectance and minimizing atmospheric effects. An adaptive image model, based on the method proposed by Steinnocher (25), was written by the authors using SML, which fused the six 30 m reflectance bands with the 15 m panchromatic band and thus enhanced edges without significantly changing spectral values. All images were converted to their corresponding UTM zone and the NAD83 projection. We found the enhanced spatial accuracy of the National Landsat Archive Production System (NLAPS)–processed Landsat imagery that we used greatly minimized image registration error. Finally, the full scenes were subset to an ~45 000 ha area surrounding the field transect locations.

In the tropical landscapes, we utilized a 15 m fused Landsat ETM+ "cloud-free" mosaic that was recently produced for the entirety of Puerto Rico (26). While phenological variation is slight in the tropical landscapes, due attention was given to selecting scenes for the mosaic from approximately the same season (Table 1). Unfortunately, cloud-free imagery could not be found for some mountainous localities, so cloud and cloud shadow masks were applied to give the appearance of a cloud-free mosaic. These images for both the TR-DRY and TR-MOIST areas were converted from radiance to reflectance values. They then were fused with the panchromatic band to obtain the enhanced resolution of 15 m, as in the boreal and

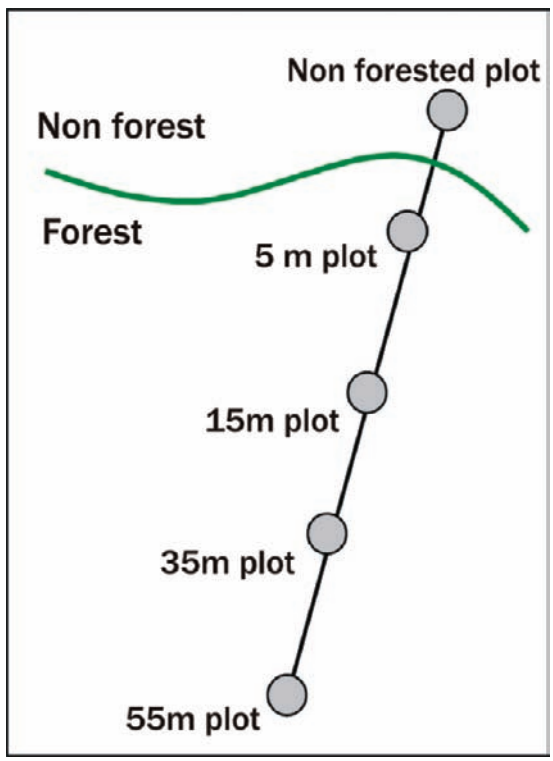

Figure 2. Illustration of a field transect.

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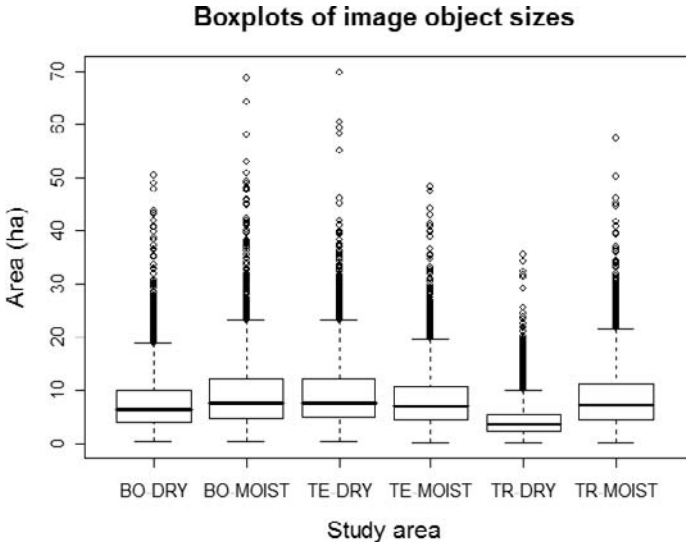

Figure 3. Box plots of the forested eCognition image object sizes per study area.

temperate areas. See Martinuzzi et al. (26) for the complete image-processing procedures used to produce the Puerto Rico "cloud-free" mosaic.

eCognition

For each study site, the six 15 m fused ETM+ reflectance bands were passed to the eCognition multiresolution image segmentation algorithm to delineate the spatial data into polygons with similar spectral values. The algorithm assembles spectrally similar and spatially adjacent pixels into image objects, or in other words, combines pixels that minimize pixel variability within groups and maximize pixel variability between groups (17). The parameters used to employ the algorithm were taken from a companion study (27) and were set with a 0.2 shape parameter and a 20 form factor, with all other parameters left as the defaults (18).

