Comparison of Surface and Planimetric Landscape Metrics for Mountainous Land Cover Pattern Quantification in Lancang Watershed, China

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Landscape pattern structure can be quantified by landscape pattern indices (LPIs). One major drawback of the commonly used LPIs is that the landscape is represented by a planar map, which depicts the projection of a nonflat surface into a 2-dimensional Cartesian space. As a result, ecologically meaningful terrain structures like terrain shape or elevation are not taken into account and valuable information is lost for further analysis. A method to compute LPIs in a surface structure has been developed by Hoechstetter et al, who calculated landscape patch surface area and surface perimeter from digital elevation models. In this paper, Hoechstetter's set of LPIs was used and extended. A parametric t*-test was used to assess the differences between the commonly used planimetric metrics and the surface landscape metrics for quantification of a mountain vegetation pattern at 3 levels (patch, category, and landscape) and for natural and anthropogenic categories in the Lancang (Mekong) watershed in China. The results show that the surface-based metrics for area, perimeter, shape, and distance to nearest-neighbor metrics were significantly larger than the same metrics derived by a planimetric approach for patch, category, and landscape levels in 2 different mountainous areas. However, diversity and evenness metrics did not feature significant differences between the surface-based landscape and the landscape represented in the planar maps. When comparing the area metrics for natural and for anthropogenic categories, significantly larger differences between these categories were found when the surface approach was used. The common planimetric method may underestimate the differences between natural and anthropogenic categories on areas and mean patch area in steep mountain areas.*

Keywords: *Mountain areas; planimetric landscape pattern index; surface landscape pattern index; natural category; anthropogenic category; land cover pattern quantification.*

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Introduction

In mountain areas, land cover and vegetation distribution are strongly affected by topographic factors (Dymond and Johnson 2002; Cantón et al 2004). Many studies demonstrated the influence of topography on spatial patterns of land cover (Brown 1994; Crave and Gascuel-Odoux 1997; Western et al 1999; Gómez-Plaza et al 2001). There is also an increasing body of knowledge of how topography influences the frequency, spread, extent, and distribution of natural disturbances such as fire, wind, or grazing (Turner et al 2001; Dorner et al 2002). However, even though some studies integrated different aspects of ecosystem dynamics and their interactions with topography (Swanson et al 1992; Allen and Walsh 1996; Wondzel et al 1996; Swanson et al 1998; Dorner et al 2002), understanding of how topography, disturbance regimes, and land cover dynamics interact to form landscape pattern is still limited (Dorner et al 2002).

Landscape ecological research could help fill this gap by quantifying the effect of topography on different aspects of landscape pattern (Dorner et al 2002).

The analysis of landscape patterns is a fundamental part of landscape ecology (Haines-Young 2005). In general, landscape pattern or landscape structure is characterized by the size, shape, and distribution of individual landscape elements throughout the landscape (Li et al 2001). A landscape can be characterized by its composition and configuration (Dunning et al 1992). Landscape composition refers to the variety and abundance of patch types within a landscape. Landscape configuration refers to the placement or spatial character of patches within a landscape, such as how the patches of the same or different land cover types are arranged in the landscape in relationship to one another. Hence, landscapes with similar composition can feature quite different configurations. Landscape structure can be quantified by landscape pattern indices (LPIs; Turner et al

2001). Numerous indices for patterns are described in the literature (O'Neill et al 1988; Turner et al 1991; Riitters et al 1995; Frohn 1998). These metrics can be used to assess the area, shape, contagion, and diversity of patches of a landscape mosaic (Hoechstetter et al 2006). The computation of most of these indices has been incorporated into landscape analysis software packages (Gardner 1999; Saura and Martinez-Millan 2000; McGarigal et al 2002). These packages vary in their utility for applications in research and management (Gergel 2007). The most widely used and known is FRAGSTATS (McGarigal et al 2002).

Landscape pattern quantification is generally conducted on land use, land cover, or both types of data derived from aerial photography, digital remote sensing, or paper maps (Turner et al 2001). However, this representation of spatial data is a "bird's eye" view (Hoechstetter et al 2006). The landscape is represented by a planar map, which results from the projection of a nonflat surface into a 2-dimensional Cartesian space. This means ecologically meaningful surface structures like terrain shape or elevation are not taken into account and valuable information is lost for further analysis (Hoechstetter et al 2006). Especially in steep mountains, the patch areas and distances between patches measured on a planar map can be considerably underestimated (Dorner et al 2002; Hoechstetter et al 2008). Attention has been given only recently to the application of surface metrics for the quantification of landscape patterns (Hoechstetter et al 2008; Hoechstetter 2009; McGarigal et al 2009).

In addition, land cover patterns are affected not only by topography but also by human disturbance. Human disturbance creates patterns in land cover that ecologists have long recognized as important to landscape-level patch mosaics (Turner et al 2001). The causes, patterns, dynamics, and consequences of disturbances are major research topics in landscape ecology (Turner et al 2001; Farina 2006). A number of comparative studies examined landscape patterns resulting from different disturbances using LPIs (Krummel et al 1987; Delong and Tanner 1996; Gluck and Rempel 1996; Foster et al 1998; Turner et al 2001; Farina 2006).

In China, land cover patterns have been dramatically altered by human activities during the last 30 years. This was largely due to population growth and rapid economic development (Verburg and Chen 2000; Fischer and Sun 2001; Long et al 2007; Wu et al 2009). Particularly in the Lancang watershed (upper Mekong River) in Yunnan Province, several drivers are related to forest change and environmental degradation, such as deforestation, introduction of a logging ban, initiation of the Slope Land Conservation Program, mining activities, road and dam construction, and establishment of rubber plantations (Wang et al 2004; Weyerhaeuser et al 2005; Liu et al 2006; Li et al 2007).

A method to compute surface LPIs has been developed, derived from the calculation of landscape patch surface area and surface perimeter from digital elevation models (DEMs; Hoechstetter et al 2008; Hoechstetter 2009). In this paper, we extend the surface method to calculate additional LPIs and validate this method under real-world conditions in 2 large, different mountainous areas to gain more insight in their operational applicability. We test whether there are significant differences between planimetric and surface LPIs for landscape pattern quantification for 2 mountainous regions (high mountains and low mountains) in the same watershed (Lancang). We also compare patterns of natural and anthropogenic land cover categories using planimetric and surface LPIs, because many mountain environments carry an anthropogenic footprint. In this study, we tested the following hypotheses:

1. There are significant differences between planimetric and surface LPIs for landscape pattern quantification.
2. There are significant differences between planimetric and surface LPIs to assess the differences between patterns of natural land cover categories and patterns of anthropogenic land cover categories.

Study area

We selected 2 research sites in 2 mountain areas in the Lancang (Mekong) watershed, Yunnan Province, China (Figure 1A). There are large differences between the southern and the northern part of the Lancang watershed. The south represents a tropical region containing Xishuangbanna Dai Autonomous Prefecture. It is one of the most important areas in China in terms of biodiversity. The northern part of the study area is well known for its water resources. Land cover patterns are strongly affected by topography in both mountain areas. From field visits, it is known that the land cover pattern is also strongly influenced by human activities. This is particularly the case in the valleys. The majority of the rural population is living in the lower altitudes or along the riversides.

