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Error propagation in raster data integration: Impacts on landscape composition and configuration

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Abstract
Integrating raster-based categorical maps from multiple sources necessitates the transformation of geometric characteristics to compare maps, as in land change analyses. By projecting maps to a new geographic reference framework and scaling pixel values to a new size, distortions of map information are introduced that can affect the proportion and arrangement of thematic classes across the landscape. Using a sample land cover dataset depicting a heterogeneous landscape, this paper examines these impacts using three common raster-based transformation methods and introduces a new vector-based method that minimizes error propagation. While relative class area was best preserved by a nearest-neighbor resampling method, distortions to the contiguity of thematic classes and the overall fragmentation of the landscape were minimized when using the vector-based projection and resampling method. Results demonstrate that more than a third of pixel values of a categorical map may be affected by common projection and scaling methods and reinforce the need for careful attention to impacts of error propagation in categorical data transformations.

Introduction
Land change studies often utilize raster-based models of geographic information, due to the ease of generalizing thematic class information (Monmonier, 1983) and the efficiency of analytical operations (Peuquet, 1979). Over the nearly four decades of digital satellite imagery, innumerate conventions of spatial resolutions and geographic reference frameworks have been employed, in accordance with changing research agendas (Aspinall, 2002). However, the direct comparison of raster-based maps necessitates that each map has the same pixel size in the same geographic reference framework (White, 2006; Foody, 2007). The quantified implications of projecting (White, 2006) and scaling (Costanza and Maxwell, 1994) categorical maps have occasionally been noted, but the combined effects of the necessary combination of these two operations have not received much attention in the literature of the geographic information science and land change research communities, in spite of the potential to affect the results of change analyses (Turner and O'Neill *et al*., 1989; Townshend and Huang *et al*., 2000). In addition to changing the calculated area of thematic classes, the depiction of landscape composition and configuration in the categorical map can be distorted, increasing the perception of landscape fragmentation (Wickham and Ritters, 1995). When preparing maps for land change analysis, these transformation methods can obscure the accurate representation of landscape heterogeneity, especially along the borders between map categories, leading to diminished or exaggerated estimates along the frontiers of most rapid land change (Griffith, 2004).

This paper examines error propagation in raster data integration, comparing several commonly used methods using landscape ecological metrics to quantify landscape composition and configuration, and introduces a model of frequency-based aggregation that preserves these critical features. This new method, involving a transformation of categorical raster-based pixel information using a vector framework, preserves the spatial arrangement and composition of the data, retaining maximum precision of landscape composition and configuration information. An empirical comparison of commonly used methods and a newly proposed upscaling technique using a sample land cover dataset surrounding the sensitive Monarch Butterfly Biosphere Reserve of Mexico demonstrates the necessity of careful preparation of raster-based categorical maps in land-change applications.

Raster Data Preparation for Land Change Analysis
To compare two raster-based categorical maps, as in land-change analyses and many other overlay operations, each image or map must have the same geometric characteristics (Foody, 2007; Congalton and Green, 2009). While fine spatial resolution imagery (<250 m/pixel) has consistently been used for local-scale land-change analysis, data cost, repeat-availability, and volume impede the ability to scale fine spatial resolution land change methods to broader spatial extents (Rogan and Chen, 2004). Coarse spatial resolution satellite imagery (>250 m/pixel) from sensors such as Advanced Very High Resolution Radiometer (AVHRR), Satellite Pour l'Observation de la Terre (SPOT) VEGETATION, and Moderate Resolution Imaging Spectroradiometer (MODIS), have enabled broad regional analyses

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and led to the development of several global land cover products, including those from International Geosphere-Biosphere Programme Data and Information System Cover (IGBP-DISCover) (Loveland and Belward, 1997; Global Land Cover (GLC2000), 2003; Bartholome and Belward, 2005), and the MODIS (MCD12Q1) Land Cover product (Friedl and Strahler *et al.*, 2002).

