

Sensitivity of GIS patterns to data resolution: a case study of forest fragmentation in New Zealand

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Abstract: Spatial pattern plays an influential role in the ecological processes of ecosystems, and landscape pattern metrics computed from remotely sensed data offer a way to quantify the correlation between pattern and process. However, the resolution of geographic data affects the landscape metrics obtained from a GIS, with consequent implications for the interpretation of biological effects studied at landscape scales. Here, we studied the effect of data resolution on estimates of three metrics of forest cover commonly used in the landscape ecology literature: percent forest cover, forest edge density, and mean fractal dimension of forest patches. Estimates of each metric were computed for six landscapes (30 × 30 km) in the North Island of New Zealand at 10 different data resolutions with pixels ranging from 30 to 1000 m. All three metrics exhibited significant changes in value as a result of changing resolution, and the sensitivity of the fragmentation metrics to data resolution was impacted in a non-linear manner by the amount of forest cover in a landscape. In landscapes with low forest cover, changing pixel size altered estimates of percent forest cover by as much as 75%. Extrapolation to correct for effects of changing resolution and different landscapes seems a likely solution in the case of some, but not all, metrics. The scaling problem hinders efforts to correlate spatial pattern with ecosystem process and the subsequent conclusions concerning biodiversity and conservation policy.

Keywords: cell size; grain; habitat fragmentation; habitat loss

Introduction

Habitat fragmentation and habitat loss are major threats to global biodiversity (Foley et al. 2005). Wilcove et al. (1986) defined habitat fragmentation as a process during which 'a large expanse of habitat is transformed into a number of smaller patches of smaller total area, isolated from each other by a matrix of habitats unlike the original'. Human activities such as land clearing and conversion of vegetation are the primary causes of habitat fragmentation (Franklin et al. 2002), which results in five primary alterations to forest cover: (1) decreased total amount of habitat; (2) increased number of habitat patches; (3) decreased size of habitat patches; (4) increased isolation of habitat patches; and (5) increased frequency of habitat edges.

Within New Zealand, habitat fragmentation has had a large influence on biological processes such as the persistence of biodiversity and the invasion of introduced species. Forest fragmentation strongly impacts the structure of invertebrate communities in New Zealand, as evidenced by studies in the podocarp (Walker et al. 2006) and *Nothofagus* forests of the South Island (Ewers et al. 2007), and kahikatea (*Dacrydium dacrydioides*) forests of the North Island (Harris & Burns 2000). In *Nothofagus* forests, forest edges were shown to alter beetle community composition over distances of more than 1 km inside forest fragments (Ewers & Didham 2008), although similar edges have had a generally positive effect on the flowering and fruit set of native *Peraxilla* mistletoes (Burgess et al. 2006). Forest fragments and forest edges do, however, appear to be more susceptible to the invasion of weeds (Wiser et al. 1998), with consequent impacts on the ecosystem processes within forest fragments (Standish et al. 2004) and on the decline of threatened plant species (Walker et al. 2006).

More widely, habitat fragmentation is one of the key topics in conservation biology (Fazey et al. 2005). Many studies of habitat fragmentation now recognise the central role played by the spatial pattern of habitat in a wider landscape, and there are many metrics of habitat fragmentation available (to researchers) that combine the various aspects of spatial features within a landscape to describe this patterning. In fact, so many variables are used to quantify fragmentation that it is becoming difficult to identify studies that can be legitimately compared with each other (Turner et al. 1989a; Fahrig 2003). This has led to a literature that is difficult to interpret, and a wide variation of conclusions about the effects of habitat fragmentation (Fahrig 2003). Nonetheless, to understand the effects of habitat fragmentation on biodiversity, appropriate metrics of habitat cover and spatial patterns are required for use in analyses of spatial data. Landscape pattern metrics have been formulated for this purpose. These are indices that have been designed with the specific purpose of measuring spatial patterns in order to quantify the degree of fragmentation across an entire landscape. Hundreds of metrics now exist covering a variety of patterns that are used to represent various aspects of habitat fragmentation (McGarigal et al. 2002).