Figure 3 shows the box plots of the image object sizes. The mean object image sizes are between 4.3 ha (TR-DRY) and 9.4 ha (TE-DRY), which are realistic sizes for forested landscape elements. For example, Gustafson and Crow (28) reported an average forest stand size of 9 ha, and Siegert and McCullough (29) report areas between 1.2 and 22.8 ha of pine stands in the Midwestern US. The large image objects shown in Figure 3 are indicative of homogeneous closed forest canopy. We assumed that the image objects generated by eCognition represented landscape units that were indicative of forest pattern at the time of the image acquisition.

Classification

The six reflectance bands were reduced into three using the tasseled cap transformation (30) to eliminate redundant spectral information and improve classification accuracy (see also Fig. 4 for explanation). After applying the tasseled cap transformation, the images were classified using the supervised maximum likelihood method in ERDAS IMAGINE. Pixels corresponding to the forested plot locations 15 m, 35 m, and 55 m inside the forest edge were used to train the forest class, while pixels from the nonforested plots 5 m outside the forest edge were used to train the nonforest class. The edge plot pixels 5 m inside the forest edge were excluded because they could occur in the same 15 m pixel as the nonforest plots, and we wanted to define the forested class more conservatively because only the forested class would be subsequently analyzed. In addition, an urban/bare ground class and a water class were added to the supervised classification where obviously present, and in the case of the TR-MOIST and TR-DRY study areas, the cloud and cloud shadows were set to "no data." After classification, the categories were reclassified as forest, nonforest (including agricultural and urban areas), water, and "no data" (clouds and cloud-shadows in the TR-DRY and TR-MOIST area). Next, the reclassified image was overlaid with the eCognition delineated image object polygon layer to classify polygons according to the majority (mode) of the classified pixels occurring within each polygon (Fig. 5). In other words, if the majority of pixels within a delineated polygon were classified as forest, then the whole polygon was classified as forest, and if the majority of pixels were classified as nonforest, then the whole polygon was classified as nonforest.

Landscape Metrics and Analyses

FRAGSTATS calculates metrics at three different hierarchical levels: landscape, class, and patch (19). The landscape level includes all of the patches within a defined landscape and was used here to characterize the study areas as a whole. The class level metrics mainly involve differences between classes; since the focus of this study was only on the forested class, no class metrics were evaluated. The patch-level metrics were calculated on the individual patches within each class, in this case, just the forested class, providing a distribution of values for these metrics that could be statistically compared among study areas.

We selected several landscape-level metrics: total area (TA) of land (excluding water, clouds, or cloud shadows), forested