With pixels much larger than the landscape elements depicted, every pixel in the map is uniquely mixed, but coarse pixels provide a necessary generalization of landscape characteristics that can aid analyses of large areas (Woodcock and Strahler, 1987; Herold *et al.*, 2006). The integration of maps of different spatial resolutions and geographic frameworks is necessary for the following reasons:

1. Fine spatial resolution data of known quality can be used to calibrate large area image classifications using coarse-resolution data and validate the resulting map products (Muchoney and Strahler, 2002; Gao *et al.*, 2003).
2. Products and analyses created with new satellite and map data products can be compared with results of previous analyses performed prior to their availability (Hansen *et al.*, 2008).
3. There is a need to integrate data from multiple datasets for land-change studies at regular intervals to conduct analyses at high temporal resolutions (Hilker *et al.*, 2009) or over long periods of time (Torres-Vera *et al.*, 2009).

Pixel Size and Scaling Operations

The process of scaling raster data transforms the cell size of the map through a process of sampling or aggregation (Wang *et al.*, 2004). While methods of downscaling exist to approximate sub-pixel features while increasing the spatial resolution (Dendoncker *et al.*, 2006), this paper is primarily concerned with the process of upscaling, or reducing the spatial resolution of the map through the processes of aggregation or sampling (Wang *et al.*, 2004). By common convention, fine spatial resolution data are generally upscaled to fit the coarse spatial resolution framework to minimize distortions of location (Pontius, 2000) and to avoid ecological fallacies (Robinson, 1950).

Geographic Reference Frameworks and Projecting Operations

The process of projecting raster data transforms the shape and arrangement of the matrix of pixel information from one geographic reference system to another (Seong, 2003). As all spatial reference systems that represent the three-dimensional surface of the Earth within a two-dimensional map introduce some type of distortion, the reference system chosen generally depends on the scale and method of analysis (Steinwand *et al.*, 1995). Local-scale datasets exploit the benefits of conformal projection systems, such as the Universal Transverse Mercator system, because the distortion of a small area is balanced with the necessary preservation of shape and direction (Tobler, 1974; Snyder, 1987). Regional and global analyses have utilized datasets based on equal-area projection systems (e.g., Sinusoidal), which minimize the distortion of area (Usery and Seong, 2001) but can alter the allocation of classes across the landscape (White, 2006).

Common Methods of Raster Data Preparation

To prepare multiple categorical maps for comparison and analysis, there are several possible permutations of processing procedures, each with implications upon the resulting transformed data. For example, raster data can be projected to a new reference framework first and then scaled to the new spatial resolution, or data can be scaled and then projected. A nearest-neighbor labeling procedure is favored when scaling categorical maps (Franklin and Wulder, 2002), because the nominal class labels of a categorical map do not facilitate mathematical operations. However, methods of selecting the majority or plurality of fine-resolution pixels within a coarse-resolution pixel have been shown to retain more consistent area measures across spatial scales (Moody and Woodcock, 1994; Eastman, 2009).

Potential Errors Introduced by Raster Data Transformations

Best practices of raster data preparation for direct comparison must preserve the integrity of each individual map to accurately represent similarities and differences between land cover maps. However, through the processes of projecting and scaling raster data, categorical maps can experience the following distortions:

1. Representation: The geographic area delineated by a given pixel may occupy a different size, shape, or location in different reference frameworks (Fisher, 1999).
2. Composition: In an upscaling operation, the relative proportion of classes can be distorted both within a single pixel and across the entire landscape (Turner *et al.*, 1989; White, 2006)
3. Configuration: Projection operations may distort the relative arrangement of grid cell matrices, effectively rearranging pixels and impacting focal operations (Steinwand, 1994; White, 2006).

Each of these distortions of data preparation can drastically impact the information used in a land cover comparison. To avoid these problems, data must be prepared in a sequence that preserves the landscape composition and configuration of the finer categorical map within the new data framework. This sequence must retain the precise location of the information of each grid cell and the proportion and arrangement of each class and value across the landscape.

