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Identification of the main factors determining landscape metrics in semi-arid agro-pastoral ecotone

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ABSTRACT

Landscape patterns in agro-pastoral ecotones are influenced by natural factors and human activities. However, the main factors that influence landscape metrics of agro-pastoral ecotones have not been fully elucidated. To further understand conditions influencing landscape formation, we conducted a series analysis to explore the relationship between ecological factors (annual average precipitation, annual average temperature, NDVI, altitude, aspect, slope, curvature, land use, and human disturbance) and landscape metrics pattern in the range of 100–5000 m spatial extent, within an agro-pastoral ecotone in Inner Mongolia, China. Using principal component analysis and the detrended canonical correspondence analysis from 43 landscape metrics, we successfully identified several key factors that determine the landscape metrics values. Agriculture and livestock grazing land use induce the landscape configuration to become homogeneous and simple. Nevertheless, our results show that the influences of human activities on landscape metrics are surprisingly not strong. Rather the natural ecological factors, in particular temperature, precipitation and altitude, had the greatest influence on landscape metrics values. This study provides a theoretical case for the scaling effects and develops techniques for identifying the key ecological factors influencing on landscape metrics, so as to improve landscape management decisions in semi-arid regions and other ecotones.

1. Introduction

Landscape metrics are influenced by various abiotic and biotic ecological factors; including annual precipitation, average temperature, soil conditions, and human activities, such as cultivation activities, livestock grazing, and urban land use (Uuemaa et al., 2013). Landscape metrics are also shaped by topographical determinants, such as altitude, aspect and land curves (Bolliger et al., 2009; Geri et al., 2010). Landscape metrics can be affected by the reciprocal relationship that exists between these physical landscape patterns and socio-economic processes (Li and Wu, 2004). As such, the scale effects, inherent limitations of landscape indices, and the improper use of these indices, have to be carefully considered and systematically tackled (Li and Wu, 2007). Among these ecological factors, human land use is regarded as the primary determinant of landscape metrics (Vogiatzakis et al., 2006; Gowda et al., 2012; Plexida et al., 2014) given the direct effects it can have on vegetation composition, land cover and landform. Many studies have considered human land use, climate variations and landform separately; however, these factors do not act in isolation and rather it is their interaction that contributes to the shape of landscape metrics.

Landscape metrics are sensitive to spatial scale, which make scale an important consideration in the determination of factors involved in shaping landscape formation. In landscape ecology studies, landscape metrics depend on the satellite imagery derived from satellite sensors. This could be an avenue for conflicting reports since these sensors can have different spatial resolutions. Thus, it is necessary to find the optimal scale for the study in which the ecological processes operate. Spatial scale context includes not only grain size which determined by remote sensing imagery, but also spatial extent which determined by analyzing unit. Landscape metric indices change with alterations in spatial extent, as demonstrated by previous studies that have systematically evaluated the effects of grain size and extent (Wu and Hobbs, 2002; Shen et al., 2004; Wu, 2004), as well as thematic detail (Baldwin et al., 2004; Castilla et al., 2009). The scale of analysis in agricultural landscape dynamics studies is often determined by data availability when considering intrinsic

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or process scale (Li and Wu, 2007). Agro-pastoral ecotone movement processes take place at whole spatial scales and require a hierarchical and pluralistic scaling approach (Wu, 2007). This was illustrated by Stefanov and Netzband (2005), who assessed urban landscape characteristics in Phoenix, Arizona, and identified weak positive and negative correlations between NDVI and landscape metrics at different spatial resolutions: 250 m, 500 m, and 1000 m. Landscape diversity, a parameter indicative of landscape spatial patterns, is also influenced by scale effects. Without analysis along a series of spatial scale little information of average alpha and Whittaker's beta diversity about landscape distribution patterns can be derived (Lira-Noriega et al., 2007). The diversity of tropical butterflies across a range of spatial scales (≈3–80 ha) confirmed the notion of scale-dependence in estimates of diversity (Dumbrell et al., 2008). However, few studies set a scale gradient in the analysis of the relationship between landscape metrics and ecological factors.