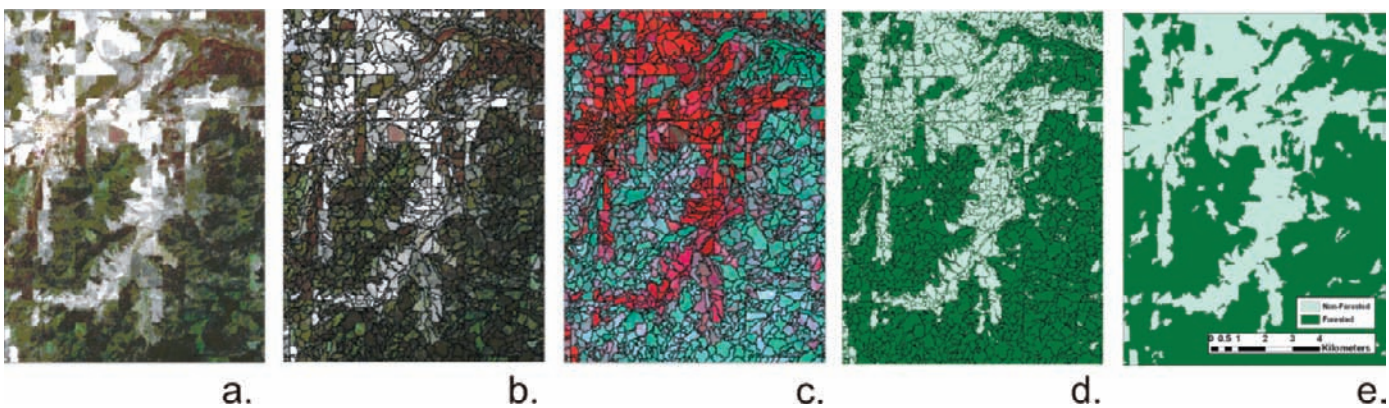

Figure 4. Illustration of an image segmentation and classification. (a) Subset of the TE-MOIST Landsat ETM+ image. (b) Landsat ETM+ image with delineated polygon layer. (c) Tasseled cap transformed image with delineated polygon layer. (d) Pixel-based maximum likelihood classified image. (e) Classified image according to the majority of the forested pixels inside each polygon.

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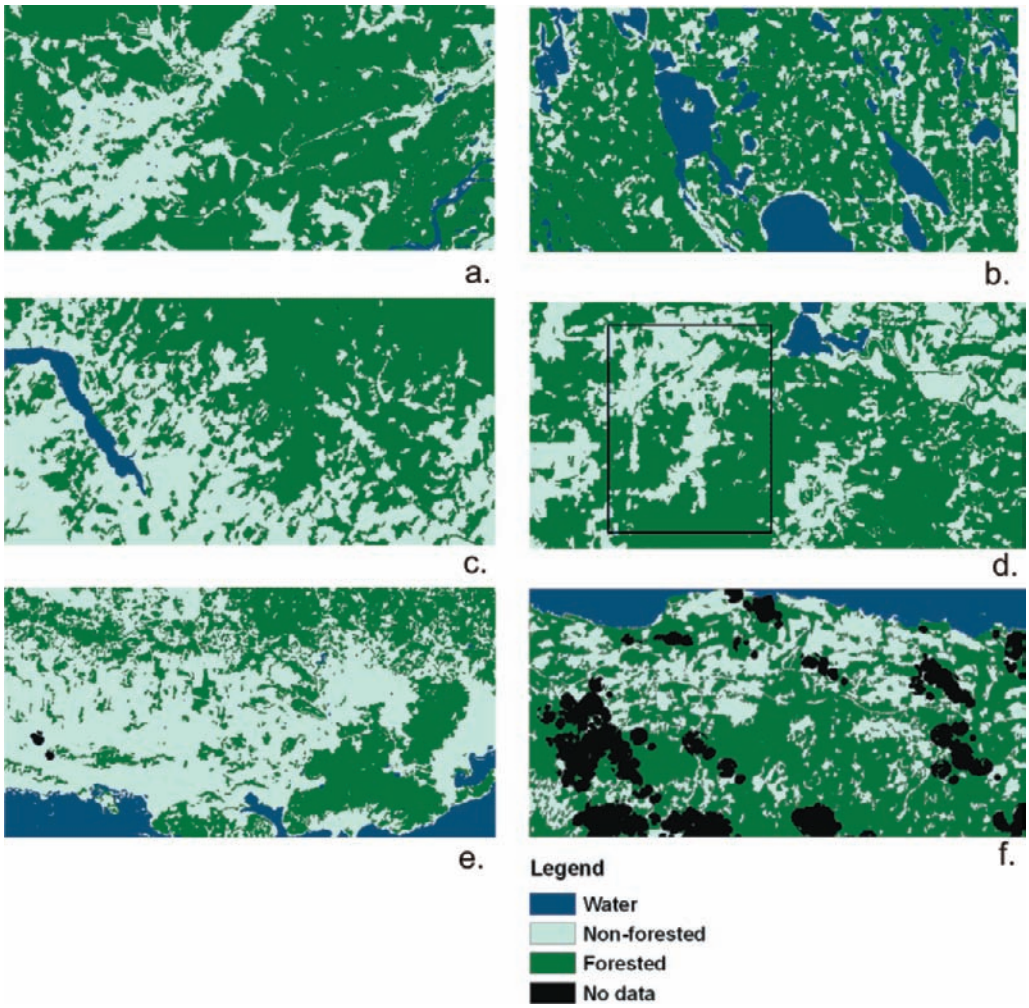

