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Effects of Changing Spatial Scale on the Results of Statistical Analysis with Landscape Data: A Case Study

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Abstract

The effect of spatial scale on spatial analysis has long, but sporadically, been recognized in human geography and more recently and acutely in landscape ecology. As the number of studies directly and systematically addressing scale effects is still limited, it remains unclear how results of different statistical analyses are affected by changing scale for different landscapes, or whether or not such effects can be predicted and, if so, in what situations. However, it is certain that erroneous conclusions may result if scale effects are not considered explicitly in spatial analysis with area-based data. With widespread use of remote sensing data and GIS, a better understanding of the issue of scale effects is much needed. The main purpose of this study, therefore, was to examine how results of statistical analysis respond to a systematic change in the scale of analysis. Specifically, we investigated how the relationship between landscape metrics (local landcover diversity and richness indices) and independent variables (TM bands and vegetation indices) would change with different sample sizes and mathematical representations of variables. The landscape under study is the Minden area of Nevada in the western Great Basin. Four different sample sizes (19x19, 15x15, 11x11, and 5x5 pixels) and four different representation forms (variance, mean, variance-mean ratio, and coefficient of variation) of the variables were used in all statistical analyses. We systematically examined the effects of changing sample size and representations of variables on the results of regression, analysis of variance, and correlation analysis. The results indicated that the relationship between landscape metrics and TM bands and vegetation indices was affected considerably by the change of sample size. Both the R^2 value and the level of statistical significance of the relationship tended to increase as sample size increased. In addition, the results of ANOVA showed that the relative importance of the TM bands and vegetation indices in the relationship varied with sample size as well. Although the spatial pattern of local-scale (or "neighborhood") diversity and richness of land-cover types in this Great Basin landscape could be adequately quantified using spectral information-based variables, the results and accuracy of such a analysis depended on both landscape composition and sample size. The linear response of the statistical relationship to the change in sample size over some range of scales indicated that scale effects could be readily predicted in certain cases. However, in general, because scale effects can further be complicated by the choice of variables and the idiosyncrasy of particular landscapes, the predictability of scale effects seems to be confined only to certain domains of scale. To find these domains multiple-scale or hierarchical analysis must be performed. This study further supports that the modifiable areal unit problem is a common one across the disciplinary boundaries of geography, ecology and other earth sciences. Unraveling the problem not only will improve our understanding of pattern and process in nature, but also will have important implications for appropriate use of remote sensing data and GIS.

I. INTRODUCTION

Spatial pattern has important effects on a variety of physical and ecological processes, including flows of energy and nutrients and dispersal and movement of plants and animals (Turner, 1989; Risser, 1990; Wiens et al., 1993; Wu et al., 1993; Hunsaker et al., 1994; Wu and Levin, 1994, 1997). To understand the interactions between pattern and process it is necessary to quantitatively characterize spatial heterogeneity over a range of scales. Because today's spatial pattern results from yesterday's dynamic processes, pattern analysis may potentially reveal critical information on properties of underlying processes. Landscape ecology, focusing on the study of the reciprocal relationship between spatial pattern and ecological processes, provides a new conceptual framework for understanding how nature works (Pickett and Cadenasso, 1995; Wu and Loucks, 1995). In recent years, numerous studies have been carried out to quantify landscape patterns using various spatial analysis methods (O'Neill et al., 1988; Turner and Gardner, 1991; Cullinan and Thompson, 1992; Plotnic et al., 1993; Wickham and Riitters, 1995; Riitters et al., 1995; Jelinski and Wu, 1996; Qi and Wu, 1996). In general, both promises and problems have been found regarding the plethora of techniques used in landscape pattern analysis (see Riitters et al., 1995, Jelinski and Wu, 1996).

Remotely sensed data and geographic information systems (GIS) have been increasingly used to facilitate large-scale studies in landscape ecology (Iverson et al., 1989; Roughgarden et al., 1991; Turner and Gardner, 1991). Landsat Thematic Mapper (TM) and NOAA satellite AVHRR data, in particular, have been widely adopted in landscape ecological studies. Based on the features of reflectance and absorption of vegetation to electromagnetic radiation, a number of vegetation indices have been developed from several TM bands (e.g., Tueller, 1989). Both the spectral values of the different TM bands and vegetation indices derived from them can be correlated with various characteristics of landscapes (e.g., Tueller, 1989, Rey-Benayas and Pope, 1995).

Landscapes are hierarchically structured in space, within which pattern and processes operate over a range of scales (O'Neill et al., 1991; Wu and Loucks, 1995). Detected spatial pattern usually varies with the scales of observation, measurement, and data analysis. Therefore, any analysis based on a single scale may provide little (or even misleading) information on the overall landscape structure under study (Wu and Loucks, 1995; Jelinski and Wu, 1996). Two concepts, grain and extent, have been particularly useful for making landscape pattern analysis scale-explicit, thus facilitating communication and comparison of the results. Grain is the "smallest unit of measure" or "the first level of spatial resolution possible with a given data set", whereas extent is the "cover" or "the total area of the study" (sensu Turner and Gardner, 1991). Studies in plant community ecology, human geography, and landscape ecology have shown that the results of spatial analysis using area-based data usually are sensitive to three kinds of related, but distinctive changes in spatial data: changes in grain size, extent (Meentemeyer and Box, 1987; Woodcock and Strahler, 1987; Turner et al., 1989; Wickham and Ritters, 1995; Qi and Wu, 1996), and aggregation zones (the zoning problem; see Openshaw, 1984; Fotheringham and Rogerson, 1993; Wu and Jelinski, 1995; Jelinski and Wu, 1996). It has been suggested, therefore, that landscape pattern should best be understood by conducting analysis on multiple scales or hierarchically (Wu and Loucks, 1995; Wu and Jelinski, 1995; Jelinski and Wu, 1996; Qi and Wu, 1996).