Impacts on Composition

As per-pixel distortions of information through projection operations are less pronounced with finer pixels than with coarser pixels, the conventional wisdom suggests the projection of finer data to fit the geographic reference framework of the coarser data; alternately, all data must be projected to another geographic reference framework. White (2006) demonstrated the local scale effects of pixel loss and replication on the projection of data from the Sinusoidal reference framework, and Usery and Seong (2001) illustrated the net changes in relative class area among equal-area reference systems. There have been efforts to assess and improve the accuracy of raster projection methodology (Seong, 2003), but the substantial impacts of misregistration on land change studies (Townshend *et al.*, 1992) have led some to suggest abandoning per-pixel comparison altogether (Townshend *et al.*, 2000). The distortion of the relative area of classes in a thematic map is most common impact associated with raster data transformation (Tobler, 1963; Dark and Bram, 2007). However, changing the size of the pixel also invokes the Modifiable Areal Unit Problem (Openshaw and Taylor, 1979), in which "zoning problems" may distort the composition of the landscape, even if relative class areas are maintained through aggregation (Jelinski and Wu, 1996; Stein *et al.*, 2009).

Impacts on Configuration

In an upscaling operation, an unequal number of finer-scale original pixels might occupy the geometric space of a resulting coarser-scale pixel (Wang *et al.*, 2004). As with changes in projection, improper scaling calculations can distort the relative proportion of each class within the landscape matrix and misrepresent the class of an individual

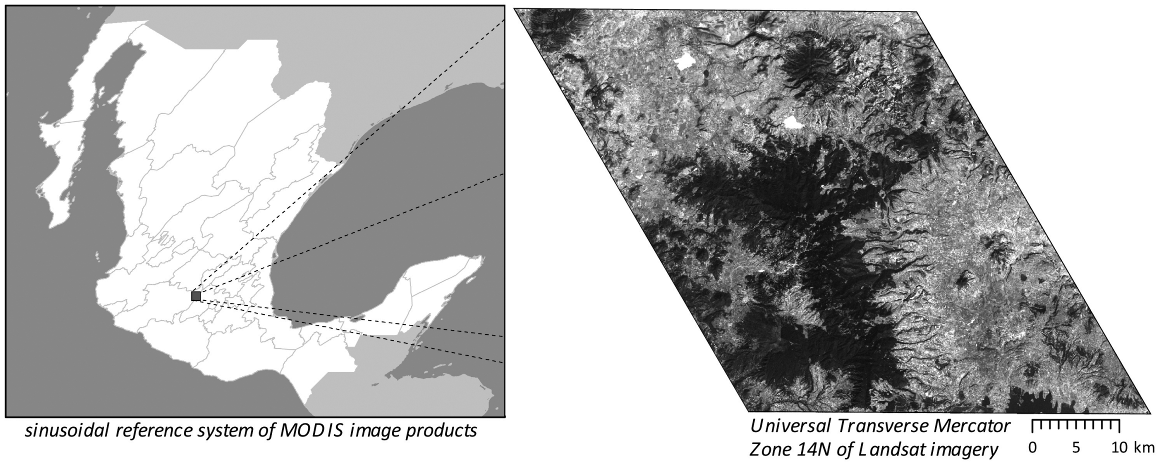

Figure 1. Study area surrounding the Monarch Butterfly Biosphere Reserve in sinusoidal and UTM reference systems.