Figure 5. Six maps of the classified study areas. (a): BO-DRY, (b) BO-MOIST, (c) TE-DRY, (d) TE-MOIST, (e) TR-DRY, (f) TR-MOIST. (The frame in map d shows the extent of Figure 4.)

area (FA), percentage forested (PFOR), number of patches (NP), patch density (PD), total edge (TE), and relative edge length (REL) (Table 2). These metrics were chosen because they have little redundancy among them yet have intuitive ecological meaning. The four patch-level metrics included: mean patch area (MPA), perimeter area ratio (PAR), proximity index (PROX), and core area of the forested patches (CORE). The distributions of the patch-level metrics (dependent variables) were analyzed using a one-way analysis of variance (ANOVA) with the nonparametric Kruskal-Wallis chi-square test (31), which indicates significant differences between the means of the patch-level metrics by study area (grouping variable). In addition, the Spearman's rank correlation coefficient (ρ) was calculated between some of the landscape-level metrics and the population density and the road length ($n = 6$) per study area (Table 1). R software was used for all statistical analyses (32).

The landscape-level and class-level metrics were calculated with FRAGSTATS based on effective areas, i.e., ~45 000 ha less those areas classified as water (all six study areas), or as "no data" due to cloud or cloud shadow masks (TR-DRY and TR-MOIST areas). FRAGSTATS was instructed to ignore the outer edge of the study area, and polygons adjacent to the water class or to the "no data" masks in order to prevent these factors from confounding the analysis. This is because the study area boundaries and the position of the cloud or cloud shadow masks have little relationship to features on the ground, yet they can alter the size and shape of adjacent polygons in the imagery and, consequently, any calculated metrics. Although water is a real landscape feature, its effect on adjacent polygon characteristics is not a function of human-induced changes, as are the urban or agricultural areas of land-use conversion of primary interest. In summary, only those forested polygons not touching the study area boundaries, water features, or "no data" masks were included in the results.

RESULTS

Landscape-Level Metrics

The percentage forested (PFOR) was highest in the boreal region, lowest in the tropical region, and intermediate in the temperate region (Table 3). PFOR was significantly negatively correlated with road length ($\rho = -0.89$, $p = 0.03$), and PFOR showed a negative but insignificant tendency toward population density ($\rho = -0.77$, $p = 0.10$). There were differences in PFOR between the dry and moist landscapes in the temperate and tropical regions; lower PFOR was found in the dry landscapes. However the difference in PFOR between the BO-DRY and BO-MOIST areas was only slight.

The number of patches (NP) was highest in the TR-DRY area and lowest in the BO-MOIST area. The NP was large in the tropical areas, and, along with a lower PFOR, it suggests a higher degree of fragmentation relative to the nontropical study areas (Table 3). Neither NP nor patch density (PD) was significantly correlated with population density ($\rho = 0.43$, $p = 0.42$ and $\rho = 0.43$, $p = 0.42$ for NP and PD, respectively) or road length ($\rho = 0.54$, $p = 0.30$ and $\rho = 0.54$, $p = 0.30$ for NP and PD, respectively). When considering the PFOR and NP results together, it is apparent that the dry areas across all climatic regions have more patches compared to their moist study area counterparts in the same region. This is also apparent in the patch density metric (PD), which shows the same pattern: higher for the dry areas, lower for the moist areas.

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Table 2. Description of the FRAGSTATS metrics employed.

Metric	Formula (units)	Description
PFOR	$\frac{FA}{TA}$ (%)	Percentage forested
NP	(unitless)	Number of forested patches
PD	$\frac{NP}{TA}$ (ha^{-1})	Density of forested patches (number per 100 ha)
TE	$\sum_{1}^{NP} e$ (km)	Total edge length of the forested patches
REL	$\frac{TE}{PFOR}$ (unitless)	Relative edge length; the total edge length corrected for the fraction of the total forested area
MPS	(ha)	Mean patch size of the forested patches
PAR	$\frac{p}{a}$ (unitless)	Perimeter area ratio of the forested patches
CORE	(ha)	Core area of the forested patches (search radius = 100 m)
PROX	$\sum_{1}^{NP} \frac{a}{h}$ (unitless)	Proximity index of the forested patches with specified neighborhood of 100 m

FA = total forested area; *TA* = total area (excluding background); *e* = edge length of patch; *p* = perimeter of patch; *a* = area of patch; *h* = distance between two patches based on edge-to-edge distance.