As a part of a research project that attempts to link spatial pattern to ecosystem properties in the Great Basin, this study examined the effects of systematically changing spatial scale on the results of particular statistical analyses. Specifically, the objectives of this study were as follows: (1) to investigate how landscape metrics such as diversity and richness relate to spectral parameters readily available from remote sensing (e.g., TM band values) and vegetation indices derived from them; and (2) to examine the effects of varying sample sizes on the results of the analysis.

II. DATA AND METHODS

The data set for this study is a land-cover map derived from empirical information on topography, vegetation distribution, and land use conditions. The data set contains fourteen land-cover types, covering the Minden area of Nevada in the western Great Basin. The geographic coordinates for the four corners are 39°9′18.3″ N and 119°51′13.7″ W, 39°6′14.2″ N and 119°30′30.0″ W, 38°54′12.3″ N and 119°54′55.8″ W, and 38°51′8.2″ N and 119°34′12.1″ W, respectively. The data set has 999 rows and 1069 columns with a linear dimension of about 30 m for each pixel, which represents a total area of 96,114 hectares (or 961.14 square kilometers). The GIS package, IDRISI™, was used for Landsat image processing and a part of the pattern analysis, while S-Plus™ was used for ANOVA, regression, and correlation analysis.

From the land-cover map, we computed three landscape metrics, diversity (H), dominance (D) and richness (R), as descriptors of landscape structure. These metrics have been widely used in landscape ecological studies (e.g., O'Neill et al., 1988, 1996; Turner, 1989; Wickham and Riitter, 1995), and are defined as follows:

Landscape Diversity

$$H = -\sum_{k=1}^{m} P_k \ln P_k$$

where H is the diversity index, m is the number of land-cover types, P_k is the proportion of the grid cells of land-cover type k (the number of pixels of the land-cover type k divided by the total number of pixels). Larger values of H correspond to more diverse landscapes which tend to have many land-cover types with similar proportions of pixels belonging to each type.

Landscape Dominance

$$D = H_{\max} + \sum_{k=1}^{m} P_k \ln P_k$$

where D is the Dominance index, H_{max} is the maximum diversity when all land-cover types are present in equal proportions (i.e. $H_{\max} = \ln m$). m and P_k are defined exactly the same as in the diversity index. This index is a measure of the extent to which one or a few land covers dominate the landscape. Small values usually correspond to landscapes with a large number of land use types of similar proportions. Apparently, a simple numerical relationship exists between diversity and dominance indices, both carrying the same non-spatial, compositional information of a landscape. While they were used together in our analysis for purposes of checking computational errors and facilitating interpretation, here we will focus primarily on the results on diversity to avoid redundancy.

Relative Richness

$$R = \frac{N}{N_{\max}} 100$$

where N is the number of different land-cover types present in an area under observation, and the $N_{\max}$ is the maximum value of richness.

Although the same basic formulas are used, in this study these metrics were calculated differently from the conventional way whereby they are computed for the entire study area or non-overlapping subregions. Because we were more interested in the characteristics of local-scale (or "neighborhood") diversity and their spatial changes, the landscape metrics were computed using a 3 by 3 pixel moving window as defined by the GIS package, IDRISI. For diversity and relative richness, respectively, a value for the metric was computed for the 9 neighboring cells, and then was assigned to the central cell. The window moves on one column at a time from the up left corner of the grid, until all the grid cells received their values. This is exactly the way these metrics are calculated using the PATTERN module of IDRISI (Eastman, 1995). As a result, the values of diversity and richness formed a 2-dimensional matrix and were represented as maps.

Three vegetation indices, RVI (Ratio Vegetation Index), NDVI (Normalized Difference Vegetation Index), and TNDVI (Transformed Normalized Difference Vegetation Index) were calculated from spectral information of the Landsat TM imagery of the study area. It was one of our objectives in this analysis to determine which of these vegetation indices would be best suited for detecting changes in the Great Basin landscapes. These indices were obtained from the following formula (Richardson and Wiegand, 1977; Tucker, 1979; Huete and Jackson, 1987):

$$RVI = \frac{Red}{NearInfrared}$$

$$NDVI = \frac{NearInfrared - Red}{NearInfrared + Red}$$

$$TNDVI = \sqrt{(NearInfrared - \mathrm{Re}\,d)/(NearInfrared + \mathrm{Re}\,d) + 0.5}$$

The Ratio Vegetation Index is simply the ratio of red to infrared brightness values and capitalizes on the increase in brightness as one moves from the red to the infrared data space. The Normalized Difference Vegetation Index is a more complex version of this simple ratio, and has been used in numerous vegetation assessment studies. Many studies have shown that NDVI is responsive to rapidly growing highly reflective plant communities such as alfalfa fields and riparian vegetation (Tueller, 1989; Rey-Benayas et al., 1995). The transformed normalized difference vegetation index, with the addition of 0.5, avoids negative values and usually is easier to interpret (Deering et al., 1975; Richardson and Wiegand, 1977; Harlan et al., 1979).

