Developing a land-cover classification to select indicators of forest ecosystem health in a rapidly urbanizing landscape


1. Introduction

The transformation of landscapes from natural to urbanized is a necessity for the progression of civilization (DeFries et al., 2004; Kremen and Ostfeld, 2005). While humans depend on essential ecological services to support their immediate needs, ecosystem processes are often altered by land-use changes, thus disrupting a variety of ecological services provided to humans by the environment (DeFries et al., 2004). Such services provide us with clean air and water, drought and flood protection, soil generation and preservation, and detoxification of wastes. When fundamental ecosystem services are altered by population growth, land development, and over-consumption of natural resources, enduring societal welfare is at risk (Kremen and Ostfeld, 2005). Thus, a thorough understanding of ecosystem responses to land-use change is imperative to evaluate the balance between short-term human needs with long-term ecosystem health and sustainability (DeFries et al., 2004; Kremen and Ostfeld, 2005).

Assessments of ecosystem health are necessary to determine the types and amount of decline in ecosystem services resulting from human modification of the environment (Kremen and Ostfeld, 2005). To quantify impacts of urbanization in a given area, correlations of measured forest health metrics to surrounding landscape characteristics are useful in examining what aspects of urban development may be linked to ecosystem functions in that area. Healthy ecosystems have the capacity to supply sufficient quantities of water, nutrients, and energy to sustain productivity while remaining resistant and resilient to stress (McLaughlin and Percy, 1999). Historically, field-based data collections in individual forest stands have been the method selected by ecologists to assess ecosystem health (McLaughlin and Percy, 1999). Parameters typically examined by ecologists include crown condition, incidences of lichens, pests, diseases, and mechanical injury to trees, and visible air pollution-induced foliar injury on vascular plants (Wear and Greis, 2002). Additionally, nutrient status and trace metals in tree rings, soils, and lichens can be measured and quantified to determine current and historical concentrations at a specific site and then compared to those observed at similar sites in neighboring areas (Wear and Greis, 2002; Styers and Chappelka, 2009). However, these site-level data represent only a small portion of the landscape in which they are contained since it is usually impossible to sample all of the study area (e.g., private property, steep ridges, and areas under water). To relate site-level information to adjacent land-uses for the purpose of land management, planning, and policy decisions, the surrounding region in which the sites are located must be evaluated. As such, studies that attempt to correlate broad-scale landscape indicators of urbanization and ecosystem health with field indicators of forest stand structure and...
has low population growth (3%) but high density (333 people/km²), which contains the city of Columbus (2000 population, 185,781), different demographic shifts in these counties. Muscogee County, which has experienced rapid growth and development during the past decade.

Land-cover class percentages for the WestGA area were documented and used as landscape indicators of forest ecosystem health. Since the WestGA area has experienced such rapid growth and development since 2000, it was necessary to have a recent and accurate land-cover classification for the region. It was also imperative that the land-cover classification and field-collected data covered the same time period (2005–2006) because in a rapidly developing landscape time is critical. At the time this classification was constructed, there were no publicly available land-cover classifications covering this region for this specific time period (e.g., NLCD and Georgia GAP). Thus, as part of this study, a land-cover classification for 2005 covering the WestGA region was constructed using Landsat imagery. These moderate-resolution images (30-m) were selected because they were readily available, cost-efficient, and already in a usable digital format. Moreover, moderate-resolution imagery, such as Landsat, is more applicable to landscape and regional assessments since there are usually fewer classification errors associated with general land-cover classifications with only a few standard classes (Smith et al., 2003). High-resolution (<5 m) aerial photographs generally result in high stand- and plot-level error due to pixel size and limited spectral properties (Tuominen and Pekkarinen, 2005). Although, textural features of high-resolution aerial photographs are capable of producing more detailed classifications, the spectral features of medium spatial resolution imagery produce better overall results than textural features when estimating various forest attributes such as those measured in this study (Tuominen and Pekkarinen, 2005).