Landscape pattern metrics can be measured from aerial photographs or satellite imagery, which is preferred over ground-truth data for reasons of practicality and expense (O'Neill et al. 1988). However, during digitisation of remotely sensed data, fine resolution of the images is often lost. Landscapes are represented as images formed of pixels (also called cells or gridsquares), and the size of the pixel (data resolution, also known as the 'grain' of the data) has a profound effect on the resultant metric value (Woodcock & Strahler 1987; Gustafson 1998; Turner et al. 2000). The appropriate level of pixel resolution for a given study is partially determined by

the extent of the study area. Studies conducted over small study areas require fine resolutions in order to capture all the detail, and coarser resolutions must suffice for larger extents. For example, global-scale land cover classifications are routinely conducted at 1-km resolution (McCallum et al. 2006), and the PRODES project annually maps forest cover across the Brazilian Amazon at 30-m resolution (www.obt.inpe.br/prodes). At the other extreme, fine resolutions of 45 inches (1.143 m) were appropriate for detailed mapping of 0.07-ha agricultural fields in the Anhui Province of China (Ozdogan & Woodcock 2006).

Problems will arise when fragmentation studies that used landscape metrics calculated from one spatial resolution are compared to results from studies that used a different resolution. This issue arises because pixel size exerts a strong influence on the calculation of spatial patterns of habitat cover (Saura 2002), such that a single value of a landscape metric calculated from data of two different resolutions means two different things on the ground. For example, Qi and Wu (1996) varied cell size from 2.25×2.25 km to 45×45 km and found that changing resolution significantly altered the estimates of three commonly used landscape pattern metrics. Similarly, Zheng et al. (2008) compared forest area estimates from 30-m and 1000-m-resolution data and calculated that the coarser resolution underestimated the global area by almost 1000 km², suggesting that the actual amount of forest cover could be underestimated by as much as 7.9% simply as an artefact of data resolution. In a more complex analysis, Turner et al. (1989b) showed that spatial information is lost with coarser resolutions, but that the rate of loss is dependent on the actual spatial arrangement of habitat in the study area. This indicates that there is no simple relationship that could be used to convert metric values calculated from one data resolution to values at a different resolution, making it even more difficult to compare the results of landscape studies that employed data of varying resolution.

A systematic examination of the pattern metrics in relation to changing scale and different landscapes is needed to enable the study of linkages between spatial patterns of habitat cover and ecological processes to continue unhindered (Wu et al. 2002). Here, we describe the effects that changing resolution of landscape forest cover data has on the computation of three landscape-pattern metrics (percent forest cover, edge density, and fractal dimension), using the North Island of New Zealand as a case study. Our two goals were to identify the relative sensitivity of metrics to data resolution and to investigate how that sensitivity is influenced by the amount of forest cover in the study area.

Methods

Study area and forest cover data

In the 1000 years since human settlement, New Zealand lowland and montane forests have been drastically reduced in area and heavily fragmented (Ewers et al. 2006). The changes have been so dramatic that the biota and landscape of New Zealand changed more in this time period than in the previous three millennia of natural processes (McGlone 1989). We selected six study areas from the North Island of New Zealand, chosen to encompass a gradient from sparse to dense forest cover (Fig. 1). Each landscape was a 30×30 km square, within which we obtained forest cover information

from the New Zealand Topographic Database (NZTopo; <http://www.linz.govt.nz>). This database provides vector data on land cover (at a scale of 1:50 000) that was derived from aerial photographs taken mostly in the 1970s and 1980s. From this database, we extracted the polygons representing indigenous forest cover that intersected our six chosen landscapes.