Total edge (TE) represents a measure for the actual forest–nonforest edge length (excluding the study area border, water, and "no data" edges), while the relative edge length (REL) is more informative when comparing the different study landscapes because it is corrected for the forested fraction. We found that the REL is higher in the drier landscapes of the temperate and the tropical regions but lower in the drier landscape of the boreal region (Table 3). The TE length had no apparent relationship with population density ($\rho = 0.09$, $p = 0.92$) or road length ($\rho = -0.03$, $p = 1.0$), whereas the REL showed a positive yet insignificant tendency toward population density ($\rho = 0.71$, $p = 0.14$) and road length ($\rho = 0.83$, $p = 0.06$).

Patch-Level Metrics

Three patch-level metrics, the mean patch area (MPA), the perimeter area ratio (PAR), and the proximity index (PROX), show highly significant ($p < 0.001$) differences between study areas, while the CORE patch-level metric was insignificant ($p = 0.095$) (Table 3). The MPA is higher for the moist areas compared to their corresponding dry areas in the same climatic zone. In addition, the MPA is higher in the boreal region than in the temperate region, which in turn is higher than in the tropical region. The shape index (PAR) shows that shape complexity is highest in the two boreal areas and lowest in the TE-DRY area. The proximity index (PROX) shows similar trends as the MPA, with primarily lower values for drier areas, and an increasing trend with increasing latitude. There were no significant differences between the core areas (CORE). While the mean values show a similar pattern as the MPA, there is great variability within the study sites and therefore no significant difference in the CORE metric.

DISCUSSION

It was difficult to detect significant trends in the landscape-level metrics based on only six study areas. On the other hand, it was easy to detect significant trends in the patch-level metrics, because hundreds of patches were generated per study area. Thus, we interpret the slightly insignificant results in the landscape-level metrics to have potential ecological significance that may merit further study, such as the negative but insignificant ($p > 0.05$) relationship we found between PFOR and population density.

Our image analysis approach was repeated in identical fashion over each landscape, allowing us to characterize the extent and nature of forest fragments, as represented by consistently derived image objects, between the selected study areas. We caution that the image objects generated by eCognition represent landscape units at the point in time the Landsat image was acquired and may not accurately indicate the true nature of the fragmentation process that has been ongoing for decades. We further caution that our six selected study areas may not represent the average degree of forest fragmentation across the dry and moist tropical, temperate, and boreal forest types. These two cautions concern a temporal and spatial scope of inference that was well beyond our ability to address. However, we do believe our analysis approach has merit as a means to objectively and consistently characterize fragmented forest landscapes.

Our results support the idea that high road density and human population density is correlated with greater forest fragmentation. For example, in Puerto Rico, where human pressure is greatest among our study areas, forest fragmentation indices show smaller mean patch area, higher patch density, and less core area (Table 3). Severe tropical forest destruction has been widely documented (33, 34), particularly in dry tropical forests (23, 35). On the other hand, the results suggest the picture is more complicated than might be attributed to human population pressure alone. Indicators of fragmentation were found to be greater in the dry environments compared to the moist environments along the climatic gradient. The number of patches and patch density were greater in the dry study areas

Table 3. Results of the landscape-level metrics (A) and the means and standard errors of the patch-level metrics, the Kruskal-Wallis chi-square test results, and their significance values (B) per study area.