Here we investigated the correlations between landscape metrics and selected biophysical factors (annual average precipitation, annual average temperature, NDVI, altitude, land slope, aspect, and land curvature) and human activity properties (land use type, human disturbance intensity) of the agro-pastoral ecotone. Among these ecological factors, we identified those that largely contributed to the landscape metrics.

2. Study area and methods

Using land use/land cover maps, we tested for the effects of processing spatial extent on landscape metrics and explored which ecological factors determine the landscape metrics characterization of spatial pattern. The process involved six steps: (i) generating land use landscape maps by field survey and satellite image, (ii) calculating landscape metrics with a series of spatial extent from 100 m to 5 km to find the optional extent, (iii) using principal components factor analysis to identify the main landscape metrics among 43 indices, (iv) assessing the values of ecological factors, i.e. temperature, precipitation, slope, aspect, curvature, altitude, NDVI, and human disturbance, (v) analyzing correlations between ecological factors and landscape metrics under the same optional spatial extent, and (vi) identifying the main factors, natural or human-derived which shape the landscape metrics. This process is illustrated in Fig. 1.

2.1. Study area

The study was conducted in an agro-pastoral ectone. An agro-pastoral ecotone is the interface between cropland and pasture. The agro-pastoral ecotone, including various kinds of landscape, is believed to be one of the most eco-sensitive regions responsive to disturbances and, thus, an ideal place for a landscape metrics study. The survey area was a northern agro-pastoral ecotone located in Helin County, in central Inner Mongolia, and characterized by a collection of flat plains, hills, and mountains with relatively equal composition (Fig. 2). The highest elevation was 2031 m and was a total area of 3401 square kilometers.

Helin County has a semi-arid temperate climate with obvious wet and dry seasons. Its annual average temperature is 5.6 °C, with a seasonal average temperature of −12.8 °C in January and 22.1 °C in July. The average annual precipitation is 417 mm, with approximately 30 mm in January and 103 mm in July. The average wind speeds are slightly higher in spring and winter than in the summer and fall seasons. The average relative humidity for the whole year does not show obvious seasonal changes. The semi-arid climate supports sandy biological communities, in which grass and shrubs are predominant in this area. Helin County consists of 9 towns and has a population of 0.187 million people. The main income for local people comes from agricultural product and livestock resources.

2.2. Creation ecological factors maps

We used the data of the 2010 LULC of the Helin County area, produced from a supervised classification model of atmospherically corrected and geo-rectified Landsat Thematic Mapper (TM) imagery. The model was originally developed based on field survey data acquired in July of 2010 and simultaneously Landsat images. The classification system performs a posteriori sorting of classes initially derived using Maximum Likelihood Classification. Geographical auxiliary map layers, such as land-use maps, image textures, or administrative maps, were also used. The final classification consisted of 7 classes and had a reported overall accuracy of ~92% or greater (Table 1).

To estimate the spatial distribution of abundance vegetation, we computed the Normalized Difference Vegetation Index (NDVI) from all raw Landsat images: NDVI = (NIR − RED)/(NIR + RED). Color copies of annual average precipitation and temperature maps, dating from 2000 to 2010 and produced by the Meteorological Administration of Helin County, were scanned and geo-referenced using the Landsat image mosaics. Due to their potential influence on ecological processes, we extracted information on: aspect (i.e., the slope facing direction), divided in eight directions from northing to Easting (i.e., cosine and sine-transformed azimuth values, respectively); slope (i.e., steepness); and altitude, all derived from the SRTM30 DEM (http://asterweb.jpl.nasa.gov/gdem.asp). The entire study area was located in the northern hemisphere where southern aspects received significantly higher radiation and more xeric conditions than northern aspects, particularly when associated with steep slopes. Western aspects were exposed to dominant westerly winds, which was associated with higher precipitation and a lower frequency of frosts. The land curvature, indicating the curve degree of a range of land, was therefore selected as an influential ecological factor.