ArcGIS and data resolution

Polygon data from NZTopo were converted into raster format using the toolbox conversion tool in ArcGIS. Each landscape was converted into 10 separate raster files covering a range of cell sizes across a gradient extending from 30 to 1000 m, encompassing the most commonly used spatial resolutions of land cover data (pixels of 30, 60, 100, 200, 250, 300, 500, 600, 750 and 1000 m). Pixels were classified as forest or non-forest according to which of the two habitat types occupied the majority of the pixel area. This method of downscaling, termed majority block voting, is commonly used in studies investigating the impacts of data resolution on landscape metrics (Saura 2004; Wu 2004; Corry & Laforteza 2007; Zheng et al. 2008), but differs from the spectrally based aggregation methods used when remote sensing land cover at different data resolutions (Zheng et al. 2008). Majority block voting retains less spatial information than spectrally based methods, but is much more widely used due to the greater simplicity of application (Ju et al. 2005). More-coarse resolution data progressively lose detail on patterns of forest cover, with some patches increasing in area as others decrease or are lost completely. It is this change in shape and patch size that results in different estimates of landscape pattern metrics as resolution changes.

Landscape metrics

Landscape pattern metrics were computed using FRAGSTATS (McGarigal et al. 2002). We performed a standard analysis that makes one estimate of a metric per landscape, as opposed to a moving-window analysis that computes a metric estimate for every pixel within the landscape. Three landscape-pattern metrics were computed for this investigation: percent forest cover, edge density, and fractal dimension. The proportion of forest cover within a landscape does not have much interpretive value as a landscape metric in its own right, but it is a central feature of modified landscapes and is integral to the computations of other class and landscape metrics. Consequently, any factors that affect the estimate of forest area, such as data resolution, will likely also affect other metrics. Edge density quantifies how much forest edge is present per unit of forest area (length of forest edge divided by area of forest), giving an indication of how fragmented the forest is within the landscape. Highly fragmented forest consisting of many small patches of habitat has a higher edge-to-area ratio than forest with the same total area formed of few large patches. Edge density is zero when there is no edge in the landscape (i.e. when the landscape contains a single patch of equal area to the total landscape area), and there is no upper limit to the value of the metric. Finally, fractal dimension measures how complex spatial patterns are by quantifying the shapes of individual patches within the landscape. Values are bounded at 1 and 2 and increase as shapes depart in complexity from a simple Euclidean shape such as a square. The fractal dimension for a patch is calculated as $\frac{2 \cdot \ln(0.25 \times P)}{\ln(A)}$, where P is the