III. ANALYSIS AND RESULTS

In previous studies (Wu et al., 1994; Wu and Jelinski, 1995; Jelinski and Wu, 1996; Qi and Wu, 1996), we have shown that, for area-based data, varying the scale of analysis (grain size) and zoning systems (orientation and configuration) of the spatial units at the same scale both may have significant effects on the results of spatial analysis. This problem has been termed the modifiable areal unit problem (MAUP) in the geography literature (Openshaw, 1984; Fotheringham and Rogerson, 1993; Amrhein, 1995; Wu and Jelinski, 1995; Jelinski and Wu, 1996). In this study, we intended to explore how systematic (or progressive) changes of the analysis scale (specifically sample size) affect the results of regression and correlation analysis based on landscape data. How do different representation forms of variables ¾ variance, mean, variance-mean ratio (V/M), and coefficient of variation ¾ interact with the scale effects? Do scale effects show any trends that are predictable?

We used the three landscape metrics (diversity, and richness) as dependent variables and TM3, TM4, TM7, NDVI, TNDVI, and RVI as independent variables in the statistical analysis. To examine scale effects, four sample sizes were used: 25 pixels (5x5), 121 pixels (11x11), 225 pixels (15x15), and 361 pixels (19x19). First, we cut forty-nine 5x5 pixel samples from each of the 9 images (diversity, dominance, richness, TM3, TM4, TM7, NDVI, TNDVI, and RVI), and then symmetrically increased the scale of analysis, from the center cell outward, to 11x11, 15x15, and 19x19 pixels (Figs. 1 and 2). As a result, there were 49 replicates for each sample size. Variance, mean, variance-mean ratio (V/M), and coefficient of variation (CV = $\frac{\sqrt{V}}{M}$) of the nine variables at each sample size (n = 49) were computed, and then used accordingly for regression analysis, analysis of variance, and correlation analysis.

Regression analysis was conducted to examine how the landscape metrics relate to TM band parameters (TM3, TM4 and TM7) and vegetation indices (NDVI. TNDVI and RVI). Variance, mean, V/M, and CV of each variable are used for each sample size, respectively. For example, at the sample size of 5 by 5 pixels, four multiple linear regression models were constructed for each of the three dependent variables (diversity, dominance, richness) in terms of their variance, mean, V/M, and CV, respectively. The analysis of variance was used to determine the relative importance of the TM band parameters and vegetation indices in the relationship. We also performed a correlation analysis to further explore the relationship between landscape metrics and TM variables. In both ANOVA and correlation analysis, only the variance of dependent and independent variables at each sample size was used as the representation form because the regression analysis had shown that variance was more sensitive to changes in the landscape metrics than mean, V/M and CV.

The results of regression analysis showed that, for the sample size of 5 by 5 pixels, there did not appear to be a linear relationship between the landscape metrics (i.e., diversity, dominance, richness) and the six independent variables (i.e., TM3, TM4, TM7, NDVI, TNDVI, and RVI). This was true for all representation forms of the variables (i.e., mean, variance, V/M, and CV). For the sample size of 11 by 11 (121 pixels), a statistically significant linear relationship was apparent between the landscape metrics and independent variables when mean, variance, and V/M, but not CV, of these variables were used for the analysis (Table 1). When the sample size increased to 15x15 and 19x19 pixels, the linear relationship of the landscape metrics with TM bands and vegetation indices became statistically significant for all four forms of measure for the variables, with progressively larger R^2 values and smaller P values (see Table 1, Figs. 3 and 4). In general, the strength of this relationship tended to increase as sample size increased for all four forms of measure (Fig. 3). However, a closer look reveals that R^2 values actually peaked at the sample size of 15x15 pixels in the cases of mean and V/M (Fig. 4).

The results of analysis of variance showed that, when variance was used as the representation form for the variables, the independent variables differed in terms of the level of significance in the relationship with landscape metrics as sample size increased (Table 2). For all the three landscape metrics, all independent variables were found insignificant at the sample size of 5x5 pixels. TM3 was statistically significant in the relationship for all the three landscape metrics at sample sizes of 11x11 pixels and larger, NDVI was significant for sample sizes of 15x15 and 19x19 pixels, and TM7 was only significant for the sample size of 19x19 pixels. The number of the spectral variables that were significant in the regression relationship increased as the sample size expanded. The results of the analysis of variance also were indicative of the relative importance of the different independent variables in the regression relationship at each sample size. Although a certain variable might be important at several sample sizes, its P value tended to decrease with the sample size (Table 2).

The results of correlation analyses, using variance as the representation form of all variables, showed that TM7 was significantly correlated with all the three landscape metrics at all four sample sizes, whereas TM 3 and TM4 were significantly correlated with these metrics when sample size was bigger than 5x5 pixels (Table 3). For all the three TM bands, R^2 values increased and P decreased as sample size expanded, indicating that the correlation between the landscape metrics and the TM bands became more significant with increasing sample size.