mixed pixel (Moody and Woodcock, 1994; Wickham and Ritters, 1995). Landscape configuration metrics can provide a measure of differences in fragmentation among data processing methods (Turner, 1989; Gustafson, 1998). An index of relative contagion (Li and Reynolds, 1993), a modification of the original contagion index proposed by O'Neill *et al.* (1988), can be used to provide an overall metric of the clustering of classes by examining pixel configuration (Gustafson, 1998), in which high contagion values indicate a landscape with fewer cohesive landscape patches and lower values indicate fragmentation of land cover lasses (Li and Reynolds, 1993). Similarly, the metric of fractal dimension utilizes the relationship between the perimeter and area of thematic classes to quantify the map composition (Riiters *et al.*, 1995), in which higher values indicate greater fragmentation and variety within local pixel arrangements. Fotheringham (1989) has suggested that fractal dimension can serve as a scale-independent metric of the distribution of a variable across the landscape; however, fractal dimension is only constant at scales where self-similarity of the overall landscape pattern exists (Jelinski and Wu, 1996).

Point-based Projection and Aggregation

In order to avoid distortions to area, composition, and configuration that may affect the results of land change studies, this paper introduces a new method of projection and aggregation for upscaling operations across raster frameworks. The mathematical equations of projecting raster and vector data differ, because vector-based functions do not necessitate the creation of a regular grid-cell lattice, which can propagate distortions due to the need for the locations of data values to conform to the resulting pixels (Steinwand *et al.*, 1995). As such, the extraction of representative point-locations, represented here by the centroid, for each pixel unit can retain the geographic precision of this information when the data are projected to a new reference system (Fisher, 1997), and the resulting array of point-based information can be aggregated into grid cells. Because both the number and proportion of points in each resulting grid cell can differ, a point-based combined transformation of projection and scaling operations can preserve the composition and configuration of thematic classes in the resulting coarsened data. This process effectively produces a continuous map of the distribution of each land cover class in the original fine-resolution map, which can be "hardened" into discrete thematic classes through plurality or other weighting methods to create a discrete thematic map at the new scale and reference system (Eastman, 2009).

Study Area and Data

The Monarch Butterfly Biosphere Reserve (Brower *et al.*, 2002), in central Mexico, is the winter breeding grounds for millions of Monarch butterflies that migrate here from North America, western Europe, and eastern Asia and Australia (Figure 1). This area is under continual pressure from illegal logging activities and changing micro-climatic conditions (Honey-Rosés, 2009).

An experimental land cover map representing the area of a 100×100 square block of 500-meter MODIS pixels was generated from a Landsat Enhanced Thematic Mapper-Plus (ETM+) scene, (path 27 row 46), acquired on 26 November 2001 with a spatial resolution of 30 m/pixel. Data were classified using a Mahalanobis distance classifier in the Idrisi Taiga software package (Eastman, 2009), with pseudo-invariant ground reference data observed in January and July 2007 using a seven-class thematic legend including water, forest, shrub, grass, built, crop, and a "mosaic" mixed natural and anthropogenic class (Christman, 2010). Within the study area, natural vegetation types cover 32.3 percent of the landscape. Human-managed land cover classes comprised 62.8 percent of the study area, including agricultural classes of crop (21.3 percent) and the mixed agricultural and natural mosaic class (41.5 percent). Though this region is rural, built cover comprised 3.0 percent of the landscape.

Methods

Projection and Scaling Operations

The original land cover map was projected and scaled in four ways using common software-independent operations within Idrisi Taiga software package (Eastman, 2009) (Plate 1):

1. Original land cover map, in the UTM reference system (Zone 14N), (30 m).
2. Projected map, transformed the Sinusoidal reference system using a nearest-neighbor operation and no scaling operation, (30 m).