The spatial distribution maps of human settlements and roads were digitized from the Helin Map that was produced by SinoMaps Press in 2010. The human activities variables maps, one illustrated distances to human settlements and another illustrated the distance to roads, were created based on experienced analysis of relationships between human activity intensity and ecological patterns or processes. Since the data are provided in vector format they were rasterized directly to match the grain size of each level of analysis.

From the aforementioned sources and creative method, we created 12 map layers including LULC maps, ecological factor maps (NDVI, altitude, aspect, slope, curvature, annual average precipitation, and annual average temperature) and human disturbance maps.

2.3. Multi spatial scale analysis on landscape metrics of LULC maps

We quantified landscape pattern indices using a suite of landscape metrics in FRAGSTATS software (McGarigal et al., 2002). We computed 43 class-level metrics indices including: CONTIG_AM, PLADJ, AI, AREA_MN, COHESION, FRAC_AM, PROX_AM, IJI, CONTIG_MN, SHAPE_AM, ED, AREA_CV, AREA_SD, SHAPE_MN, PARA_SD, PARA_CV, CONTIG_SD, PROX_SD, AREA_AM, PROX_MN, FRAC_MN, SHAPE_SD, CLUMPY, SHAPE_CV, FRAC_SD, FRAC_CV, LSI, PD, NP, CONNECT, ENN_SD, ENN_MN, ENN_CV, PAFRAC, DIVISION, SPLIT, PARA_MN, CONTIG_CV, NLSI, PARA_AM, ENN_AM, PROX_CV. The meaning, calculated formula and its ecological usage, can be referenced through the help file in FRAGSTATS software and related studies (Wu and Hobbs, 2002; McGarigal et al., 2002).

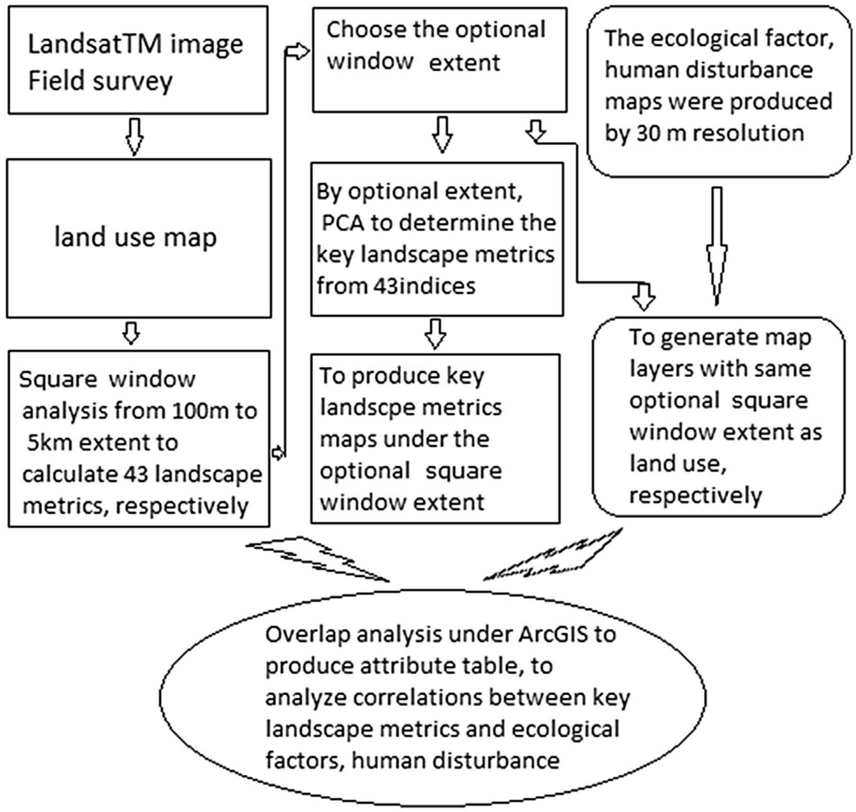

Fig. 1. The figure shows the study route and steps for identifying the key factors which influencing landscape metrics in the study area, Helin County, Inner Mongolia, China.