The northern study area is located in the Weixi and Lanping counties of Yunnan Province, China ($26°7'12''$N~$27°53'24''$N; $98°58'12''$E~$99°37'48''$E; Figure 1B). The 4 great rivers of Southeast Asia (Yangtse, Lancang, Irrawaddy, and Salween) pass through the mountains here. This area is a typical steep mountain area, with altitudes ranging between 1500 and 4500 m. Because of the considerable altitudinal differences, the climate varies significantly as the elevation changes. The climate can be divided into 4 zones from the riverside to the top of the mountain: warm temperate, temperate, cold temperate, and subfrigid (Deng et al 1997). The vertical climate gradient influences the distribution of

FIGURE 1 Location of the samples in (A) the 2 study areas; 4 test sites were selected in both (B) the northern study area (N1–N4) and (C) the southern study area (S1–S4). See also Figures 2 and 3.
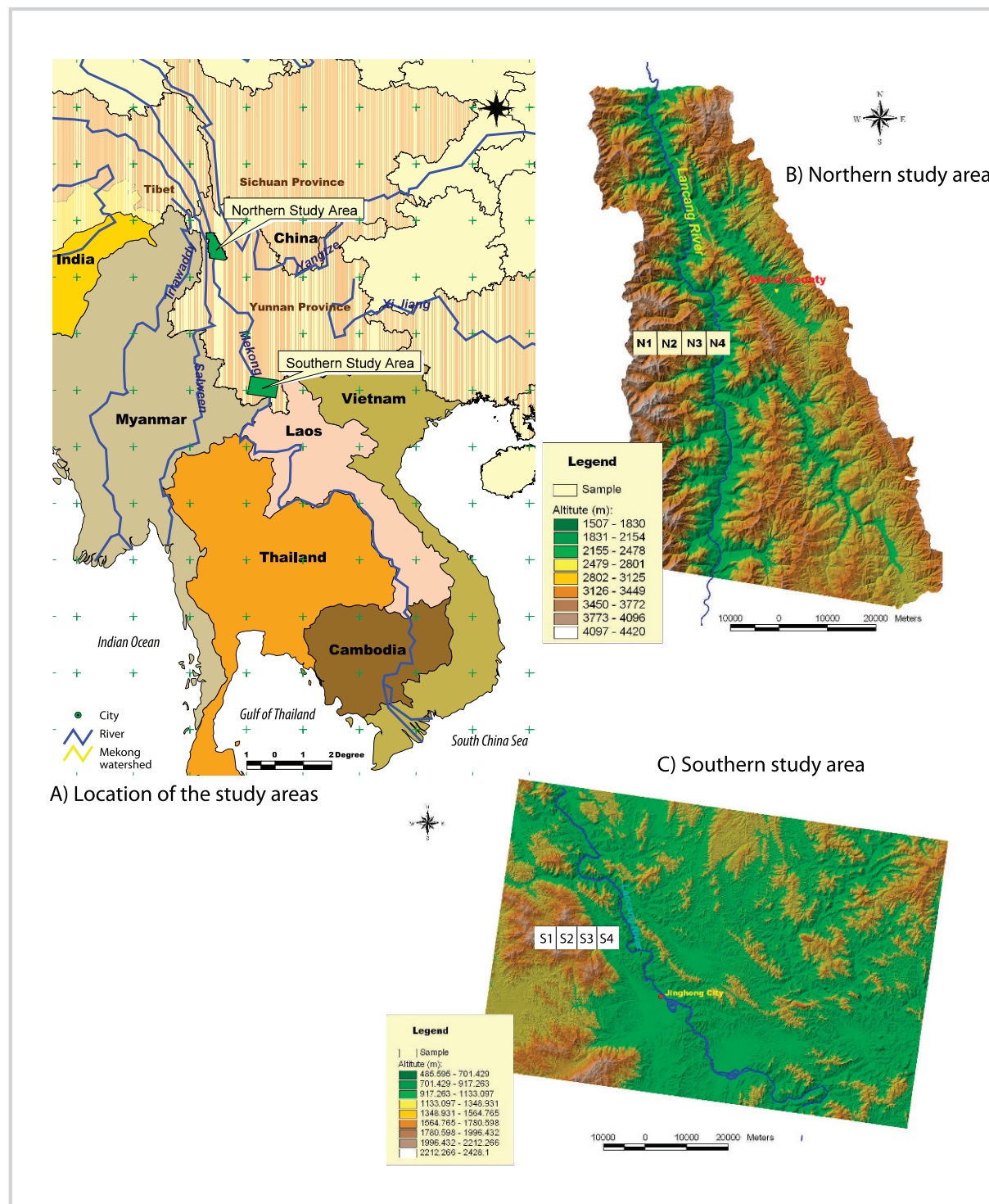
land cover and vegetation. However, the land cover distribution is also affected by human activity and topographic variables, such as slope and aspect (Zhang et al 2009).

The southern study area in Xishuangbanna Prefecture covers about 50,000 ha (22°00′N~23°50′00″N; 100°00′12″E~102°00′E; Figure 1C). It belongs to the lower catchment of Lancang River. Xishuangbanna is home to

TABLE 1 Vegetation classes in the classification procedure.

Northern study area			Southern study area		
Type	Class	Kappa	Type	Class	Kappa
NC	Fir and spruce forest	0.9241	AC	Old rubber trees	0.8688
NC	Pine forest	0.9244	AC	Young rubber trees	0.8843
NC	Oak forest	0.9129	NC	Evergreen forest	0.9543
NC	Mixed forest	0.9454	SH	Low-density forest and tall shrubs	0.7829
SH	Low-density forest and tall shrubs	0.8620	NC	Deciduous forest	0.8674
SH	Dwarf shrub and meadow	0.9246	SH	Shrub and grass land	0.9601
AC	Agriculture land	0.9661	AC	Agriculture land	0.9282
NC	Snow	0.9989	AC	Burnt land	0.6802
NC	Water	0.9983	NC	Water	0.9491
CS	Mountain-cast shadow	0.9956	CS	Cloud- and mountain-cast shadow	0.7779

NC, natural category; SH, shrub category; AC, anthropogenic category; CS, cast shadow category.

the richest biological and ethnic diversity in China. The maximum altitude range is about 2000 m. Even though the climate varies with elevation in the south, the effects of topography are smaller than in the northern study area. The climate of the region is mostly seasonal. The monthly average temperature ranges between 16.4 and 22.0°C. Between May and October, the southwest monsoon air masses bring about 80% of the annual rainfall, whereas the dry and cold air of the southern edges of the jet stream dominates the weather pattern between November and April. Annual rainfall varies between 1200 mm in the Lancang valley and 1900 mm at altitudes above 1500 m.

Material and methods

Spatial data
Land cover maps for the 2 study areas were prepared to conduct pattern analysis. The maps resulted from classification of Land Satellite (Landsat) Thematic Mapper (TM) image data (the northern image was acquired December 26, 2003, and the southern image was acquired March 1, 2004). A feed-forward back-propagation algorithm artificial neural network was used (Zhang et al 2007). One of the main advantages of neural networks for classification is that they are independent of the distribution of the class-specific data in feature space. It is therefore possible for a single class to be represented in feature space as a series of clusters (rather than a single cluster). The land cover classes are listed in Table 1. The selection of the land cover classes was based on a threefold rationale: relation to major plant communities, feasibility to be identified using Landsat TM image data, and relevance to land cover change. The image processing

protocol used to prepare the land cover maps was described by Zhang (2011). The kappa value is 0.94 for the land cover map in the northern study area, while the southern land cover map featured a kappa of 0.91.

Four landscape sections covering 5000 × 5000 m with an altitude gradient from 1590 to 4326 m were selected as test sites in the north (N1–N4; Figures 1 and 2). Four test sites of the same size were also selected in the southern study areas (S1–S4; Figures 1 and 3). The 4 southern test sites are located between the Jinghong basin and the highest peak in Xishuangbanna Prefecture. Considering the distance between the river and the mountain ridge, the resolution of the DEM (25 m), and the scale of the land cover map (derived from TM image data with 30-m resolution), it was assumed that these test sites cover the entire range of topographic variation.