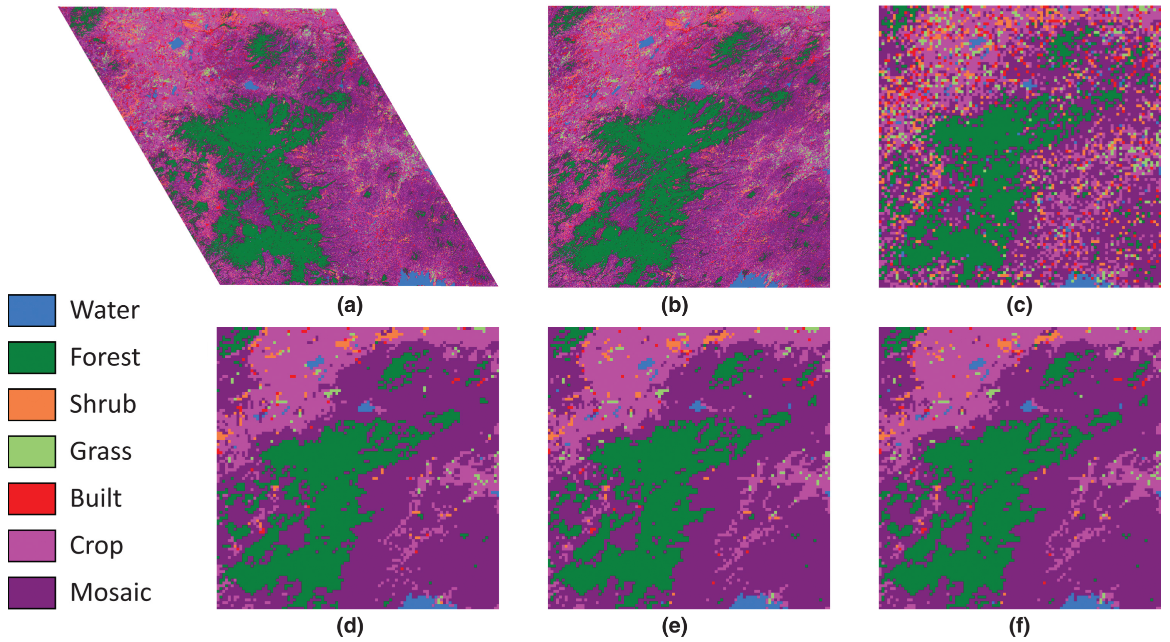

Plate 1. Landscape Composition at different scales and projections (See Tables 1, 2, and 3).

3. Projected + nearest-neighbor scaled map, transformed to the Sinusoidal reference system using a nearest-neighbor operation and a nearest-neighbor scaling operation (500 m).
4. Projected + plurality-based scaling map, transformed to the Sinusoidal reference system using a nearest-neighbor operation and scaled using plurality aggregation, (500 m).
5. Plurality-based scaling + projected map, with 500 m/pixel resolution, first scaled using plurality aggregation, then projected to the Sinusoidal reference framework using a nearest-neighbor operation, (500 m).
6. Vector-based projection and scaling with frequency aggregation map, first projected as a matrix of point-based data within a vector framework to the sinusoidal reference system, then scaled using frequency-based aggregation of point data, (500 m) (Plate 2).

Among transformation operations, "nearest-neighbor" rescaling refers to a case in which the Euclidean distance between the centroid of the representative pixel value for a location within the original spatial resolution or geographic