IV. DISCUSSION AND CONCLUSIONS

The results of our study have shown that the spatial pattern of local-scale or neighborhood diversity and richness in the Minden landscape could be characterized using TM spectral data. But sample size or the scale of analysis played an important role in relating the landscape metrics to TM spectral variables. With explicit specification of this scale effect, it seems feasible to use TM spectral information or vegetation indices to quantify and monitor spatial changes in the Great Basin landscape. However, several points are worth further discussion.

Scale effects

Several studies have shown that changing scale may significantly affect the pattern quantification of an entire landscape or its subregions using, for example, richness and information theory-based metrics (Turner et al., 1989; Wickham and Ritters, 1995; O'Neill et al., 1996) and spatial autocorrelation indices (Legendre and Fortin, 1989; Jelinski and Wu, 1996; Qi and Wu, 1996). Specifically, the scale being changed in our study is sample size, or may be regarded as extent with 49 replicates (see Fig. 2). Our study further has suggested that statistical analyses like regression, ANOVA, and correlation analysis with landscape data are also affected by changing scale. The effect of changing sample size on these analyses can be considerably large (Fig. 4). Of particular interest was that R^2 values increased monotonically in the variance and CV graphs (A and D in Fig. 4), whereas a peak became apparent at the 15x15 sample size in both mean and V/M graphs (B and C in Fig. 4). Further studies are needed to confirm whether this peak was indicative of a characteristic scale at which a real structural change in the landscape takes place. Because of scale effects, ecological conclusions based on such analyses should be made with explicit specification of scales (grain size and extent). Our results seem to suggest that this effect may be predictable within a certain domain of scales in some cases (see Fig. 4 for regions that correspond to nearly linear change in R^2 values).

Effects of different representation forms of variables

Scale effects were further complicated by the effect of different representation forms of variables used for the landscape analysis. For example, the four representation forms (variance, mean, V/M, and CV) for the 9 variables in this study resulted in somewhat distinctive patterns of change in R^2 values with increasing sample size (Fig. 4). For example, while diversity and richness seemed to exhibit similar patterns for each representation form at finer scales, variance was most sensitive to changes in diversity and richness pattern. The higher sensitivity of variance to change in the analysis scale is attributable, at least in part, to the fact that its values are larger than those of V/M or CV in which variance is "scaled down" by mean.

Relationship between TM bands/derived vegetation indices and spatial pattern of land-cover richness and diversity

The results of regression analysis indicated that neighborhood diversity and richness were significantly correlated to TM band parameters and vegetation indices. The strength of the correlation seemed to increase with sample size (or calculation scale). This was evidenced by the increasing R^2 values and decreasing P values for the regression relationship, as well as by ANOVA and correlation analysis. In particular, the results suggested that the selected TM bands and vegetation indices could detect and predict changes in local-scale diversity and richness at sample sizes from 11x11 to 19x19 pixels with increasing accuracy. Clearly, use of variance as the representation form of variables at the 19x19 sample size gave the best result (R^2 larger than 0.7 for all three metrics; see Table 1 and Fig. 4). The results of both ANOVA and correlation analysis further suggested that TM3 and NDVI were the most consistent and best predictor variables.

TM3 band has been shown to be a good indicator of green vegetation (e.g., Tucker, 1979; Baret and Guyot, 1991). Rey-Benayas and Pope (1995) indicated that TM spectral data have the potential of measuring landscape diversity. While our results seem to support this claim, the choice of appropriate sample size will be critically important to achieve high accuracy. On the other hand, vegetation indices derived from several bands using different mathematical formulations may indicate quantitative and qualitative differences in the properties of vegetation because significant differences in reflectance and absorption of radiation exist between vegetation and other geographical characteristics of the landscape (Tueller, 1989). According to our analysis, normalized difference vegetation index (NDVI) appeared to be better than RVI and TNDVI for characterizing local-scale diversity and richness pattern in this particular desert landscape (Table 2). Numerous studies have shown that NDVI is a sensitive indicator of green biomass (Tucker, 1979, Tueller, 1989). Out study suggested that, together with TM3 and TM7, NDVI was a good predictor of diversity and richness in the landscape of our study. However, it is worth emphasizing again that the accuracy of these variables as predictors of land-cover diversity and richness not only depends on landscape composition, but also on sample size.

In conclusion, we emphasize that scale effects represent an important and challenging issue that must be considered explicitly in all landscape analysis. Based on this and previous studies it seems unlikely to find “universal” rules that can be used to accurately predict scale effects over a wide range of scales or across different types of analysis and landscapes. This is in part because scale effects are further complicated by the choice of variables and the idiosyncrasy of particular landscapes. Yet, as this study suggests, responses of the statistical relationship to changes in analysis scale may exhibit simple (e.g., linear or monotonic) patterns over some ranges of scale, implying that scale effects could be readily predicted within these domains of scale. To find scale domains where predictions or extrapolations can be readily made, multiple-scale or hierarchical analysis must be performed. This study further supports that the modifiable areal unit problem is common across the disciplinary boundaries of geography, ecology and other earth sciences.

Unraveling the problem will not only improve our understanding of pattern and process in nature, but also will have important implications for appropriate use of remote sensing data and GIS.