patch perimeter measured in metres (FRAGSTATS adjusts

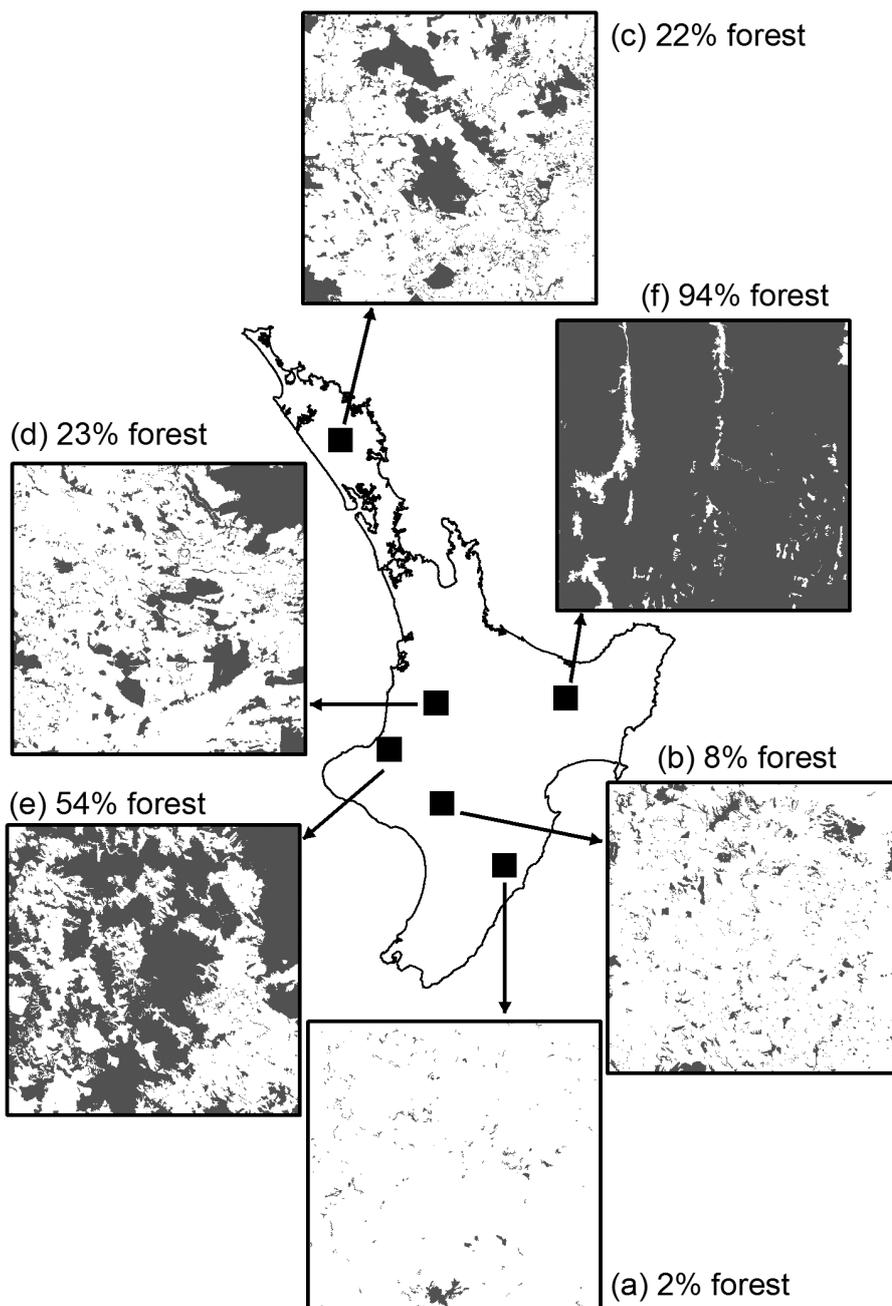


Figure 1. Distribution of forest (grey) and non-forest (white) cover within each of the six New Zealand landscapes. Landscapes are each 30×30 km and forest cover is mapped using vector data from the New Zealand Topographic Database.

this estimate to correct for the raster bias in perimeter calculations), and A is the area of the patch in square metres. To gain a single estimate of fractal dimensions for a landscape, the fractal dimensions of all patches within that landscape are averaged.

Statistical analyses

We used beta regression to investigate the relationship between \log_{10} -transformed cell size and percent forest cover for each of the six landscapes. Beta regression models proportional data (bounded between 0 and 1) as a function of one or more predictor variables with a logit link function (Cribari-Neto & Zeileis 2010). Multiple linear regression was used to investigate the combined effects of \log_{10} -transformed cell size and percent forest cover on the two fragmentation indices (edge density and

mean fractal dimension). Full models including an interaction term were fitted and then manually simplified to remove non-significant terms, with the best model being chosen based on Akaike Information Criterion (Burnham & Anderson 2002). All analyses were conducted using the statistical computing program R (version 2.9.0; R Development Core Team 2009).

Results

Percent forest cover

Estimates of percent forest cover were significantly impacted by data resolution (Table 1). In five of the six landscapes, the estimate of percent forest cover decreased as pixel size increased (Fig. 2), suggesting that forest cover estimates are consistently

Table 1. Results of multiple beta regression examining estimated forest cover as a function of \log_{10} -transformed data resolution in six New Zealand landscapes. The overall model had a pseudo $R^2 = 0.993$ and is portrayed in Fig. 2. The parameter phi is a precision parameter used in beta regression, and is a measure of dispersion with larger values equating to smaller amounts of variance in the response variable (Cribari-Neto & Zeileis 2010).