The land cover classes of the 2 land cover maps were grouped into 3 categories: natural (NC), shrub (SH), and anthropogenic (AC). Cloud- and mountain-cast shadows (CS) were excluded from further analysis (Table 1). In the northern study area, 4 of the 6 NC types are natural forest without much human disturbance. The alpine vegetation—featuring alpine talus, meadows, and rhododendron shrubs—is covered by snow in winter. It is therefore labeled "snow" as apparent from a Landsat TM winter image, which was acquired on December 26, 2003. The water class includes Lancang River and a few alpine lakes. In the northern study area, agriculture land is the only AC. In the southern study area, NC includes 2 types of natural forest, evergreen forest and deciduous forest, as well as water. The 2 forest types occupy most of Mengyang National Nature Reserve and Naban River Biosphere Reserve. As in the north, the water category includes Lancang River and a number of lakes. AC includes old and young rubber trees, agriculture land, and burnt land. In the

FIGURE 2   (A) Landscape map derived from the 2003 vegetation map in the northern study area. (B) Surface landscape map derived from the 2003 vegetation map draped over the corresponding DEM data in the northern study area. NC, natural category; SH, shrub category; AC, anthropogenic category; CS, cast shadow category.
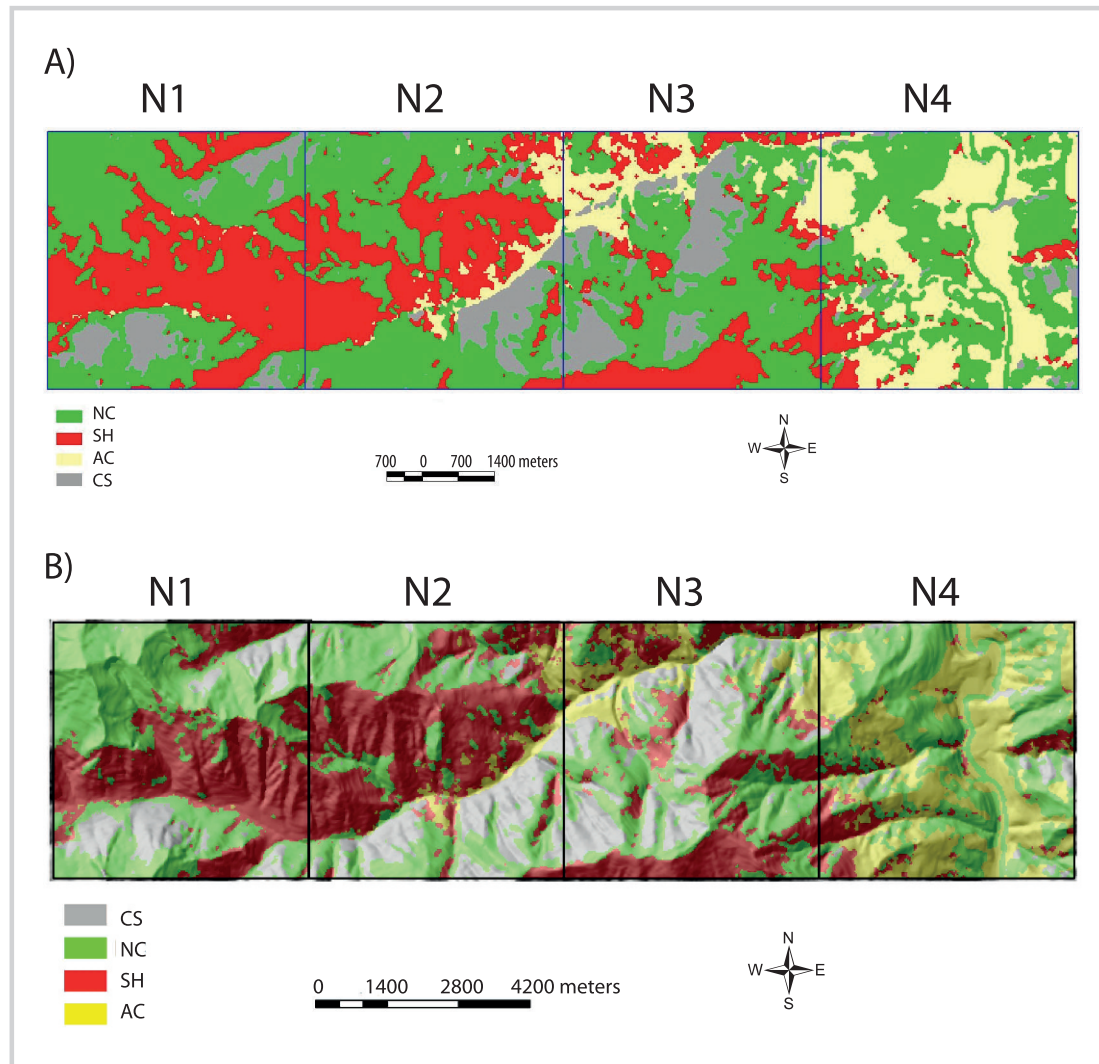
southern study area, rubber plantations in particular are responsible for deforestation, forest fragmentation, and loss of high-diversity rain forest (Li et al 2007, 2009).

Shrubs constitute a separate category, because it is difficult to group shrubs into either NC or AC. For instance, "low-density forest and tall shrubs" includes fully grown shrubs, such as rhododendron and willow, as well as disturbed vegetation, such as fallow land and shifting grassland (Xu et al 1999). The spectral response patterns of these shrub types are similar. Moreover, dwarf shrubs and meadows can be both natural and disturbed vegetation.

For the 2 study areas, we used 25-m resolution DEM data produced by the China State Bureau of Surveying and Mapping (National Administration of Surveying, Mapping, and Geoinformation, http://en.sbsm.gov.cn/). The DEM data were projected into the Universal Transverse Mercator (UTM) projection system. The UTM zone number is 47, and the reference datum is WGS84.

Landscape metrics

To quantitatively assess the spatial nature of mountainous landscape structure, LPIs were used. Based on work by De Clercq et al (2006) pertaining to forest fragmentation, a set of landscape metrics was selected from those available in FRAGSTATS (McGarigal et al 2002; *Supplemental data,* Table S1; http://dx.doi.org/10.1659/mrd-journal-D-10-00119. S1). The calculation of most of these metrics is based on patch area and perimeter length. In this study, category area proportion (P_i) was also selected, because P_i is used to calculate several other metrics (Gergel 2007).

Calculation of surface LPIs

Dorner et al (2002) proposed a simple method to calculate the surface area each raster pixel by *projected area/cos(slope)*. However, in our study area, where slopes are often steeper than 84 degrees, the surface areas by Dorner's method were unrealistically large. Hence, we used a method originally