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Table 1. Results of linear regression between the landscape metrics (diversity, dominance, richness) and TM3, TM4, TM7, NDVI, TNDVI, and RVI at 4 different sample sizes (5x5, 11x11, 15x15, and 19x19 pixels). Variance, mean, V/M and CV of the nine variables at each sample size are used separately in the analysis.

Measure	Landscape Indies	R^2	P-value	R^2	P-value	R^2	P-value	R^2	P-value
		5 * 5 (25 pixels)		11 * 11 (121 pixels)		15 * 15 (225 pixels)		19 * 19 (361 pixels)	
	Diversity	0.1637	0.3964	0.3943	0.0015**	0.4459	0.0003**	0.7679	0.0000**
Variance	Dominance	0.2191	0.1950	0.311	0.0138*	0.4240	0.0006**	0.9999	0.0000**
	Richness	0.1192	0.6183	0.3179	0.0117*	0.5500	0.0000**	0.7049	0.0000**
	Diversity	0.256	0.1117	0.3778	0.0024**	0.4553	0.0002**	0.3883	0.0018**
Mean	Domanence	0.1473	0.4735	0.3494	0.0052**	0.4872	0.0001**	0.4232	0.0006**
	Richness	0.2471	0.1286	0.3449	0.0059**	0.4361	0.0004**	0.4022	0.0012**
	Diversity	0.2505	0.1218	0.2531	0.0492*	0.4166	0.0163*	0.3889	0.0174*
V/M	Domanence	0.2293	0.1682	0.3231	0.0103*	0.5485	0.0000**	0.3181	0.0116*
	Richness	0.2315	0.1534	0.2933	0.0211*	0.5731	0.0000**	0.4207	0.0007**
	Diversity	0.1278	0.5725	0.1568	0.2919	0.2214	0.0966	0.5232	0.0001**
CV	Domanence	0.1138	0.6469	0.1808	0.1994	0.2180	0.1031	0.2885	0.0236*
	Richness	0.1359	0.5305	0.1448	0.3478	0.2511	0.0534	0.2514	0.0531

* $P \leq 0.05$

** $P \leq 0.01$

Table 2. Results of analysis of variance between the landscape metrics (diversity, dominance, richness) and TM3, TM4, TM7, NDVI, TNDVI, and RVI at 4 different sample sizes. The variance value of each variable at each sample size is used in the analysis.

Sample size	Diversity vs.	P value	Dominance vs.	P value	Richness vs.	P value
5X5	TM3	0.08091	TM3	0.42235	TM3	0.17482
	TM4	0.59403	TM4	0.61092	TM4	0.76886
	TM7	0.41344	TM7	0.74131	TM7	0.57186
	NDVI	0.94461	NDVI	0.36995	NDVI	0.80863
	RVI	0.15879	RVI	0.05845	RVI	0.23338
	TNDVI	0.69449	TNDVI	0.06810	TNDVI	0.44635
11X11	TM3	0.00015**	TM3	0.01066*	TM3	0.00077**
	TM4	0.39013	TM4	0.09552	TM4	0.72986
	TM7	0.64337	TM7	0.68709	TM7	0.18886
	NDVI	0.03771*	NDVI	0.02759*	NDVI	0.16830
	RVI	0.06890	RVI	0.06370	RVI	0.15953
	TNDVI	0.71911	TNDVI	0.38048	TNDVI	0.97257
15X15	TM3	0.00002**	TM3	0.00249**	TM3	0.00000**
	TM4	0.55443	TM4	0.21824	TM4	0.79383
	TM7	0.20461	TM7	0.08522	TM7	0.11359
	NDVI	0.00206**	NDVI	0.01068*	NDVI	0.01075*
	RVI	0.04888*	RVI	0.01108*	RVI	0.01462*
	TNDVI	0.84668	TNDVI	0.16059	TNDVI	0.95484
19X19	TM3	0.00000**	TM3	0.00000**	TM3	0.00000**
	TM4	0.63878	TM4	0.00000**	TM4	0.97097
	TM7	0.00006**	TM7	0.00000**	TM7	0.00025**
	NDVI	0.00000**	NDVI	0.00000**	NDVI	0.00000**
	RVI	0.42321	RVI	0.31253	RVI	0.27869
	TNDVI	0.94307	TNDVI	0.56559	TNDVI	0.50972

* $P \leq 0.05$; ** $P \leq 0.01$

Table 3. Results of correlation analysis between the landscape metrics (diversity, dominance, richness) and TM3, TM4, and TM7 at 4 different sample sizes. The variance value of each variable at each sample size is used in the analysis.

TM (Variance)	Diversity		Dominance		Richness	
	R^2	P	R^2	P	R^2	P
5x5 pixels						
TM3	0.2866	0.0365*	-0.125	0.7789	0.2266	0.0799
TM4	0.0772	0.3180	0.0018	0.4955	0.0775	0.3174
TM7	0.3205	0.0219*	-0.096	0.7221	0.2473	0.0019*
11x11 pixels						
TM3	0.5082	0.0001**	0.3620	0.0154*	0.4769	0.0004**
TM4	0.3602	0.0060**	0.3537	0.0069**	0.2994	0.0238*
TM7	0.4849	0.0004**	0.3223	0.0127*	0.3512	0.0094**
15x15 pixels						
TM3	0.5697	0.0041**	0.3820	0.0248*	0.6361	0.0013**
TM4	0.3664	0.0052**	0.3312	0.0107*	0.3672	0.0051**
TM7	0.5478	0.0000**	0.4496	0.0007**	0.6043	0.0000**
19x19 pixels						
TM3	0.6020	0.0000**	0.4048	0.0050**	0.6677	0.0000**
TM4	0.3680	0.0020**	0.3374	0.0095**	0.5114	0.0015**
TM7	0.6728	0.0000**	0.4204	0.0001**	0.7118	0.0000**