| | Estimate | SE | <i>z</i> -value | <i>P</i> -value |
|--------------------------------------|----------|-------|-----------------|-----------------|
| Intercept | -2.42 | 0.50 | -4.853 | <0.001 |
| \log_{10} (resolution) | -1.04 | 0.23 | -4.584 | <0.001 |
| Landscape B | 1.87 | 0.55 | 3.417 | <0.001 |
| Landscape C | 1.73 | 0.52 | 3.339 | <0.001 |
| Landscape D | 1.75 | 0.52 | 3.39 | <0.001 |
| Landscape E | 2.67 | 0.51 | 5.226 | <0.001 |
| Landscape F | 4.71 | 0.55 | 8.523 | <0.001 |
| \log_{10} (resolution):landscape B | -0.07 | 0.25 | -0.294 | 0.769 |
| \log_{10} (resolution):landscape C | 0.68 | 0.23 | 2.915 | 0.004 |
| \log_{10} (resolution):landscape D | 0.71 | 0.23 | 3.052 | 0.002 |
| \log_{10} (resolution):landscape E | 0.97 | 0.23 | 4.223 | <0.001 |
| \log_{10} (resolution):landscape F | 1.32 | 0.25 | 5.324 | <0.001 |
| Phi | 265.11 | 48.75 | 5.438 | <0.001 |

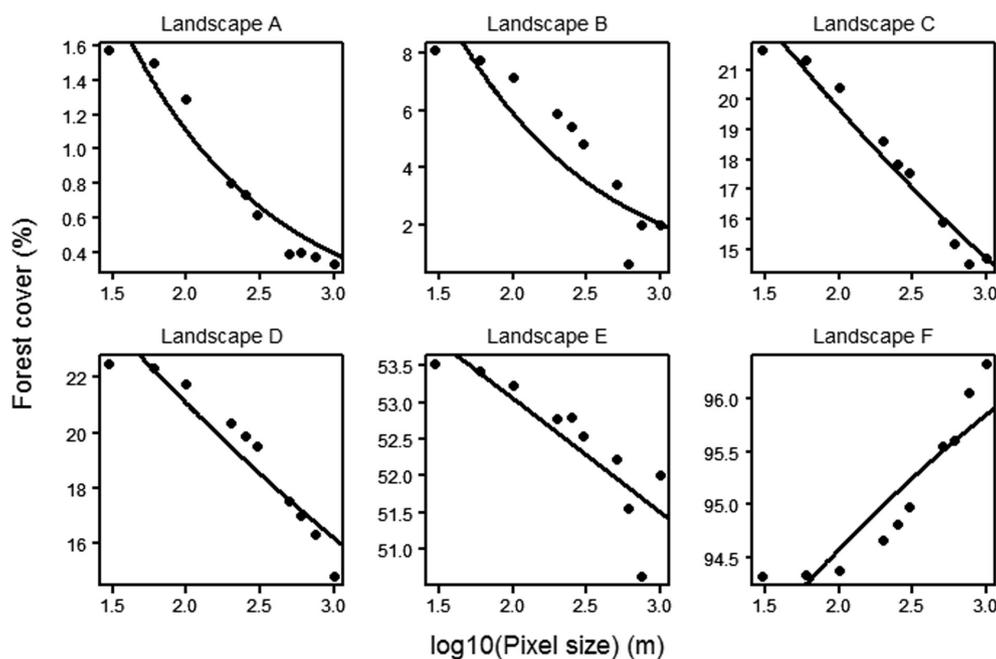


Figure 2. Estimates of percent forest cover change as pixel size increases. Landscapes A–F correspond to the landscapes shown in Figure 1a–f, respectively. Solid lines represent fitted lines from the beta regression (Table 1).

underestimated by analyses using coarse resolution data. This effect was particularly extreme in landscapes with less than 10% forest cover, in which forest cover estimates at the coarsest pixel sizes were less than one-quarter of the estimates at the finest pixel sizes. This equated to a 75% difference in forest cover estimate ($[\text{maximum} - \text{minimum}] / \text{maximum}$). In landscapes with 10–30% forest cover, estimates of forest cover at coarse pixel sizes differed from fine pixel estimates by more than 30%. However, in the landscape with highest forest cover, the pattern was reversed and there was a positive increase in forest cover estimate with pixel size (Table 1, Fig. 2). The slope of the relationship between percent forest cover and pixel size was not consistent across landscapes (Table 1).