FIGURE 3   (A) Landscape map derived from the 2004 vegetation map in the southern study area. (B) Surface landscape map derived from the 2004 vegetation map draped over the corresponding DEM data in the southern study area. NC, natural category; SH, shrub category; AC, anthropogenic category.
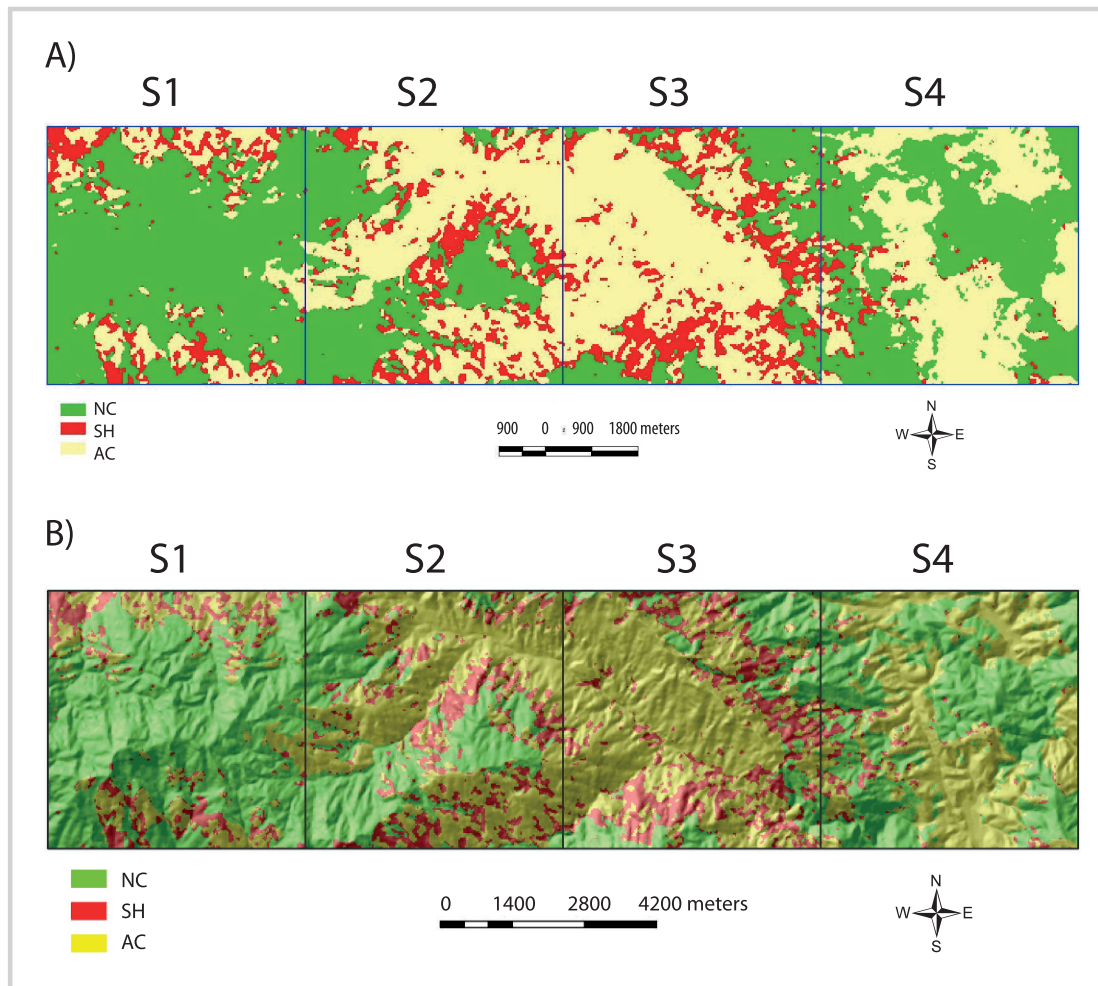
developed by Jenness (2004) and adapted by Hoechstetter et al (2008) to calculate landscape metrics. This technique is based on a moving window algorithm and estimates the surface area for each pixel using a triangulation method (Jenness 2004). The authors describe the computing protocol as follows. First, the center points of each of the 9 cells in the 3-dimensional space are used to calculate the Euclidian distance between the focal pixel and the 8 adjacent pixels. Next, the lengths of the triangle sides and the area of each triangle are calculated using the Pythagorean theorem. Finally, the portions of each triangle area that lay within the cell boundary are summed to determine the total surface area of the cell. This method is preferred over Dorner's, because it can be expected to provide more accurate results; all 8 neighbors of the pixel of interest are included in the calculation, instead of only the 1 defining the slope angle (Hoechstetter et al 2008).

Additional computation steps have to be conducted to obtain the surface area not only for each pixel but also for each patch in a landscape to include these new geometry values into the calculation of common landscape metrics

(Hoechstetter et al 2008). Jenness (2008) developed an ArcView extension tool, which can be used to calculate various surface and topographic characteristics for points, lines, or polygons in a theme. We converted the raster vegetation maps into vector format (including the polygon theme of patches and polylines, or edges, of patches). To minimize the errors in raster-to-vector conversion, polygon boundaries followed cell edges. No polygons were eliminated or aggregated. In this way, the thematic error is negligible, as shown by Wade et al (2003). The resulting vector file containing the patch structure of the concerned landscape mosaic is overlaid with the corresponding DEM. Then, surface area values of the pixels within each patch were summarized. We adapted Jenness's method to calculate surface perimeters of each patch by adding the line segments forming the surface edge (Jenness 2004) if they are part of the patch boundary (polygon boundaries).

For the calculation of nearest surface distance between patches, Dorner (2002) proposed the surface distance between center points in adjacent cells

$(\sqrt{d\text{Elevation}^2 + \text{dist}^2})$ by simple application of the Pythagorean theorem using Euclidean distance and difference in elevation. Previous studies suggested that the shortest path can be calculated by using the Dijkstra algorithm (Hoechstetter et al 2008) or the cost distance (Foltête et al 2008). Although this approach may be suitable for the computation of the surface distance between neighboring pixels, its application for measuring the surface distance between 2 patches (ie 2 clusters of pixels or vector polygons) situated far from each other requires enormous computation power, particularly for large areas. In this study, we used the nearest features ArcView extension tool (Jenness 2007) to generate the nearest connecting lines between patch edges. Afterward, we used the surface tool (Jenness 2008) to calculate the surface length of the nearest connecting lines between patches. This calculation is easy and fast, and the ArcView extension is freely available (Jenness 2007).

Based on the surface area and perimeter for each patch, surface LPIs were calculated (*Supplemental data,* formulas in Table S1; http://dx.doi.org/10.1659/mrd-journal-D-10-00119.S1). The patch analysis for ArcView (Rempel 2012) was used to calculate the corresponding planimetric LPIs based on the experimental zones in the 2 study areas.

Differences between LPIs for NC and AC were calculated as

$$\delta LPIs\_P = LPIs\_P_{NC} - LPIs\_P_{AC}$$

$$\delta LPIs\_S = LPIs\_S_{NC} - LPIs\_S_{AC} \qquad (1)$$

where

- $LPIs\_P_{NC}$ = the value of planimetric LPIs for NC
- $LPIs\_S_{NC}$ = the value of surface LPIs for NC
- $LPIs\_P_{AC}$ = the value of planimetric LPIs for AC
- $LPIs\_S_{AC}$ = the value of surface LPIs for AC

Paired-sample test

We propose to test 2 hypotheses with questions involving differences between 2 variances. The 2 variances are not independent, because each observation in the first sample is related to an observation in the second sample. Therefore, a paired-sample test was used to test the 2 stated hypotheses. The distribution of the variables' population was assessed by means of *P-P* plots (SPSS 13.0) prior to the paired *t*-test.

Results

Hypothesis 1: There are significant differences between planimetric and surface LPIs

Patch level: The values of planimetric and surface LPIs for all patches in test sites N1 and S1 were compared. For illustration, the planimetric and surface LPIs values of 8 randomly selected patches are shown in Figure 2. Some patches feature the same shape index, with a value of 1 (in

bold in Table 2). This means that the shapes of these patches are rectangular, because they were derived from a raster file of a planar TM image. However, the surface shape metrics are larger than 1, meaning that the shapes of these patches quantified by the surface method are more complex than the square ones obtained by the planimetric approach.

Table 3 also shows that in both study areas the values for most metrics derived from the surface method are significantly larger than those derived from the planimetric method at the patch level. This is not the case for the fractal dimension index (FRAC): FRAC_S is slightly higher than FRAC_P.