* $P \leq 0.05$
** $P \leq 0.01$

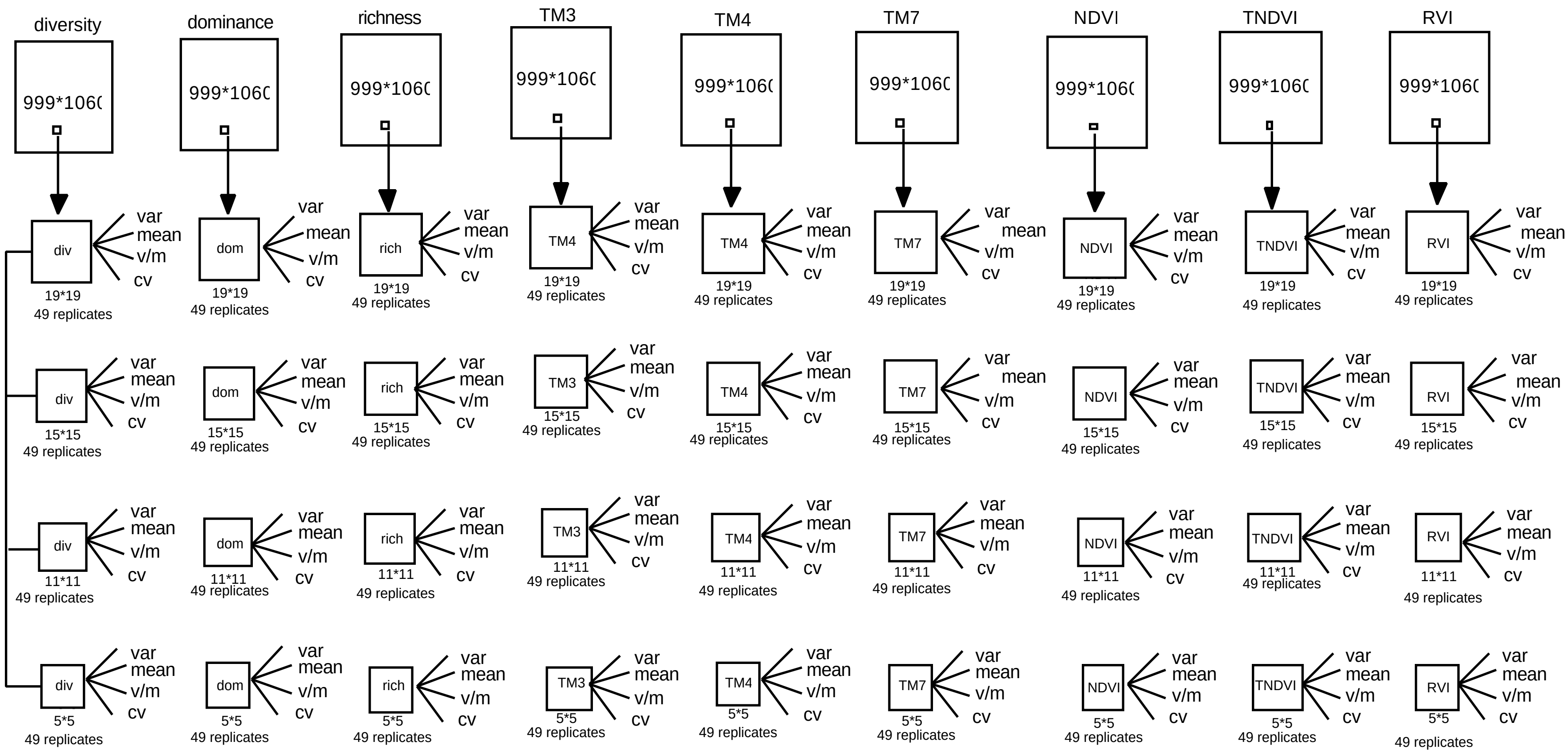


Fig. 1. Schematic representation of the analysis design: 3 dependent variables (diversity, dominance, and richness); 6 independent variables (TM3, TM4, TM7, NDVI, TNDVI, and RVI); 4 different representation forms of variables (mean, variance, variance/mean ratio, and coefficient of variation); and 4 different sample sizes (5x5, 11x11, 15x15, 19x19 pixels, respectively).