A Landsat 5 Thematic Mapper (TM) image from September 2005 and two images from 2004 (August and December) were used as a stacked image layer to produce a land-cover classification for the WestGA region for the year 2005 (U.S. Geological Survey, 2005). Since no other cloud-free summer or winter imagery of the area was available for 2005, the leaf-on (August) and leaf-off (December) images from 2004 were used to distinguish between deciduous and coniferous forests and improve other class assignments for the September 2005 image. Each image was radiometrically and geometrically corrected by the USGS to account for errors due to topographic relief and atmospheric interference (U.S. Geological Survey, 2005). Pre-classification processing included the registration of each image to the September 2005 image to ensure they were in the same coordinate system (UTM Zone 16N; datum NAD 83; spheroid WGS 84) and aligned properly for classification and overlay analysis. The initial classification scheme developed for the entire three-county scene contained the following five land-cover characterization classes: water/wetlands, deciduous forest, evergreen forest, rural pasture, and bare ground (the latter contains cutover pine plantations, cultivated agricultural lands, and land under development). The procedure was accomplished using a hybrid classification method (Bluyan et al., 2003), and each pixel was classified according to the most dominant class represented within the pixel.

A separate scheme for 2005 was developed for the urban areas in WestGA (as delineated by the U.S. Census Bureau 2000 Decen-
nal Census) to increase the accuracy of the classification. The additional step was taken to avoid grouping urban and residential vegetation with forest and pasture land classes in rural areas which had similar spectral characteristics. Urban areas were first subset and masked from the stacked TM image using Census 2000 urban area delineations, and were then grouped into four classes using an unsupervised classification. Areas of urban growth since 2000, as evident from the imagery, were included in the subset mask. The resulting image contained the following four classes: water/wetlands, urban vegetation (includes all photosynthetically active plants with similar spectral characteristics as deciduous and/or evergreen tree species), urban grasses (includes all grassy areas), and urban/built-up (includes land-covered by structures and impervious surfaces). The urban area classification was compared to the initial three-county classification to examine any discrepancies between classes prior to overlaying and recoding procedures. Once the urban areas were classified, the image was overlaid with the initial classification to produce an eight-class
final image. The final classification image contained the following eight land-cover characterization classes: urban/built-up, bare ground, rural pasture, urban grasses, urban vegetation, deciduous forest, evergreen forest, and water/wetlands. Once this final land-cover classification for the entire area had been produced, an accuracy assessment was conducted using high-resolution 1-m color Digital Ortho Quarter Quads (DOQQs) (date of imagery February 1999; accessed USGS Seamless Data Server June 13, 2006), the Landsat TM images, and field-based ground-truthing to verify the classification of 30 randomly generated points. For the purposes of this study, the following five class combinations were used as the final variables in the analysis: forest (urban vegetation + deciduous forest + evergreen forest), rural pasture, all grasses (rural pasture + urban grasses), urban/built-up, and non-vegetated land (urban/built-up + bare ground). The eight classes from the final classification image were combined into these five generalized classes to reduce the possibility of error associated with a greater number of classes. Since terrestrial forest ecosystem health was the target of this study, the water/wetlands class was not included in the analysis. For more detailed information on the entire classification process, the reader is referred to Styers (2008).

### 3.2. Landscape indicators of ecosystem health

Landscape pattern metrics for the WestGA area were also collected and used as landscape indicators of forest ecosystem health. Landscape pattern data were obtained using the 2005 land-cover classification as input into Fragstats, which is a spatial pattern analysis software program designed to compute a multitude of classification as input into Fragstats, which is a spatial pattern analysis software program designed to compute a multitude of classification as input into Fragstats, which is a spatial pattern analysis software program designed to compute a multitude of classification as input into Fragstats, which is a spatial pattern analysis software program designed to compute a multitude of classification as input into Fragstats, which is a spatial pattern analysis software program designed to compute a multitude of landscape pattern metrics for categorical maps (McGarigal et al., 2002). The WestGA study area was delineated by census tract boundaries. Only the census tracts containing the location of the 12 field study sites were used in this analysis. Since the focus of this study was terrestrial forest ecosystem health, only the land-cover class (urban vegetation + deciduous forest + evergreen forest) was used in calculating the patch density, edge density, and perimeter-area fractal dimension landscape indicator metrics that were used as variables in the analysis. However, to calculate overall landscape diversity and evenness of all possible land-cover types, each of the eight land-cover classes from the final classification scheme was used as input variables.