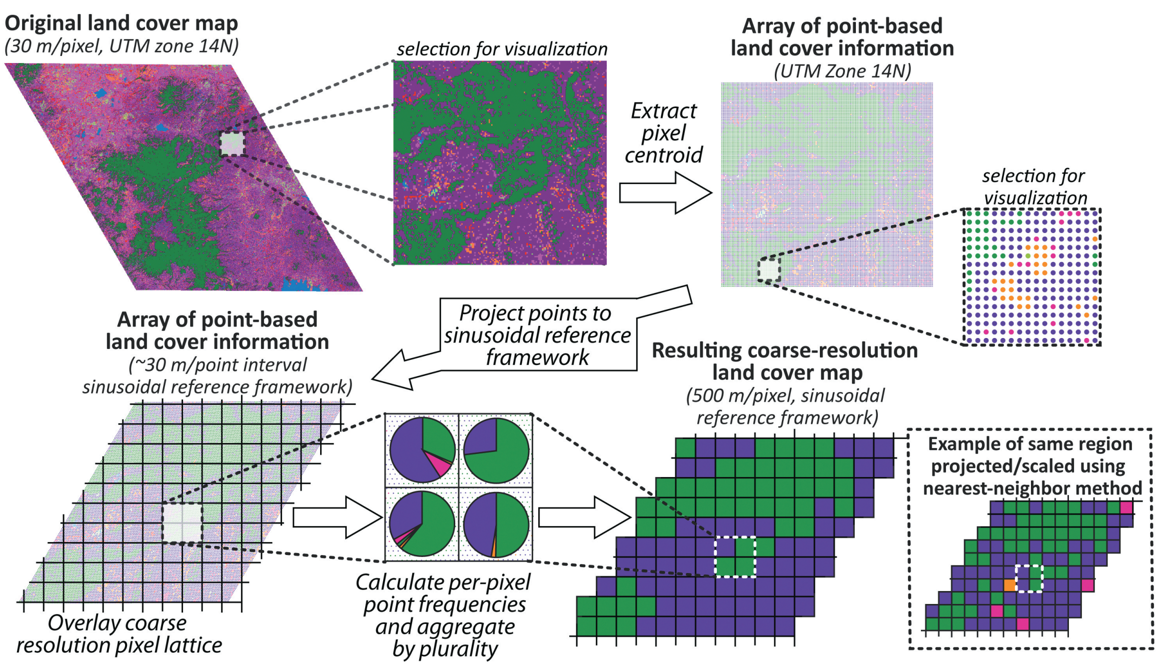

Plate 2. Vector-based projection and scaling with frequency aggregation.

TABLE 1. CLASS AREA FOR EACH TRANSFORMED MAP (SEE PLATE 1)

	Class area as percent						
Map	Water	Forest	Shrub	Grass	Built	Crop	Mosaic
(a)	1.90%	21.95%	6.41%	3.93%	3.04%	21.29%	41.47%
(b)	1.91%	21.92%	6.41%	3.93%	3.04%	21.28%	41.49%
(c)	1.96%	22.37%	5.94%	3.99%	3.41%	21.17%	41.16%
(d)	1.15%	22.32%	1.35%	0.88%	0.47%	19.58%	54.25%
(e)	1.23%	22.45%	1.29%	0.93%	0.44%	19.75%	53.91%
(f)	1.23%	22.40%	1.28%	0.85%	0.40%	19.58%	54.26%

reference framework, and the centroid of the representative pixel location in the resulting spatial resolution or geographic reference framework is used to determine the class identity of the resulting pixel. "Plurality aggregation" refers to a rescaling operation in which the relative frequency of class identities of the finer resolution pixels in the original spatial resolution and geographic reference framework occupying the region covered by a coarser resolution pixel in the resulting spatial resolution and geographic reference framework are used to determine the class identity of each pixel. "Frequency-based aggregation" refers to a similar rescaling operation to the "plurality aggregation" above, but the representative locations in the original geographic reference framework are depicted by points, and the frequency of points is determined by the geographic overlap of these features with individual pixels in the resulting spatial resolution and geographic reference framework. See Plate 2 for a detailed explanation of this method. In all references to ~500 m/pixel resolution, the exact pixel size is 463.3 m/pixel in the Sinusoidal reference framework.

Area Calculations and Landscape Composition Metrics

The total area and relative proportion of each class across the landscape was calculated in each of the transformed maps (Table 1). Metrics of relative contagion and fractal dimensionality per map were calculated using the IAN image analysis program (DeZonia and Mladenoff, 2004). The relative contagion metric representing the degree to which classes were clumped into discrete patches, and the fractal dimension metric represents the arrangement of different pixel values across the landscape (Gustafson, 1998).

Map Comparison

Each of the four projected and scaled maps (Plate 1) was compared using raster crosstabulation to evaluate similarities and differences among maps. Differences among maps were compiled into a single figure to illustrate the number of different classes ascribed to a given pixel across all maps (Figure 2a) as well as the pixels with the same class among all transformed maps (Figure 2b).