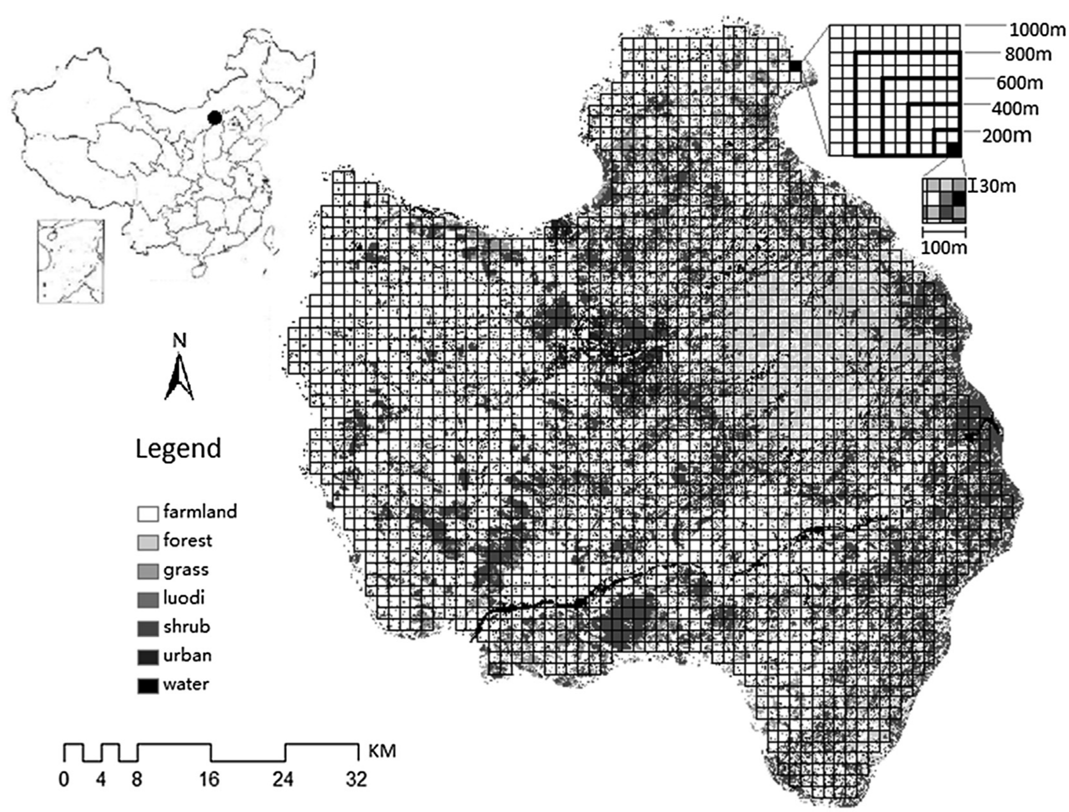

Fig. 2. Location and land use distribution of the study area in Helin County, northern China. This study used 1 km × 1 km squares as basic units for grid window analysis, totally 2610 squares. The figure also shows the spatial extent ranged from 100 m to 5 km.

Table 1
Seven LULC categories were used to show the land cover in the study area, Helin County, Inner Mongolia, China.