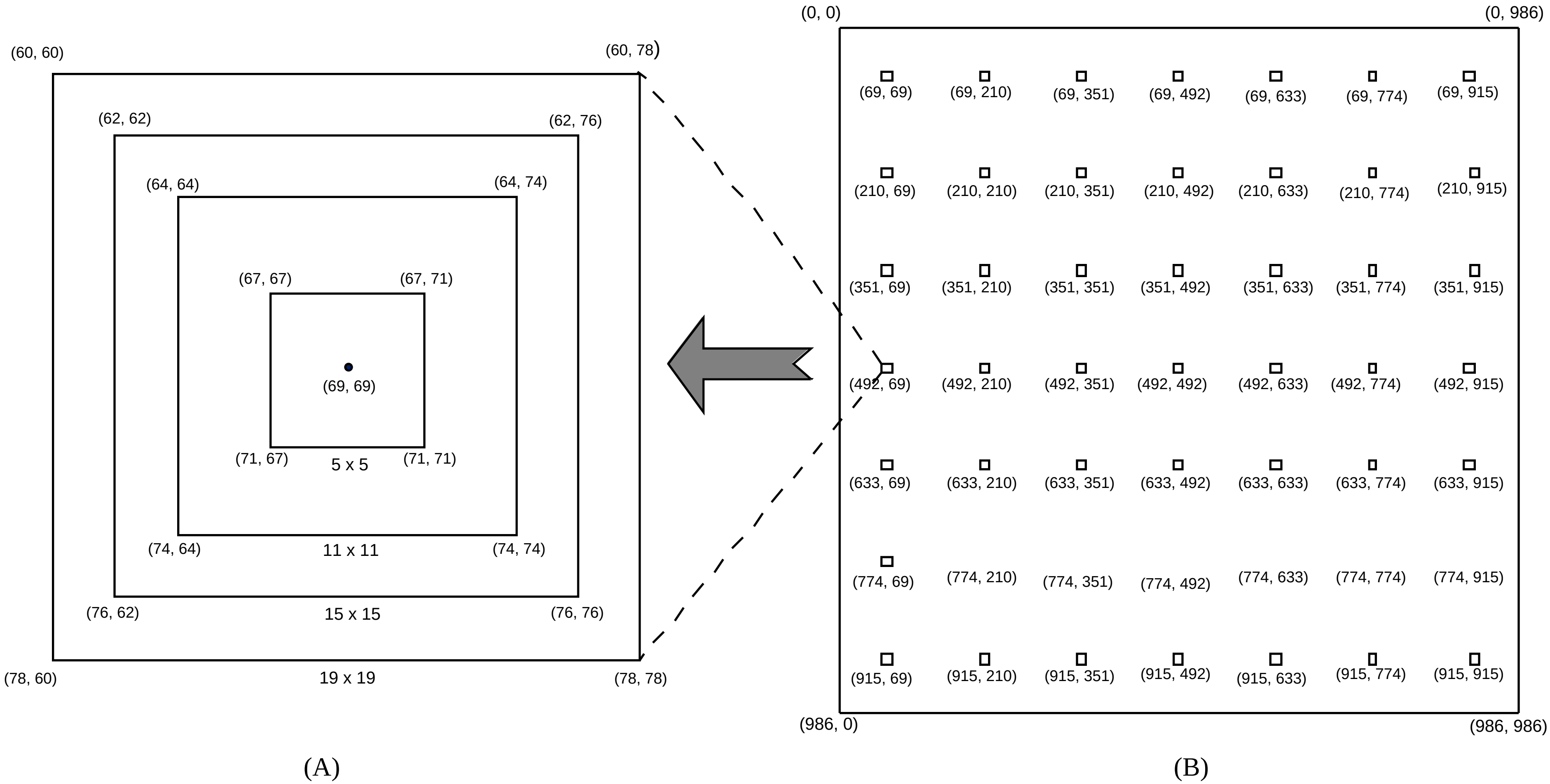
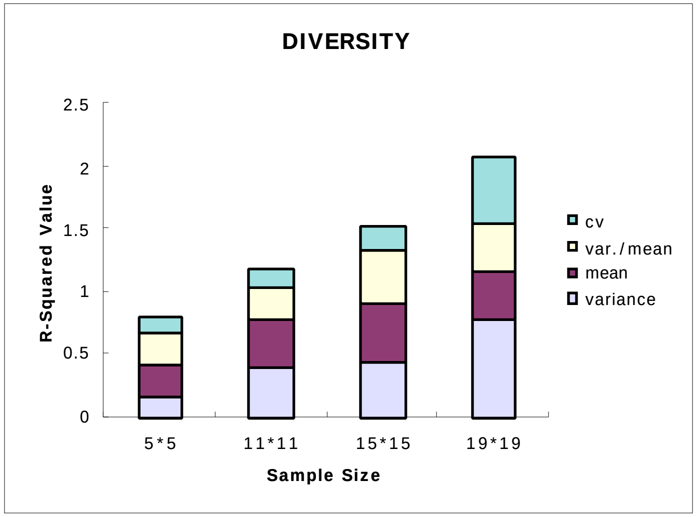
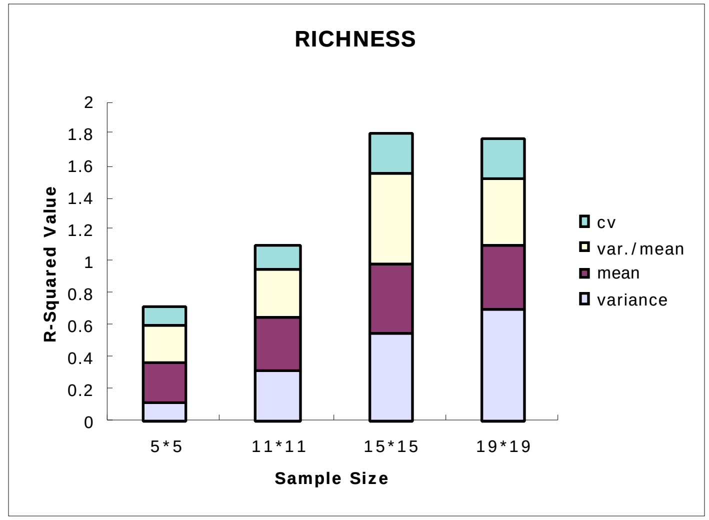


Fig. 2. Illustration of the layout of samples of four different sizes: 5x5, 11x11, 15x15, and 19x19 pixels. The numbers in the parentheses in (B) are the coordinates of the center cells in each sample.