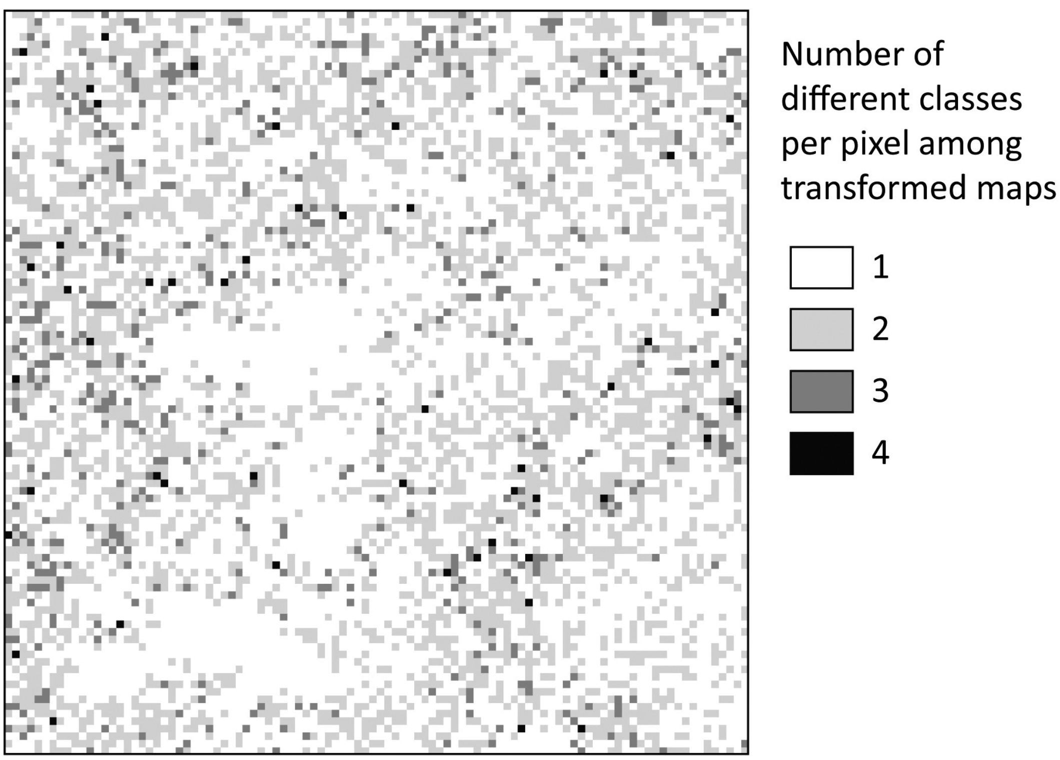

Figure 2. Per-pixel differences among transformed maps at ~500 m/pixel resolution.

Results

Map Composition
Each transformation method resulted in differences to the absolute and relative area of classes, compared to the original map. The nearest-neighbor scaling method most closely retained the overall proportions of the original fine-resolution map. Plurality- and frequency-based scaling operations had the greatest impact upon the least frequent classes, diminishing the overall class proportions of the Shrub, Grass, and Built categories, with a net increase in the overall area of the Mosaic mixed class. Full class area results are summarized in Table 1.

Landscape Contagion
Relative contagion changed substantially with different transformation operations (Table 2). In the unprocessed map, the relative contagion was 52.8. Upon projection of the map without scaling, the relative contagion increased to 61.9. Scaling operations had varying effects: the nearest neighbor operation (Plate 1c) yielded a relative contagion of 26.8; maps using the plurality-based raster scaling method (Plates 1d and 1e) both yielded a relative contagion of 52.2; the point-based frequency aggregation transformation (Plate 1f) yielded a relative contagion of 52.6. Higher values indicate more spatial cohesion, and lower values indicate more spatial dispersion in landscape configuration of thematic classes.