Categories	Descriptions
Grassland	Prairies, pasture, and high or short grassland
Farmland	Row crop by type, cereal grains, potato, feedlots, vineyards
Shrub	Shrub, semi-shrub, scatter shrub, bushwood, low or high shrub
Forest	Open or closed forest, including young, old forest
Urban and town	Residential, industrial, commercial and recreation areas, roads and rails
Water	Rivers and streams, pond, lake and reservoir
Barren land	Soil or sandy dunes without vegetation

The LULC maps in vector format for the entire Helin County area were converted into an Arc Grid format for a set of synoptic metric analyses providing a basic representation of landscape pattern. Effects of spatial extent were analyzed using the window analysis method of FRAGSTATS 4.1 software. The grid landscape datasets for the entire regional area and outer 5 km buffer zone were included in the analysis. This study used the following areas for window analysis: 100 × 100, 200 × 200, 400 × 400, 600 × 600, 800 × 800, 1000 × 1000, 3000 × 3000 and 5000 × 5000 square meters.

2.4. Optional window extent and key landscape metrics indices identification

Following the calculation of landscape metrics from areas of 100 × 100 m to 5 × 5 km, the optional window extent was selected and the values of landscape metrics were found to be near equal to the average values in the range of 100 × 100 m to 5 × 5 km. Thus, using this optional window extent (1 km^2), the key landscape metrics were identified. In order to reduce the redundancy in landscape metrics indices, principal component factor analysis (PCA) was used to identify the main landscape metrics that influence landscape variability and characteristics. After PCA, 11 metrics indices were identified: PD, ED, PARA_MN, PARA_AM, LSI, PAFRAC, ENN_MN, PROX_CV, AI, CONTIG_MN, and SHDI (Table 2).

2.5. Correlation analysis between key landscape metrics and ecological factors

In order to explore possible correlations between landscape metrics and ecological factors, the vector format of every natural factor and human disturbance map were converted into Arc Grid format using the same resolution size as that of LULC. These correlatives were overlapped with the same project system and coordination system on ArcGIS desktop. The attribute tables of ecological factors that were derived from the result of FRAGSTATS analysis with 1 squared kilometer block unit were combined to guarantee they are analyzed in the same spatial windows. Landscape metrics and ecological factors were extracted from 2610 windows, respectively. The combined dbf format table was then converted into Microsoft Excel format. The data were stored in the file landscape.xls, where one sheet represents the landscape pattern data, and the other one the ecological factor data.

In the exported database, all the variables were submitted to a Shapiro–Wilk test (W test) in order to test for normality, a basic requirement for further application of parametric tests. The variables related to the landscape metrics showed normal distribution; however, the metrics for AREA, PERIM, SHAPE, CORE and PROX did not show normal distribution and were, therefore, transformed logarithmically (Legendre and Legendre, 1998; Freitas et al., 2005). Consequently, the choice of units does not play any role (as long as the various units are linearly related). In this study, we used detrended canonical correspondence analysis (DCCA) to study the correlations between landscape metrics and ecological factors. In DCCA with detrending by segments and Hill's scaling, the length of the longest axis provides an estimate of the variation extent in the data set (the value 4.9 for our data set suggests that the use of unimodal ordination methods is quite appropriate here). The unconstrained ordination provides the basic overview of the compositional gradients in the data. It is also useful to include the ecological factor data in the analysis – they will not influence the

Table 2
List of key landscape metrics used in the study.