Category level: At the category level, all surface metrics are significantly larger than the planimetric metrics, with the exception of P_i (Table 3). Both the total category area (CA) and the mean area (A_MN) of each category are underestimated by the planimetric method. The 2 shape metrics (FRAC and SHAPE) illustrate that the shape of each category is more irregular than its projection on a flat surface. For the Euclidian nearest-neighbor distance (ENN), the surface distance is significantly larger than the planimetric distance, which means that the mean nearest distance of each landscape category on a terrain surface is much larger than the mean nearest distance derived from a planar surface. No significant difference could be found between surface and planimetric P_i ($P > 0.05$; Table 3). This might be due to the formula of P_i, whereby the ratio of CA to total area (TA) could reduce the difference between surface and planimetric P_i.

Landscape level: The trends observed at patch and category levels are also visible at the landscape level (Table 3). There are a few exceptions. The values of the surface FRAC_MN are not significantly higher than the planimetric FRAC_MN index. Moreover, the diversity and evenness indices (SHDI and SHEI, respectively) obtained from the surface approach show no significant difference compared to those obtained by the planimetric approach (Table 3). These results reflect the results of the P_i index at the category level, because the calculation of SHDI and SHEI is based on the P_i of categories.

Hypothesis 2: There are significant differences between planimetric LPIs and surface LPIs for NC and AC patterns

Table 4 presents the differences between NC patterns and AC patterns quantified by both planimetric LPIs and surface LPIs in the 2 study areas. In the northern test sites, the CA and A_MN of AC are smaller than those of NC, which means that AC is patchier and more fragmented than NC. The values of SHAPE_MN and FRAC_MN of NC are larger compared to those of AC. The shape of NC is more complex than the shape of AC patches. The ENN values of NC are smaller than those of AC, indicating that NC is less fragmented than AC in the northern study area.

TABLE 2 Subset of patch LPIs using both surface geometries (*LPIs*_S) and plane geometries (*LPIs*_P) for NC. (Table extended on next page.)

A_S	A_P	P_S	P_P	ENN_S	ENN_P	SHAPE_S
…	…	…	…	…	…	…
0.64	0.54	390.03	360.00	267.82	254.56	1.2169
0.09	0.09	122.26	120.00	60.68	60.00	1.0024
0.10	0.09	124.17	120.00	42.44	42.43	1.0011
0.50	0.36	300.99	240.00	80.61	67.08	1.0639
0.62	0.54	379.88	360.00	75.97	60.00	1.2021
0.10	0.09	127.16	120.00	30.03	30.00	1.0001
1.74	1.44	878.57	780.00	81.75	67.08	1.6671
0.67	0.54	329.83	300.00	176.40	169.71	1.0067
…	…	…	…	…	…	…

TABLE 3 Results of *t*-tests assessing the differences between planimetric LPIs (*LPIs*_P) and surface LPIs (*LPIs*_S) at 3levels. (Table extended on next page.)

Levels	Pairs	Northern study area			
		SD	*t*	df	*P* Sig.
Patch	A_S–A_P	26.45	2.119	113	0.036*
	P_S–P_P	792.89	3.171	113	0.002**
	SHAPE_S–SHAPE_P	0.31	4.712	113	0.000***
	FRAC_S–FRAC_P	0.00	1.887	113	0.062
	ENN_S–ENN_P	14.56	7.323	113	0.000***
Category	CA_S–CA_P	119.75	4.752	11	0.001**
	A_MN_S–A_MN_P	2.87	3.645	11	0.004**
	SHAPE_MN_S–SHAPE_MN_P	0.01	7.594	11	0.000***
	FRAC_MN_S–FRAC_MN_P	0.00	5.392	11	0.000***
	ENN_MN_S–ENN_MN_P	6.74	6.605	11	0.000***
	P_i_S– P_i_P	0.01	−0.236	11	0.818
Landscape	TA_S–TA_P	104.10	10.487	3	0.002**
	A_MN_S–A_MN_P	1.61	3.772	3	0.033*
	SHAPE_MN_S–SHAPE_MN_P	0.00	4.815	3	0.017*
	FRAC_MN_S–FRAC_MN_P	0.00	2.402	3	0.096
	ENN_MN_S–ENN_MN_P	1.96	11.658	3	0.000***
	SHDI_S–SHDI_P	0.01	1.193	3	0.319
	SHEI_S–SHEI_P	0.01	1.193	3	0.319

***$P < 0.001$, **$P < 0.01$, *$P < 0.05$.

TABLE 2 Extended. (First part of Table 2 on previous page.)

SHAPE_P	FRAC_S	FRAC_P
...	...	...
1.2247	1.0448	1.0472
1.0000	1.0007	**1.0000**
1.0000	1.0003	**1.0000**
1.0000	1.0146	**1.0000**
1.2247	1.0421	1.0472
1.0000	1.0000	**1.0000**
1.6250	1.1047	1.1014
1.0206	1.0015	1.0047
...	...	...

TABLE 3 Extended. (First part of Table 3 on previous page.)

Southern study area			
SD	t	df	P Sig.
7.65	2.660	348	0.008**
142.28	4.431	348	0.000***
0.01	4.265	348	0.000***
0.00	0.124	348	0.901
3.53	11.149	348	0.000***
97.77	5.417	11	0.000***
2.57	3.984	11	0.002**
0.01	6.734	11	0.000***
0.00	3.683	11	0.004**
4.80	7.483	11	0.000***
0.01	−0.961	11	0.357
21.94	19.666	3	0.000***
0.12	10.142	3	0.002**
0.00	19.283	3	0.000***
0.00	0.797	3	0.484
0.46	15.882	3	0.001**
0.00	−2.323	3	0.103
0.00	−2.323	3	0.103

Except for test site S3, the CA of NC is larger than that of AC in the southern study areas. The values of A_MN_S show that the mean patch area of NC also is larger than that of AC. This indicates that AC is patchier and more fragmented than NC in this area. The ENN values of NC are smaller than those of AC in S1 and S4 but larger than those of AC in S2 and S3. This illustrates that NC is less isolated than AC in S1 and S4 (Figure 3). Conversely, the isolation of NC is higher than that of AC in S2 and S3 (Figure 3). Based on field knowledge, S1 features mountaintops with high altitudes (more than 2000 m) and is not suitable for rubber plantation and other crop types, such as paddy rice and sugarcane plantations. S4 is located in Naban River Biosphere Reserve. In these 2 sites, NC is larger and less fragmented than AC. Both SHAPE_MN_P and SHAPE_MN_S show that the shape of AC is more complex than the shape of NC in the southern study area, except for test site S1. The values of FRAC of NC are higher than those of AC in test sites S1 and S3. In contrast, the values of FRAC of NC are lower than those of AC in test sites S2 and S4. Figure 3 shows that S2 and S3 are dominated by AC. About 45% of the area is AC in S4. The shape of AC is complex, because it includes several ACs (Table 1).

In the northern study area, the surface basic area metrics (δCA_S and δA_MN_S) are significantly larger than the planimetric basic area metrics (δCA_P and δA_MN_P) when comparing NC and AC patterns (Table 5). This indicates that the differences between CA and A_MN of NC and those of AC are underestimated when using the planimetric method in the northern study area. We found that δENN_S is significantly larger than δENN_P ($t = -3.562$, $P < 0.05$). However, there are no statistically significant differences between other surface shape indices and planimetric shape indices to quantify the differences between NC and AC shape structure. In addition, there are no significant differences between the surface method and the planimetric method for quantifying the differences between the proportion of NC and that of AC. In the southern study area, however, the results show that there are no significant differences between surface LPIs and planimetric LPIs when comparing NC and AC.

Discussion

Differences between planimetric LPIs and surface LPIs for landscape pattern quantification

Area metrics in all 3 levels (patch, category, and landscape) generated by surface geometries are significantly larger than those derived by planimetric ones in the 2 mountainous areas studied in the Lancang watershed in China. This indicates that the common planimetric method could lead to an underestimation in rough terrain areas. This confirms some results reported by Dorner et al (2002). The mean patch area is one of the

TABLE 4　Differences between NC and AC (NC-AC) quantified by planimetric LPIs (δ*LPIs*_P) and surface LPIs (δ*LPIs*_S) in the 2 study areas. (Table extended on next page.)