Fractal Dimension
The fractal dimension of the maps also varied by processing type (Table 2). In the original map, the fractal dimension was 1.533, which increased to 1.572 upon projection without scaling. Among the transformed maps, the fractal dimension metric of the scaled maps varied from 1.637 (Plate 1c), indicating the most dispersion among categorical classes, to 1.477 (Plate 1f), in which classes were most agglomerated.

Map Differencing
Differences among transformed maps varied widely, with as high as 36.0 percent difference between two transformed maps (Figures 2c and 2d) (Table 3). Even among the most similar transformed maps (Figures 2e and 2f), 2.1 percent of all map pixels were different, with the least prevalent land covers experiencing greatest disparity, such as shrub (9.4 percent difference), built (5.0 percent), and grass (4.7 percent). Between the two maps that underwent the same transformation operations in opposite order (Figures 2d and 2e), 9.8 percent of all pixels were different. Only 60.8 percent of pixels shared the same value in the resulting maps, and 5.9 percent of all pixels had three or more different values, depending on transformation methodology (Figure 2).

Table 2. Landscape Metrics for Each Transformed Map (See Plate 1)

Map	Landscape Metrics: Relative Contagion	Fractal Dimension
(a)	52.776	1.533
(b)	61.902	1.572
(c)	26.773	1.637
(d)	52.248	1.492
(e)	52.200	1.483
(f)	52.612	1.477

Table 3. Percent Discrepancy among Transformed (Projected + Scaled) Maps (See Plate 1)

Map	(d)	(e)	(f)
(c)	35.99%	34.23%	34.09%
(d)		9.79%	9.44%
(e)			2.09%

Discussion
Results of this research show that data transformation methodology has a quantifiable effect upon the resulting composition and configuration of categorical maps in which data has been both projected and upscaled. As others have noted (Moody and Woodcock, 1994; Usery and Seong, 2001), the distortion of per-class area is one of the most pronounced effects of these operations, independently. However, the increased proportions of the most prevalent classes may be ascribable to the generalization of features in coarse resolution thematic maps, eliminating small patches of under-represented classes. With respect to the landscape composition, while the contiguity of map classes varied by transformation method, the newly introduced point-based frequency aggregation method (Plate 1f) yielded the most contiguous, agglomerations of similar pixel values, and the relative contagion metric was closest in value to the unprocessed map.

Similarly, the fractal dimension of the transformed maps varied across scaling and projection methods, but the plurality-based raster methods and the frequency-based vector method generated a landscape arrangement with greater class agglomeration, based on both the relative contagion and fractal dimension. While landscape metrics have been shown to be sensitive to changes in pixel size (Turner *et al.*, 1989; Wickham and Ritters, 1995), results indicate that transformation methodology may also play a critical role in the consistency of landscape metrics across scales.

This study evaluates differences among common raster data transformation methods and introduces a model through which raster data are projected in the form of point-based vector coordinates and scaled though frequency-based aggregation of the resulting composition. With this preparation method, neither quantity nor location is misrepresented, minimizing the propagation of error in categorical raster data transformation. By exploiting the precision of projection within a vector data model and the generalizability and analytical methods of a raster data model, this method maximizes the integrity of the original data and enables an accurate depiction of landscape composition.

The results of this paper affirm the need for frequency-based aggregation when projecting and scaling data, demonstrating the misrepresentation of landscape composition and apparent change that can occur through inadequate preparation within a raster model. Without direct and deliberate action to preserve true landscape characteristics and composition, the transformation of raster data with different geometric characteristics into a common framework for direct comparison can cause distortions in the absolute and relative location of pixel information, as well as the total composition of the landscape categories. As the methods of geographic information science increasingly permeate a vast number of related applications, researchers must address the fundamental techniques for data manipulation that enable data integration within our interdisciplinary community.

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