Edge density

Edge density and pixel size were negatively correlated ($F_{1,56} = 41.9, P < 0.001$), indicating a reduction in the amount of edge per unit area as pixel size increases. Consequently, the apparent degree of fragmentation, as represented by edge density, is likely underestimated when using coarse-resolution data. Predictably, edge density values also decreased with percent forest cover ($F_{1,56} = 41.2, P < 0.001$), reflecting the lower level of fragmentation in landscapes of high forest cover. However, the rate at which edge density appeared to change with forest cover was dependent on pixel size, with a significant interaction detected between pixel size and forest cover ($F_{1,56} = 17.1, P < 0.001$). This interaction showed that

the effect of pixel size on edge density was reduced at high forest covers.

Fractal dimension

Mean fractal dimension varied significantly between landscapes of differing resolution and percent forest cover. Mean fractal dimension was negatively correlated with pixel size ($F_{1,56} = 26.6$, $P < 0.001$), but in contrast to edge density there was a positive relationship between percent forest cover and mean fractal dimension ($F_{1,56} = 62.1$, $P < 0.001$). This latter result suggests that as pixel size increases, the apparent complexity of habitat patch shapes decreases. A weakly significant interaction term was also detected between percent forest cover and \log_{10} -transformed cell size ($F_{1,56} = 4.54$, $P = 0.038$), indicating that the relationship between forest cover and fractal dimension was strongest when pixel sizes were small.

Discussion

There are too many landscape pattern metrics in common usage to allow for easily comparable research on the impacts of habitat fragmentation on biodiversity and ecological processes. It is well acknowledged that different metrics are not directly comparable because they are based upon different aspects of spatial pattern (Turner et al. 1989a). This recognition has led to attempts to formulate a standard list of metrics for use in investigations (e.g. Riitters et al. 1995; Schindler et al. 2008). Riitters et al. (1995) developed three criteria to describe the ideal set of landscape pattern metrics; the set should be small in number, should span all the important dimensions of landscape pattern and structure, and there should be no redundancy (i.e. the metrics should be uncorrelated with each other). Furthermore, it is important that the metrics are either immune to differences in resolution, or are affected in a predictable way so that simple calibrations can be used to correct for the effects of resolution.

We found that estimates of three landscape-pattern metrics were very sensitive to changes in resolution across a gradient of pixel sizes extending from a fine scale of 30 m to a coarse 1-km resolution. Of particular interest was the fact that coarse-resolution data repeatedly underestimated the amount of forest cover within a landscape. This result is in line with other published literature (Ozdogan & Woodcock 2006; Corry & Laforteza 2007; Zheng et al. 2008), suggesting that published estimates of forest area based upon coarse data should be regarded as underestimates. However, the relationship between data resolution and forest cover estimates is not linear across the full spectrum of forest covers observed in New Zealand landscapes, indicating that there is no simple conversion factor that can be used to generate a resolution-independent estimate. Moreover, we found that coarse-resolution data tended to overestimate forest cover when there is a lot of forest in the landscape. This result is mirrored by the results of Zheng et al. (2008), who found that under some conditions coarse-resolution data would overestimate rather than underestimate forest cover. Specifically, they found that if a landscape contained more than 50% forest cover when mapped at 30-m resolution, then mapping that same landscape at 1000-m resolution would overestimate forest cover. The underestimates of forest cover in landscapes of low forest cover arises from the same mechanism as overestimates in landscapes of high forest cover. Majority block voting assigns a value to a pixel depending on which

land use type occupies the largest area, so when a binary land cover classification of forest or non-forest is used, the dominant land use type in the region has a higher probability of being selected than the subordinate land use type. Because a gain in one land use type is directly equivalent to a loss of the other (Zheng et al. 2008), whether a particular land cover type is under- or overestimated depends on whether it is the dominant or subordinate type in the region being analysed. This threshold for switching from being under- to over-estimated does not, however, necessarily occur at exactly 50% forest cover in the landscape (Fig. 2 Landscape E), as differences in the spatial patterning of forest cover can influence the final location of the threshold (Zheng et al. 2008).