Forest patch density (ForPD) is expressed as the number of patches per 100 ha within each of the sampling units (i.e., census tract). Forest edge density (ForED) reports the length of edge (in m/ha) within each of the sampling units. The fractal dimension (ForPAFrac) reflects patch shape complexity and is appealing because it can be used across a range of spatial scales. Fractal dimension ranges from 1 to 2, or from shapes with very simple perimeters to those with very complex perimeters, respectively. Shannon’s diversity index (LS SHDI) expresses the proportion of the landscape occupied by a particular patch type (i.e., the five land-cover characterization classes) (McGarigal et al., 2002). Landscape diversity is 0 where there is only one patch, and increases to infinity as the number of different patch types increases and/or the areal distribution among patch types becomes more even. Similarly, Shannon’s evenness index (LS SHEI) represents the evenness of areal distribution among patch types (McGarigal et al., 2002). Landscape evenness is 0 where the areal distribution among patch types is uneven, or where there is dominance of only one patch type, and increases toward 1, where there is perfect evenness among distribution of area among patch types.

### 3.3. Population, housing, and road densities

Data from the 2000 Decennial Census were used to calculate population, housing, and road densities for each of the census tracts that contained field plots so these could be used as three additional urbanization variables (U.S. Census Bureau, 2006). These data were also used to validate the representation of “urban” areas of WestGA in the urban land-cover class by comparing correlations between our land-cover pattern data and U.S. Census Bureau 2000 Decennial Census data (U.S. Census Bureau, 2006).

### 3.4. Field indicators of forest health

Forest stand structure and condition data collected from 12 field study sites (4 urban, 4 developing, 4 rural, with data averaged from three 0.05-ha plots per site; 36 total plots) during 2005–2006 were included as the 30 biological variables in this assessment. These variables were selected because: (1) they were developed for use as industry-standard protocol for the Forest Inventory and Analysis National Program by the USDA Forest Service (USDA Forest Service, 2006), (2) they have been proven useful as forest health indicators in previous studies (McCune et al., 1997; McIntyre, 2000; McKinney, 2002; Wear and Greis, 2002; Geiser and Neitlich, 2007; Styers and Chappelka, 2009), and (3) the values for many of these variables are significantly different between land-use types in WestGA (Styers, 2008). For a list of these variables see Table 1.

### 3.5. Correlation matrix

A total of 43 variables (Table 1) were obtained to represent a mix of biological, land-cover, and landscape pattern metrics suitable to describe the current condition of ecosystem health in WestGA: 30 biological variables from field-based measurements, and 13 urbanization variables from — from land-cover characterization data, 5 from landscape pattern data, and 3 from census data (Styers, 2008). A multivariate correlation matrix (Spearman’s Rho) was constructed to determine which of the urban and biological variables were significantly correlated (Medley et al., 1995).

### 4. Results

#### 4.1. Land-cover

Land-cover characterization classes for WestGA included urban/built-up, bare ground (areas under development, cultivated areas, and harvested timberlands), rural pasture, urban grasses (lawns, grassy lots, and gold courses), urban vegetation (trees and large shrubs), deciduous forest, evergreen forest, and water/wetlands. Urban/built-up land accounted for 4% of the total land area in WestGA. Forty-one percent of total land-cover was evergreen forest, which included many areas of extensively managed pine plantations, while 31% was deciduous forest, and 1% was urban vegetation. Rural pasture land-cover and urban grasses accounted for 6% and 1% of land, respectively. Bare ground accounted for another 12%, and 4% of land represented water/wetlands. The overall classification accuracy for the WestGA land-cover classifications was 93% (Kappa = 0.9080).

#### 4.2. Landscape pattern

Landscape pattern metrics measured for the three-county area in WestGA were based on forest land-cover in 2005 and included forest patch density (ForPD), forest edge density (ForED), forest perimeter–area fractal dimension (ForPAFrac), landscape Shannon’s diversity index (LS SHDI), and landscape Shannon’s evenness index (LS SHEI). Forest patch density ranged from 0.66 to 22.24 patches/100 ha, increasing steadily from rural to urban land-use types. Forest edge density ranged from 54.17 to 162.32 m/100 ha, also increasing from rural to urban land-uses. Fractal dimension
values were 1.41–1.56 for rural to urban lands in WestGA. Landscape diversity values for rural to urban land-use types in WestGA were 0.59–0.98. Landscape evenness values were 0.37–0.71 for rural to urban lands in WestGA.