Test site[a]	δCA_S (ha)	δCA_P (ha)	δA_MN_S (ha)	δA_MN_P(ha)	δSHAPE_MN_S
N1	1531	1267	31.63	26.15	0.2769
N2	948	757	11.19	8.86	0.0884
N3	791	634	10.51	8.37	0.0581
N4	130	67	13.75	11.22	0.1583
S1	1766	1623	100.89	92.84	0.1935
S2	269	240	9.70	8.85	−0.0003
S3	−336	−306	15.48	14.55	−0.0513
S4	180	132	0.28	−0.01	−0.1166

[a]Test sites in the north are N1-N4; test sites in the south are S1-S4.

most important indices of quantitative measurements to assess landscape or habitat fragmentation (Batistella et al 2003). In this study, the surface mean patch area is significantly larger than its planimetric equivalent, both at category and at landscape levels. This means that the landscape fragmentation in rough mountain areas could be overestimated when it is measured by the planimetric mean patch area metric.

A number of important ecological processes can be influenced by patch shape (McGarigal et al 2002). Patch shape has been shown to influence interpatch processes such as small mammal migration (Buechner 1989) and woody plant colonization (Hardt and Forman 1989), and to influence animal foraging strategies (Forman and Godron 1986; Farina 2006). Similar to results reported by Hoechstetter et al (2008), the features of the 2 selected shape metrics (SHAPE and FRAC) are not consistent. The SHAPE metric features higher values for the surface variant than for the planar approach at all 3 levels (patch, category, and landscape). This metric tends to increase with increasing area, even if the perimeter increases at the same time (Hoechstetter et al 2008). The surface FRAC metric is significantly larger than the planimetric FRAC, but only at the category level. This can be explained, because FRAC is calculated by regressing logP on logA, which can reduce the differences between A_P and A_S and between P_P and P_S. This corresponds with research work reported by McGarigal et al (2002). The FRAC index appeared to be less sensitive to differences of patch shape than is the SHAPE index. Hoechstetter et al (2008) also mentioned that the shape metrics are less sensitive to terrain complexity than the area and perimeter metrics.

In addition, ENN is an important index for landscape configuration quantification (McGarigal et al 2002). It quantifies a number of important ecological processes (Opdam 1991; McGarigal et al 2002). According to the results listed previously, the surface basic ENN is significantly larger than the common planar ENN metric in all 3 levels.

At the landscape level, richness and evenness can be used to quantify landscape spatial heterogeneity (Farina 2006). The results of SHDI and SHEI show that the heterogeneity of the surface mountain landscape has no significant difference compared with the heterogeneity represented in the planar maps, both in the northern and the southern study areas. The calculations of SHDI and SHEI are based on the proportion of categories (P_i). Again, even though CA is significantly different between the surface method and the planimetric approach, the ratio of CA and TA (P_i) for categories does not feature a significant difference when using a surface method or a planimetric method.

Comparison between the use of planimetric LPIs and surface LPIs for NC patterns and AC patterns

Previous studies mentioned that the structure of anthropogenic landscapes is often more patchy (or fragmented) than that of natural landscapes; manmade landscapes have a more linear structure than landscapes shaped by nature (Farina 2006). In this study, the results show that AC is indeed more fragmented than NC in both study areas. In the northern study area, shape metrics illustrate that the shape of NC is more complex than the shape of AC. The ENN values indicate that the isolation of AC is higher than that of NC in the northern study area. In the southern study area, AC includes rubber plantations, agriculture land, and burned land. Indigenous minority people practice shifting cultivation on hillslopes (Xu et al 1999). Even though this traditional type of cultivation ended in 1983, fire was still used to open land for farming and rubber plantations in the mountain areas. This probably causes the shape of AC to be very irregular in the southern study area.

In the northern study area, the surface area metrics are significantly higher than the planimetric area metrics. This indicates that the common planimetric method underestimates the differences between NC and AC on areas and mean patch area in steep mountain areas.

TABLE 4 Extended. (First part of Table 4 on previous page.)

δSHAPE_MN_P	δFRAC_MN_S	δFRAC_MN_P	δENN_S (m)	δENN_P (m)
0.2718	0.0187	0.0192	−165.66	−158.68
0.0831	0.0075	0.0067	−85.10	−71.62
0.0621	0.0051	0.0062	−69.25	−63.56
0.1568	0.0099	0.0100	−25.18	−21.38
0.1932	0.0048	0.0046	−25.35	−23.25
−0.0002	−0.0013	−0.0013	21.75	20.79
−0.0532	0.2591	0.2557	77.47	76.59
−0.1125	−0.0120	−0.0113	−3.84	−2.78

The effects of human disturbance are probably underestimated. For the distance index, the differences between NC connectivity and AC connectivity are underestimated using the planar ENN index in the northern study area. However, for the shape metrics, there are no significant differences between surface and the planar methods.

In the southern study area, there are no significant differences between the surface and the planimetric methods, which were used to compare the differences between NC and AC. There are several explanations for the different outcome of the t-test results in the southern study area and the northern study area. First, the southern study area is less mountainous than the northern study area. Hoechstetter et al (2008) focused on the effects of topography and surface roughness on the values of landscape metrics. Their results also revealed that area and distance metrics possess a high sensitivity to terrain complexity, whereas the values of shape metrics change only slightly when surface geometries are

considered. Second, the northern study area is less densely populated, and most of the area is not suitable for agriculture; thus, AC is much smaller in the northern study area than in the southern study area. Most AC occurs in the relatively flat area along the Lancang riverside. In contrast, in the southern study area, the human disturbance is much stronger than in the northern study area. This causes AC to be more aggregated. Third, fire is a major disturbance. This causes the shape of AC to be very irregular. These 3 issues reduce the differences between surface and planimetric metrics in the southern study area.

Many minority ethnic groups are living in the 2 mountainous study areas, such as the Tibetans, Naxi, Bai, Lisu, Pumi, Yi, Nu, Dulong, Dai, Lahu, and Jingpo. Culture is one of the major driving forces for landscape changes (Bürgi et al 2004). Different minority ethnic groups across the study areas use their land in unique ways, which may yield different spatiotemporal patterns of land cover change. For instance, the southern study

TABLE 5 Results of t-tests assessing the differences between planimetric LPIs ($δLPIs$_P) and surface LPIs ($δLPIs$_S) for NC patterns and AC patterns.

Pairs	Northern study area				Southern study area			
	SD	t	df	P Sig.	SD	t	df	P Sig.
δCA_S–δCA_P	83.51	4.044	3	0.027*	71.52	1.326	3	0.277
δA_MN_S–δA_MN_P	1.58	3.955	3	0.029*	3.69	1.371	3	0.264
δSHAPE_MN_S–δSHAPE_MN_P	0.00	−0.913	3	0.428	0.00	−0.406	3	0.712
δFRAC_MN_S–δFRAC_MN_P	0.00	−0.513	3	0.643	0.00	−806	3	0.479
δENN_MN_S–δENN_MN_P	4.20	−3.562	3	0.038*	1.51	−444	3	0.687
$δP_L$_S–$δP_L$_P	1.24	1.057	3	0.368	0.01	1.259	3	0.132

***P < 0.001, **P < 0.01, *P < 0.05.

area is the traditional home of upland minority people ("hill tribes"), including Dai, Hani (called Akha in Thailand), and Bulang (Xu et al 2005). Hani (Akha) and Bulang people traditionally practice shifting cultivation in the uplands and rice paddy cultivation in the lowlands (Xu et al 1999, 2005; Rerkasem et al 2009). From field observations, it is also known that the local people open forest and shrubland below 1000 m for rubber plantations. In the northern study area, the Tibetan people practice seasonal shifting grazing along elevation gradients (ie summer grazing land with higher elevation and winter grazing land with lower elevation; Buntaine et al 2006). This study illustrates that the effects of human disturbance can be better quantified by using surface LPIs. Therefore, this approach can also be used to quantify the land cover change caused by cultural driving forces in the study areas, as well as elsewhere in China's culturally diverse Yunnan Province. This approach therefore offers an opportunity to quantify those changes and establish a link to sustainable rural management and planning.