Ideally, the relationship between metrics of forest cover and resolution would be predictable and capable of being corrected. However, we found that the relationship between forest cover estimates and pixel size was not consistent among landscapes. Consequently, there is no easily identifiable equation that could estimate forest cover in landscapes in a manner that is independent of data resolution. Similarly, estimates of edge density and fractal dimension within landscapes were both sensitive to data resolution, but in a complex manner: the slope of those relationships was dependent on the amount of forest cover in a landscape.

Our results indicate that it is crucial for studies that rely on remotely sensed land cover data and patterns to always state which cell size is used in the analysis. Ideally, studies should also attempt to analyse the impact that data resolution may have on a study's results and their interpretation (Qi & Wu 1996). Qi and Wu (1996) went on to stress the need for the development of methods to extrapolate and convert landscape metric values between different resolutions, reflecting earlier calls by other authors (Turner et al. 1989b; Costanza & Maxwell 1994). The use of scalograms, which are plots of landscape pattern metric against cell size (e.g. Fig. 2), could be used to correct for differences in resolution and extrapolate an estimate of a metric (Wu et al. 2002), but this is only valid if there is a tight relationship between the metric estimate and pixel size. Our results, in line with those of Saura (2002), imply that there is some possibility of extrapolating metrics across resolutions and landscapes. For example, edge density appears to be a predictable and scalable metric, assuming that the actual amount of forest cover in a given landscape is a known variable. In addition, Saura (2002) found that indices such as landscape division and the area weighted mean shape index are comparable among data of varying spatial resolution. Mean patch fractal dimension, however, has a less convincing relationship with pixel size, suggesting it is an erratic and unpredictable metric when compared across landscapes and cell sizes. Whatever the metric that researchers choose to employ, they should either ensure that it is not dependent on pixel size, or that they understand how metric estimates might be expected to vary with pixel size.

It is important to remember that the estimation of landscape pattern metrics is not an end in itself. Rather, landscape metrics are commonly used as predictors of biodiversity patterns within and among landscapes, and even employed directly as surrogates for biodiversity (Innes & Koch 1998). It is for these subsequent analyses of biodiversity that accurate data on spatial patterning are so critical. Clearly, the choice of metric is integral to any analysis, as some metrics may correlate with certain aspects of biodiversity and not others. For example, Bailey et al. (2007) found that edge density was negatively correlated with the species richness of large arthropods, but

did not correlate with species richness of any other arthropod taxonomic group. Similarly, Honnay et al. (2003) calculated a variety of landscape metrics from 20-m-resolution maps and found that plant species number correlated positively with patch diversity metrics, fragmentation metrics correlated only with threatened species diversity, and mean fractal dimension did not correlate with anything. However, correlations between landscape metrics and measures of biodiversity or ecological functions are likely prone to considerable error due to the potentially confounding influence of data resolution on metric values. For example, Turner et al. (2000) found that changing the spatial resolution of habitat data altered estimates of carbon flux and net primary productivity from a fragmented landscape in the USA. Similarly, changes to the resolution of land cover data resulted in strong changes to cost-surface models used to model animal dispersal across fragmented landscapes in the USA and Italy (Corry & Laforteza 2007). Clearly, much more investigation needs to be carried out into the relationships between data resolution and landscape pattern metrics, and how those relationships impact analyses of biodiversity or ecological processes in fragmented landscapes. Until then, it will not be safe to employ a landscape pattern metric as a surrogate for biodiversity. At that stage it will be imperative that the estimates of landscape metrics are accurate, whether that is accomplished by using fine-resolution data or a trustworthy method of extrapolation.

Conclusions

A central tenet of landscape ecology is that landscape pattern and process are inextricably linked, but inaccurate and incomparable estimates of landscape pattern metrics are a problem for studies of ecological process. Policymakers rely upon datasets such as the ones discussed here to make decisions about environmental quality and, therefore, it is important that the information correctly reflects the real world. Of the three metrics of forest cover that we investigated here, none were immune to changes in data resolution. In fact, even estimates of forest area, one of the most basic forms of data used in conservation planning, are sensitive to data resolution. Consequently, researchers should take considerable care when generalising results from studies conducted using data of different resolutions, and even more care when using landscape metrics as a surrogate for biodiversity.

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