4.3. Data correlations

The goal of the multivariate correlation matrix was to determine which urban and biological variables were moderately to highly correlated. However, to validate if the satellite-derived urbanization variables truly represented “urban” areas in WestGA, correlations were first compared between land-cover pattern data and U.S. Census Bureau 2000 Decennial Census data (i.e., population, housing, road densities). With the exception of % grasses, all of the satellite-derived metrics had significant ($p \leq 0.10$) correlations of $\rho \geq 0.65$ with the three census datasets, thus validating the use of these urbanization variables in this correlation analysis. Additionally, many of the biological field indicator variables were significantly ($p \leq 0.10$) correlated with the 10 urbanization variables derived from the land-cover classification (Table 2) and subsequent fragmentation analyses (Table 3). In all, there were 152 significant correlations (Styers, 2008).

5. Discussion

Columbus, GA is a moderately sized city but urban development is occurring at a rapid pace (U.S. Census Bureau, 2006). Urban/built-up land accounted for 4% of the total land-cover in 2005 across the three-county WestGA. Although these percentages are nominal overall, urban/built-up land in the region continues to increase in response to population growth. Census data (U.S. Census Bureau, 2006) indicate that in Harris County alone population growth increased (56% from 1990 to 2005) at a rate nearly three times that of the national average (15% from 1990 to 2005). Urban census tracts were characterized by high percent cover of urban/built-up land (42–56%) and low percent cover of forest land (37–51%). By contrast, rural and developing sites had very low percent cover of urban/built-up land (0–1% and 2–11%, respectively) and very high percent cover of forest land (71–85% and 78–82%, respectively).

Since a majority of the land in WestGA is forested (73% in 2005), the goal of the landscape pattern analysis was to gain more detailed information about how forested land patches were patterned across the landscape and if there were differences between land-use types. Forest patch density was greatest in urban sites (10–22 patches/100 ha) versus rural and developing sites (0.66–2.26 and 1.73–2.23 patches/100 ha, respectively). This suggests more patchiness among urban forests in WestGA, possibly resulting from forest fragmentation due to land development. Similarly, forest edge density was also greatest in urban sites (122–162 m/100 ha) versus rural and developing sites (54–69 m and 68–76 m/100 ha, respectively), and is consistent with research by Zipperer (1993), who reported increased deforestation and higher perimeter-to-area ratios in forested patches in urban areas of Maryland.

Perimeter-area fractal dimension measures the complexity of the shape of forest patches. Typically, urban and managed forests have more regular, simple perimeter shapes (values near 1) while unmanaged, natural forests have more irregular, complex perimeter shapes (values near 2). Urban sites in WestGA have fractal dimension values ranging from 1.46 to 1.56 versus rural and developing sites (1.41–1.45 and 1.45–1.49) and developing (1.45) sites which have slightly lower values, although these values were not significantly different between land-use types. The similarity in values across sites could possibly be attributed to the large amount of managed pine plantations located in rural areas of the WestGA region sampled, which is evident from the high percentages of evergreen forest and bare ground land-cover in rural (41–50% and 8–18%, respectively) and developing (42–47% and 1–12%, respectively) areas of WestGA.

To gain further insight into the diversity and evenness of land-cover types across land-use areas, landscape Shannon’s diversity and evenness indices were calculated for the WestGA region. Results suggest that urban areas are significantly the most diverse,