In addition, the 2 study areas are an important habitat of endangered fauna species (Li and Li 2003; Xiao et al 2003; Zhang and Wang 2003). Wildlife researchers often report area values for a region of interest, such as home-range size or number of hectares of a particular habitat type (Jenness 2004). Home ranges of mountain-dwelling wildlife species and their available resource assessment might be better estimated by using surface area and distance rather than planimetric area and distance. The surface integrating LPIs may also be valuable for conservation planning and evaluating the protection efficiency of current protected areas and conservation strategies in steep mountainous areas.

Conclusions

In this paper, we tested surface LPIs against planar LPIs in 2 mountainous areas in China. Our case demonstrates that the surface approach may provide more realistic results for landscape structure analysis when applied in steep mountain areas. The calculation of surface LPIs is not included in currently available landscape analysis software packages. However, surface LPIs may allow us to gain a better understanding of the vegetation or landscape pattern in the mountain study areas. Moreover, because topography influences the landscape pattern and the landscape pattern can be quantified by LPI, to better understand the correlations between landscape pattern and topography, surface LPIs made it possible to quantify topographic influence on landscape pattern. This may prove its utility when it is applied to quantify land cover and vegetation changes in mountain areas and to mountainous regional planning. In short, this study represents an example of using surface-based LPIs for land cover pattern quantification in 2 large and very different mountain areas. The large difference between the 2 mountain areas warrants the assumption that the approach developed here is sufficiently generic to be applicable to mountain areas elsewhere.

REFERENCES

Allen TR, Walsh SJ. 1996. Spatial and compositional pattern of alpine treeline, Glacier National Park, Montana. *Photogrametric Engineering and Remote Sensing* 62:1261–1268.
Batistella M, Robeson S, Moran EF. 2003. Settlement design, forest fragmentation, and landscape change in Rondônia, Amazônia, *Photogrammetric Engineering and Remote Sensing* 69(7):805–812.
Brown DG. 1994. Predicting vegetation types at treeline using topographic and biophysical disturbance variables. *Journal of Vegetation Science* 5:641–656.
Buechner M. 1989. Are small-scale landscape features important factors for field studies of small mammal dispersal sinks? *Landscape Ecology* 2:191–199.
Buntaine MT, Mullen RB, Lassoie JP. 2006. Human use and conservation planning in alpine areas of northwestern Yunan, China. *Environment, Development and Sustainability.* http://www.springerlink.com/content/1573-2975/?k=buntaine.
Bürgi M, Hersperger AM, Schneeberger N. 2004. Driving forces of landscape change—current and new directions. *Landscape Ecology* 19:857–868.
Cantón Y, Barrio GDel, Solé-Benet A, Lázaro R. 2004. Topographic controls on the spatial distribution of ground cover in the Tabernas badlands of SE Spain. *Catena* 55:341–365.

Crave E, Gascuel-Odoux C. 1997. The influence of topography on time and space distribution of soil surface water content. *Hydrological Processes* 11:203–210.
De Clercq EM, Vandemoortele F, De Wulf RR. 2006. A method for the selection of relevant pattern indices for monitoring of spatial forest cover pattern at a regional scale. *International Journal of Applied Earth Observation and Geoinformation* 8:113–125.
Delong SC, Tanner D. 1996. Managing the pattern of forest harvest: Lessons from wildfire. *Biodiversity and Conservation* 5:1191–1205.
Deng M, Zhang P, Zhao B, Wang Y. 1997. *The Forest in Lanping Pumi Autonomous County* [in Chinese]. Kunming China: Yunnan Ethnic Press.
Dorner B, Lertzman K, Fall J. 2002. Landscape pattern in topographically complex landscapes: Issues and techniques for analysis. *Landscape Ecology* 17:729–743.
Dunning JB, Danielson BJ, Pulliam HR. 1992. Ecological processes that affect populations in complex landscape. *Oikos* 65:169–175.
Dymond CC, Johnson EA. 2002. Mapping vegetation spatial patterns from modeled water, temperature and solar radiation gradients. *ISPRS Journal of Photogrammetry & Remote Sensing* 57:69–85.
Farina A. 2006. *Principles and Methods in Landscape Ecology.* 3rd edition. Dordrecht, the Netherlands: Springer.

Fischer G, Sun L. 2001. Model based analysis of future land-use development in China. *Agriculture, Ecosystems and Environment* 85:163–176.

Foltête JC, Berthier K, Cosson JF. 2008 Cost distance defined by a topological function of landscape. *Ecological Modelling* 210:104–114.

Forman RTT, Godron M. 1986. *Landscape Ecology.* New York, NY: John Wiley & Sons.

Forster DR, Knight DH, Franklin JF. 1998. Landscape patterns and legacies resulting from large infrequent forest disturbances. *Ecosystems* 1:497–510.

Frohn RC. 1998. *Remote Sensing for Landscape Ecology: New Metric Indicators for Monitoring, Modeling and Assessment of Ecosystems.* Boca Raton, FL: Lewis Publishers, p 99.

Gardner RH, editor. 1999. *RULE: Map Generation and a Spatial Analysis Program.* New York, NY: Springer-Verlag.

Gergel SE. 2007. New directions in landscape pattern analysis and linkages with remote sensing. *In:* Wulder MA, Franklin SE, editors. *Understanding Forest Disturbance and Spatial Pattern.* Boca Raton, FL: CRC Press Taylor and Francis Group, pp 173–208.

Gluck MJ, Rempel RS. 1996. Structural characteristics of post-wildfire and clearcut landscape. *Environmental Monitoring and Assessment* 39:435–450.

Gómez-Plaza A, Martínez-Mena M, Alvadalejo J, Castillo VM. 2001. Factors regulating spatial distribution of soil water content in small semiarid catchments. *Journal of Hydrology* 253:211–226.

Haines-Yong R. 2005. Landscape pattern: context and process. *In:* Wiens John, Michael Moss, editors. *Issues and Perspectives in Landscape Ecology.* London: Cambridge University Press, pp 103–111.

Hardt RA, Forman RTT. 1989. Boundary form effects on woody colonization of reclaimed surface mines. *Ecology* 70:1252–1260.

Hoechstetter S, Thinh NX, Walz U. 2006. 3D-indices for the analysis of spatial patterns of landscape structure. *In:* Kremers H, Tikunov V, editors. *Proceedings InterCarto-InterGIS 12. International Conference on Geoinformation for Sustainable Development.* Berlin: Deutsche Gesellschaft für Kartographie, pp 108–118.

Hoechstetter S, Walz U, Dang LH, Thinh NX. 2008. Effects of topography and surface roughness in analyses of landscape structure: A proposal to modify the existing set of landscape metrics. *Landscape Online* 3:1–14.

Hoechstetter S. 2009. *Enhanced Methods for Analysing Landscape Structure: Landscape Metrics for Characterising Three-dimensional Patterns and Ecological Gradients.* Berlin, Germany: Rhombos-Verlag.

Jenness JS. 2004. Calculating landscape surface area from digital elevation models. *Wildlife Society Bulletin* 32(3):829–839.