(A)



(B)

Fig. 3. Accumulative R^2 values for the multiple linear regression between landscape metrics and spectral variables as a function of increasing sample sizes (5x5, 11x11, 15x15, and 19x19 pixels). Dependent variables are diversity (A), dominance (not shown here), and richness (B), and independent variables are TM3, TM4, TM7, NDVI, TNDVI, and RVI. Variance, mean, V/M and CV of the nine variables at each sample size are used separately in the analysis (see also Table 1).

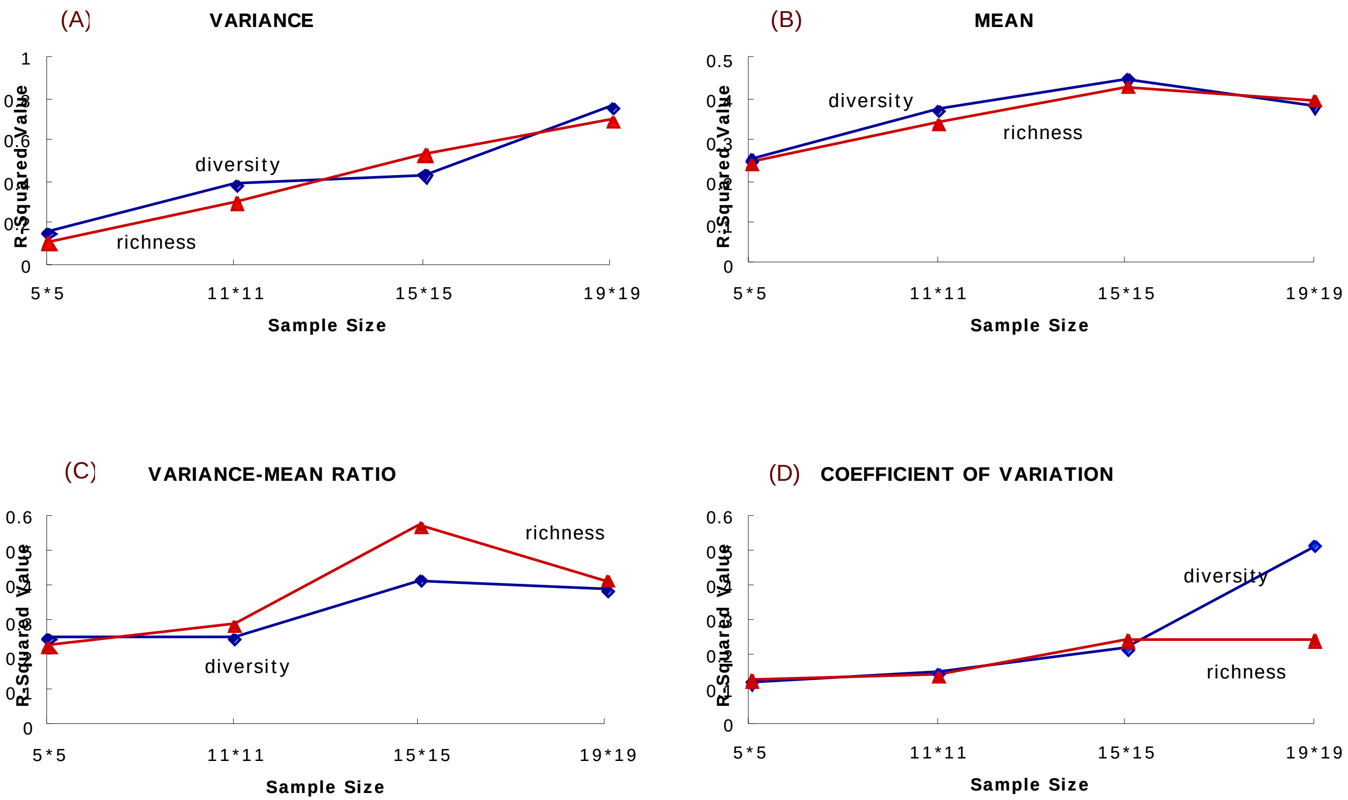


Fig. 4. R^2 values for the multiple linear regression between landscape metrics and spectral variables as a function of increasing sample sizes (5x5, 11x11, 15x15, and 19x19 pixels). Dependent variables are diversity, dominance (not shown here), and richness, whereas independent variables are TM3, TM4, TM7, NDVI, TNDVI, and RVI. Variance (A), mean (B), V/M (C) and CV (D) of the nine variables at each sample size are used separately in the analysis. Also refer to Table 1 for numerical values.