<table>
<thead>
<tr>
<th>Biological variables</th>
<th>Urbanization variables</th>
</tr>
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<tbody>
<tr>
<td>Total number of tree stems $&gt;10$ cm dbh/ha [#Stems $&gt;10$]</td>
<td>Population density [PopDens]</td>
</tr>
<tr>
<td>Total number of hardwoods/ha [#HW]</td>
<td>Housing density [HousDens]</td>
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<tr>
<td>Total number of pines/ha [#Pines]</td>
<td>Road density [RoadDens]</td>
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<tr>
<td>Hardwood:pine ratio [HW:Pine]</td>
<td>% Forest [%Forest]</td>
</tr>
<tr>
<td>Total number of tree species [#TreeSpp]</td>
<td>% Pasture [%Pasture]</td>
</tr>
<tr>
<td>Mean dbh (cm) of all mature trees [MeanDBH]</td>
<td>% Grasses (pasture + lawn) [%Grasses]</td>
</tr>
<tr>
<td>Basal area (m$^2$/ha) [BA]</td>
<td>% Urban/built-up [%Urban/BU]</td>
</tr>
<tr>
<td>Median age of stand [MedAge]</td>
<td>% Non-vegetated land (urban + bare ground) [%Non-veg]</td>
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<tr>
<td>% Peak canopy cover [%CanCov]</td>
<td>Forest patch density [ForPD]</td>
</tr>
<tr>
<td>Mean upper canopy height [m] [UpCanHlt]</td>
<td>Forest edge density [ForED]</td>
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<tr>
<td>Mean subcanopy height [m] [SubCanHlt]</td>
<td>Forest perimeter-area fractal shape [ForPAFrac]</td>
</tr>
<tr>
<td>Total number of tree stems $2.5–10$ cm dbh/ha [#Stems 2.5–10]</td>
<td>Landscape Shannon’s landscape diversity index [LS SHDI]</td>
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<tr>
<td>Mean number of sapling stems $0.635–2.5$ cm/ha [#Stems 0.635–2.5]</td>
<td>Landscape Shannon’s landscape evenness index [LS SHEI]</td>
</tr>
<tr>
<td>Mean number of seedling stems $&lt;0.635$ cm/ha [#Stems $&lt;0.635$]</td>
<td>% Woody stems/ha [%Woody]</td>
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<tr>
<td>% Woody stems/ha [%Woody]</td>
<td>% Herbaceous plants/ha [%Herb]</td>
</tr>
<tr>
<td>% Leaf litter/ha [%Leaf]</td>
<td>% Bare ground/ha [%BGC]</td>
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<tr>
<td>% Trees with injury from insects [%InjInsects]</td>
<td>% Trees with injury from diseases [%MechInj]</td>
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<tr>
<td>% Trees with injury from diseases [%DInj]</td>
<td>% Trees with injury from mechanical damage [%MechInj]</td>
</tr>
<tr>
<td>% Insect + disease + mech. damage for all trees [% + D + M]</td>
<td>% Hardwood trees with lichens [%HWWlich]</td>
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<tr>
<td>Mean number of lichen species per hardwood tree [#LicSppHW]</td>
<td>Mean lichen abundance rank for all hardwood trees [LicAbdHW]</td>
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<tr>
<td>Mean number of crustose lichen species on water oaks [#CruSppWO]</td>
<td>Mean number of foliose lichen species on water oaks [#FolSppWO]</td>
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<tr>
<td>Mean number of foliose lichen species on water oaks [#FolSppWO]</td>
<td>Crustose:foliose ratio (on water oaks) [Cru:FolWO]</td>
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<tr>
<td>Mean lichen abundance rank for water oaks [LicAbdWO]</td>
<td>Mean dominance of crustose over foliose (on water oaks) [DomCru/FolWO]</td>
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with landscape diversity values ranging from 0.91 to 0.98, meaning that areas elsewhere (McKinney, 2006). One suggestion is that as areas (e.g., no urban/built-up land-cover present) or that one or more opening sites (0.59–0.82 and 0.67–0.76, respectively) suggest that the significantly lower diversity value ranges for rural and developing areas (i.e., land-cover class types) than rural or developing areas. The percentage of forest land-cover in WestGA was inversely (Rho = 0.66; p = 0.01) correlated with each of the 13 urbanization variables derived from the land-cover classification and subsequent fragmentation analyses. The main purpose of this analysis was to demonstrate the utility of these data correlations as a land management and planning tool. As such, some examples of these are briefly discussed below.

The percentage of forest land-cover in WestGA was inversely correlated with population (Rho = −0.87; p = 0.03), and road (Rho = −0.93; p = 0.04) densities. These correlations seem obvious, but they are nonetheless important. Cordell and Macie (2002) reported that Harris and Meriwether counties are ranked among the greatest in the country for 2020 projected population pressures on forested land and wildlife habitat. These data are also supported by the land-cover and census population data analyses, that reveal that Harris County had the most forested land area in the WestGA region (81% of land was forested in 2005) yet also had the greatest population growth rate in the region.
from 1990 to 2005 (56%), which is nearly three times greater than the national average (19%).