	BO-DRY	BO-MOIST	TE-DRY	TE-MOIST	TR-DRY	TR-MOIST	Chi-squared (d.f. = 5)	p value
A. Landscape-level metrics								
TA (ha)	44 504	38 178	43 837	44 347	41 033	34 077		
FA (ha)	30 583	29 093	23 959	28 421	16 689	22 569		
PFOR (%)	67.9	64.5	53.2	63.1	37.0	50.1		
NP	133	62	129	116	342	172		
PD	0.30	0.14	0.29	0.26	0.76	0.38		
TE (km)	1445	1753	1630	1615	1719	1365		
REL	47.3	60.2	68.0	56.8	103.0	60.5		
B. Patch-level metrics								
MPA	230.0 (159.6)	469.2 (320.1)	185.7 (149.8)	245.0 (215.6)	48.8 (20.7)	131.2 (105.0)	65.136	<0.001
PAR	425.9 (19.7)	425.9 (40.7)	293.5 (14.6)	393.2 (19.9)	395.1 (10.4)	418.0 (29.4)	38.910	<0.001
PROX	28 678 (5,142)	57 920 (1,0163)	11 102 (3,550)	34 336 (6116)	4005 (599)	24 016 (3550)	39.198	<0.001
CORE	594.3 (438.5)	647.9 (434.5)	216.3 (198.2)	508.2 (481.8)	99.3 (49.0)	224.1 (191.8)	9.381	0.095

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compared to the moist study areas in the same climatic region, while the percentage forested area and the mean patch area were smaller. However, forest canopy structure is also naturally more open in drier forest types, which is likely confounding these results aimed at isolating the human forces of fragmentation.

The increased influence of historic fires on drier forested ecosystems also may be contributing to fragmentation. This is a difficult factor to tease apart, as ignitions may be caused by lightning or by humans. The former cause is much more likely in Alaska, while in Puerto Rico, fires were virtually nonexistent prior to human settlement (23, 36). Introductions of exotic African grasses are causing the development of cyclic fires in the seasonally dry forest of the TR-DRY area, which may also be contributing to greater fragmentation. Our results support other studies (23, 35) that have shown the dry tropical forest ecosystem is particularly fragmented and threatened or endangered. Restoration of less-fragmented dry forest ecosystems may be hindered by the persistence of frequent fires in the grass sward encroaching upon forest edges, often along roads where human ignitions are more likely.

The methods presented in this study represent a way to characterize fragmented forest landscapes across different forest ecosystems using a consistent image data source, processing, and analysis approach. Others have demonstrated the limitations of purely pixel-based image analysis approaches (14, 37). Classification of image pixels often results in a "salt and pepper" effect because many pixels are below the minimum mapping unit (MMU) size of interest and which would inflate the number of patches, increase edge length, and have otherwise undesirable consequences on the patch metrics (38). The "salt and pepper" effect is often removed by passing moving windows (such as pixel median or majority filters) over the classified image (39) or establishment of an MMU (40). By first segmenting and thereafter classifying the images, we could avoid the problems caused by single-pixel classification units.

Despite eCognition's capability to delineated discrete units representing landscape pattern, more research is necessary to determine how the procedure works for different types of imagery on different types of edges. Remote-sensing imagery with higher spatial resolution (27) or multidate image delineation (14, 41) has the ability to more precisely locate an edge in the field. Further research could focus on the detectability of different types of edges and their relationships to different processes, such as fragmentation.

Besides comparing study areas, landscape metrics can be used to parameterize models and perform risk assessment over larger landscapes. For instance, wildland fire prevention has to deal with the increased complexity of the urban-wildland interface (42; 2007 Caribbean Fire Ecology and Management Symposium outcome). The total edge (TE) calculated exemplifies a metric that could be used as an index of the amount of urban-wildland interface and perhaps as a measure of fire risk. Often these borders are sensitive locations for forested ecosystems that are vulnerable to invasive species and anthropogenic disturbance. The metrics employed in this study could improve our understanding of the dynamic wildland-urban interface (WUI) across fragmented landscapes.

CONCLUSION

As might be expected, landscapes with higher population and road density are more fragmented. In addition, our results indicate that landscapes in drier climate have a higher degree of fragmentation as compared to their moister counterparts in the same climatic region. Drier climates produce more dispersed vegetation that can appear more fragmented as characterized by our analysis techniques. Separating the competing influences of land use and climate on the patch characteristics of forest fragments is an issue for future research. We encourage further testing of our remote-sensing, image segmentation, and patch analysis methods in other forested landscapes spanning a human population density gradient, or a moisture gradient, within boreal, temperate, or tropical forest types.

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