Jenness JS. 2007. *Nearest Features Extension for ArcView 3.x, v. 3.8b.* Flagstaff, AZ: Jenness Enterprises. www.jennessent.com/arcview/nearest_features.htm; accessed on 15 February 2007.

Jenness JS. 2008. *Surface Tools (surf_tools.avx) Extension for ArcView 3.x, v. 1.6b.* Flagstaff, AZ: Jenness Enterprises. www.jennessent.com/arcview/surface_tools.htm; accessed on 11 February 2008.

Krummel JR, Gardner RH, Sugihara G, O'Neill RV, Coleman P. 1987. Landscape patterns in a disturbed environment. *Oikos* 48:321–324.

Li H, Aide T, Ma Y, Liu W, Cao M. 2007. Demand for rubber is causing the loss of high diversity rain forest in SW China. *Biodiversity and Conservation* 16:1731–1745.

Li H, Ma Y, Liu W, Liu W. 2009. Clearance and fragmentation of tropical rain forest in Xishuangbanna, SW China. *Biodiversity and Conservation* 16:1731–1745.

Li X, Lu L, Cheng G, Xiao H. 2001. Quantifying landscape structure of the Heihe River Basin, north-west China using FRAGSTATS. *Journal of Arid Environments* 48:521–535.

Li Z, Li H. 2003. *Digital Information Technology in Protection of Tropical Rain Forest* [in Chinese]. Kunming, China: Yunnan University Press.

Liu W, Hu H, Ma Y, Li H. 2006. Environmental and socioeconomic impacts of increasing rubber plantation in Menglun Township, southwest China. *Mountain Research and Development* 26(3):245–253.

Long H, Tang G, Li X, Gerhard KH. 2007. Socio-economic driving forces of land-use change in Kunshan, the Yangtze River Delta economic area of China. *Journal of Environmental Management* 83:351–364.

McGarigal K, Cushman SA, Neel MC, Ene E. 2002. *FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps.* Computer software program produced by the authors at the University of Massachusetts, Amherst. http://www.umass.edu/landeco/research/fragstats/fragstats.html; accessed in March 2012.

McGarigal K, Tagil S, Cushman SA. 2009. Surface metrics: An alternative to patch metrics for the quantification of landscape structure. *Landscape Ecology* 24:433–450.

O'Neill RV, Krummel JR, Gardner RH, Sugihara G, Jackson B, DeAngelis DL, Milne BT, Turner MG, Zymunt B, Christensen SW, Dale VH, Graham RL. 1988. Indices of landscape pattern. *Landscape Ecology* 1:153–162.

Opdam P. 1991. Metapopulation theory and habitat fragmentation: A review of holarctic breeding bird studies. *Landscape Ecology* 5:93–106.

Rempel RS, Kaukinen D, Carr AP. 2012. *Patch Analyst and Patch Grid.* Thunder Bay, Ontario: Ontario Ministry of Natural Resources, Centre for Northern Forest Ecosystem Research. http://www.cnfer.on.ca/SEP/patchanalyst/; accessed on 2 April 2012.

Rerkasem K, Yimyam K, Rerkasem B. 2009. Land use transformation in the mountainous mainland Southeast Asia region and the role of indigenous knowledge and skills in forest management. *Forest Ecology and Management* 257:2035–2043.

Riitters KH, O'Neill RV, Hunsacker CT, Wickham JD, Yankee DH, Timmins SP, Jones KB, Jackson BL. 1995. A factor analysis of landscape pattern and structure metrics. *Landscape Ecology* 10:23–39.

Saura S, Martinez-Millan J. 2000. Landscape patterns simulation with a modified random clusters method. *Landscape Ecology* 15:661–678.

Swanson FJ, Wondzell SM, Grant GE. 1992. Landforms, disturbance, and ecotones. *In:* Hansen AJ, di Castri F, editors. *Landscape Boundaries: Consequences for Biotic Diversity and Ecological Flows.* New York, NY: Springer Verlag, pp 304–323.

Swanson FJ, Kratz TK, Caine N, Woodmansee RG. 1998. Landform effects on ecosystem patterns and processes. *BioScience* 38:92–98.

Turner MG, Gardner RH, O'Neill RV. 2001. *Landscape Ecology in Theory and Practice.* New York, NY: Springer Verlag.

Turner SJ, O'Neil RV, Conley W, Conley MR, Humphries HC. 1991. Pattern and scale: Statistics for landscape ecology. *In:* Turner MG, Gardner RH, editors. *Quantitative Methods in Landscape Ecology.* New York, NY: Springer Verlag, p 536.

Verburg PH, Chen Y. 2000. Multiscale characterization of land-use patterns in China. *Ecosystems* 3:369–385.

Wade TG, Wickham JD, Nash MS, Neale AC, Riitters KH, Jones B. 2003. A comparison of vector and raster GIS methods for calculating landscape metrics used in environmental assessments. *Photogrammetric Engineering and Remote Sensing* 69(12):1399–1405.

Wang S, Van Kooten C, Wilson B. 2004. Mosaic of reform: Forest policy in post-1978 China. *Forest Policy and Economics* 6:71–83.

Western AW, Grayson RB, Blöschl G, Willgoose GR, McMahon TA. 1999. Observed spatial organization of soil moisture and its relation to terrain indices. *Water Resources Research* 35:797–810.

Weyerhaeuser H, Wilkes A, Kahrl F. 2005. Local impacts and response to regional forest conservation and rehabilitation programs in China's northwest Yunnan Province. *Agricultural Systems* 85:234–253.

Wondzel SM, Cunningham GL, Bachelet D. 1996. Relationships between landforms, geomorphic processes, and plant communities on a watershed in the northern Chihuahuan Desert. *Landscape Ecology* 11:351–362.

Wu J, Cheng X, Xiao H, Wang H, Yang L, Ellis EC. 2009. Agricultural landscape change in China's Yangtze Delta, 1942–2002: A case study. *Agriculture, Ecosystems and Environment* 129:523–533.

Xiao W, Ding W, Cui L, Zhou R, Zhao Q. 2003. Habitat degradation of *Rhinopithecus bieti* in Yunnan, China. *International Journal of Primatology* 24(2):389–398.

Xu J, Fox J, Lu X, Podger N, Leisz S, Ai X. 1999. Effects of swidden cultivation, population growth, and state policies on land cover in Yunnan, China. *Mountain Research and Development* 19:123–132.

Xu J, Fox J, Vogler JB, Zhang P, Fu Y, Yang L, Qian J, Leisz S. 2005. Land-use and land-cover change and farmer vulnerability in Xishuangbanna Prefecture in southwestern China. *Environmental Management* 36(3):404–413.

Zhang L, Wang N. 2003. An initial study on habitat conservation of Asian elephant *(Elephas maximus),* with a focus on human elephant conflicts in Simao, China. *Biological Conservation* 112:453–459.

Zhang Z, Verbeke L, De Clercq EM, Ou X, De Wulf R. 2007. Vegetation change detection using artificial neural networks with ancillary data in Xishuangbanna, Yunnan Province, China. *Chinese Science Bulletin* 52(Supp. II):232–243.

Zhang Z, Wang W, Ou X, Wu W. 2009. The correlations between vegetation spatial pattern and environmental factors in Meili Snow Mountain [in Chinese with English abstract]. *Journal of Yunnan University* 31(3):311–315.

Zhang Z. 2011. *Quantification of Vegetation Change in Upper and Middle Mekong Watershed Using Spaceborne Remote Sensing Data* [PhD thesis], Ghent, Belgium: Ghent University.

SUPPLEMENTAL DATA

TABLE S1 Selected LPIs and their formula. P, perimeter; A, area of patch. Source: McGarigal et al 2002.

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