The percentage of urban land versus the combined injury to trees resulting from pest, disease, and mechanical injury were positively correlated (Rho = 0.64; p = 0.05; Fig. 3). As the amount of urban land increased, so did the amount of injury. Typically, urban forests experience greater disturbance than rural areas, often rendering them more susceptible to other forms of environmental stress (Zipperer, 2002a). Findings from several previous studies have also suggested that urban systems have a higher incidence of pests and diseases (McLaughlin and Percy, 1999; McIntyre, 2000; McKinney, 2006). In WestGA, however, mechanical injury scores were greatest, and could possibly be linked to hurricane and ice storm damage in the region prior to sampling. Even though limb breakage from these events was evident in all of the sites measured (urban, developing, and rural), the scores were greatest in urban areas.

The percentage of urban land versus number of lichen species, or lichen species richness, were negatively correlated (Rho = −0.52; p = 0.06; Fig. 3). Gombert et al. (2004) reported that lichen diversity in France was influenced by “environmental artificiality” and air pollution exposure, resulting in lower lichen diversity in urban versus rural areas. Lichen diversity also varies due to exposure to air pollutants such as SO2 and NO2 (McCune et al., 1997; Gombert et al., 2004; Frati et al., 2006; Geiser and Neitlich, 2007). Further, edge effects resulting from forest fragmentation due to urban land development can have major impacts on lichen species diversity (Renhorn et al., 1997; Esseen and Renhorn, 1998).

The number of tree species per site, or tree species richness, and forest patch density were negatively correlated (Rho = −0.62; p = 0.01; Fig. 3). As the number of forest patches increased the number of tree species decreased. A high number of forest patches in a given area typically indicates many small, fragmented forest patches, whereas a low number indicates fewer, larger forested patches (Zipperer, 1993, 2002b). Since urban forests are usually small due to encroaching residential and commercial land development, these areas typically have a higher number of forest patches per unit area, or high forest patch density (Zipperer, 2002b). In many of these urban forests, tree species richness is generally lower than in surrounding rural forests (McKinney, 2002; Burton et al., 2005). The percentage of mechanical injury and landscape diversity was positively correlated (Rho = 0.83; p < 0.001; Fig. 3). As noted earlier, mechanical injury was observed across the WestGA region, possibly resulting from large, infrequent disturbances. Nevertheless, injury scores were greatest in urban areas. Urban areas also had the greatest landscape diversity values, indicating a variety of land-cover patch types in these areas. As land became fragmented and diversified from urban development, the likelihood of mechanically injured trees also increased.

6. Conclusions

Regional ecosystem assessments that use satellite-derived imagery can be conducted in order to identify specific areas within a region that may appear stressed and warrant further ground-based analyses. For example, areas identified on satellite imagery as having high percentages of impervious surfaces and housing densities but low percentages of forest land-cover are likely those areas noted as “stressed” or “unhealthy” during ground-based field surveys. Thus, the ability to predict land-use patterns over a broad landscape scale by combining relatively simple land-cover and statistical analysis techniques provides a cost- and time-efficient means for monitoring forest ecosystem health.

Results from this study suggest that the land-cover classification procedure used herein is adequate for selecting landscape indicators of ecosystem health for the WestGA region. These indicators
correlated well with many field-measured biological responses of ecosystem health, validating its utility as a land management and planning tool. Therefore, this tool is a good surrogate for field-based forest health assessments since results from this analysis indicate that the two differing methods produce similar results for forest ecosystem health in a given area of WestGA. The percentage of forest land-cover had correlations to several of the urbanization variables, and was strongly inversely correlated with population, housing, and road densities. Previous analyses have reported that lichens are good bioindicators of forest ecosystem health (Nash and Gries, 1986; McCune et al., 1997; Esseen and Renhorn, 1998; Gombert et al., 2004; Frati et al., 2006; Geiser and Neitlich, 2007) and these results support those findings. Lichen incidence, abundance, and species richness were among several variables significantly correlated with landscape variables including % urban/built-up, forest, and rural pasture land-covers, forest patch and edge densities, forest perimeter-area fractal dimension, and housing, population, and road densities. These correlations could be used to create predictive statistical and GIS models to discern what factors are related to ecosystem health and to identify the areas that warrant further ground-based studies. Such methods could prove useful to land managers by providing a quick and simple method to assess broad areas of land in a single analysis, enabling funds to be reserved for more in-depth analyses in areas identified as “impaired” through the use of this tool.

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