Landscape metrics		Description
Area	PD (Patch density)	The number of patches per unit area (unit: patches/100 ha)
Edge	ED (Edge density)	The total length of all edge segments per ha for the land-cover class or landscape of consideration (unit: m/ha)
Shape	PARA_MN (Mean Perimeter Area Ratio)	PARA equals the ratio of the patch perimeter (m) to area (m^2)
Shape	PARA_AM (Area Weighted Mean Perimeter Area Ratio)	It differs from the PARA in that it's weighted by patch area so larger patches will weigh more than smaller ones.
Shape	LSI (Landscape Shape Index)	A modified perimeter-area ratio of the form that measures the shape complexity of the whole landscape
Shape	PAFRAC (Perimeter–Area Fractal Dimension)	The fractal dimension of the entire landscape which is equal to 2 divided by the slope of the regression line between the logarithm of patch area and the logarithm of patch perimeter
Proximity/ Isolation	ENN_MN (Mean Euclidian Nearest Neighbor Index)	The distance (m) to the nearest neighboring patch of the same type, based on shortest edge-to-edge distance.
Proximity/ Isolation	PROX_CV (Coefficient of Variation of Proximity Index)	PROX equals the sum of patch area (m^2) divided by the nearest edge-to-edge distance squared (m^2) between the patch and the focal patch of all patches of the corresponding patch type whose edges are within a specified distance (m) of the focal patch
Contagion/ Interspersion	AI (Aggregation index)	The ratio of the observed number of the adjacencies to the maximum possible number of like adjacencies given the proportion of the landscape comprised of each patch type, given as a percentage
Contagion/ Interspersion	CONTIG_MN (mean Contagion)	Measures spatial aggregation of patches by computing the probability that two randomly chosen adjacent grid cells will be of the same patch type
Diversity	SHDI (Shannon's Diversity)	Compositional diversity as determined by a combination of richness (number of different patch types) and evenness (proportional distribution of area among patch types)
Diversity	SHEI (Shannon's Evenness)	The observed SHDI divided by the maximum SHDI for that number of patch types. It measures the degree of evenness of area distribution among patch types

landscape metrics and samples ordination, but they will be projected afterwards to the ordination diagram. Eigenvalues, landscape metrics scores (maximum relative complexity), and factor scores were extracted for the first four canonical axes. Landscape metric indices, ecological factor and human disturbance scores on the first two canonical axes were plotted in ordination diagrams. Canonical correlations between landscape metrics and environmental axes were tested for significance using the randomization test of Canoco (Monte Carlo unrestricted permutation, 1000 iterations). In this test, strength of the landscape to environment correlation is measured as the canonical correlation between ecological scores that are weighted averages of landscape metrics values, and ecological scores that are linear combinations of ecological variables (biophysical and human disturbance factors) (Ter Braak, 1995). Additionally, we used a logistic regression analysis to estimate the importance of the highlighted ecological variables in influencing landscape metrics formation.

3. Results

3.1. Sufficiency of the sampling and data normality

Here, we verified that the quantification of the landscape metric variables occurring in the agro-pastoral ecotone was sufficient. Parameters calculated by mean, standard deviation, and variance in each landscape unit are illustrated in Appendix 1 (electronic version only).

3.2. The landscape metrics changes along spatial extent

In order to determine the optional spatial extent, a series of area extents were used to calculate landscape metrics. The influence of spatial scale on landscape metrics was found to be highly significant. Among the 43 metric indices, there was a common tendency for the metric indices to increase or decrease with a constant direction along the changing window size. Within these spatial extents, the indices at 1 squared kilometer showed a median value for variables including landscape shape, proximity, texture, diversity, and patch size (Appendix 2 electronic version only). Thus, we concluded that 1 square kilometer was an appropriate optional extent.

3.3. Principal component analysis of landscape metrics

Three notable components were extracted from the landscape metrics (Appendix 3 electronic version only), with the first contributing to 49.8% variance of initial eigenvalues, while the second and third contributed to 26.9% and 16.4%, respectively. In the first component, PARA_AM, ENN_AM and PROX_CV played significant negative roles and CONTIG_AM, AI and COHESION played significant positive roles in landscape metrics formation. Thus, the first component represented the ecological quality of texture structure in the agro-pastoral landscape. In the second component, PD, ED and LSI played significantly positive roles, and ENN play significantly negative role. Due to these relationships, the second component represented the ecological quality of other class small spaces in the agro-pastoral area. In the third component, only PAFRAC and PARA_MN played prominent positive roles, and so, demonstrated the ecological quality of large spaces such as farmland in the agro-pastoral area. These results are summarized in Appendix 3 (electronic version only) and Fig. 3.

3.4. Main variables influencing landscape metrics

Landscape metric indices, land use and ecological factor vectors

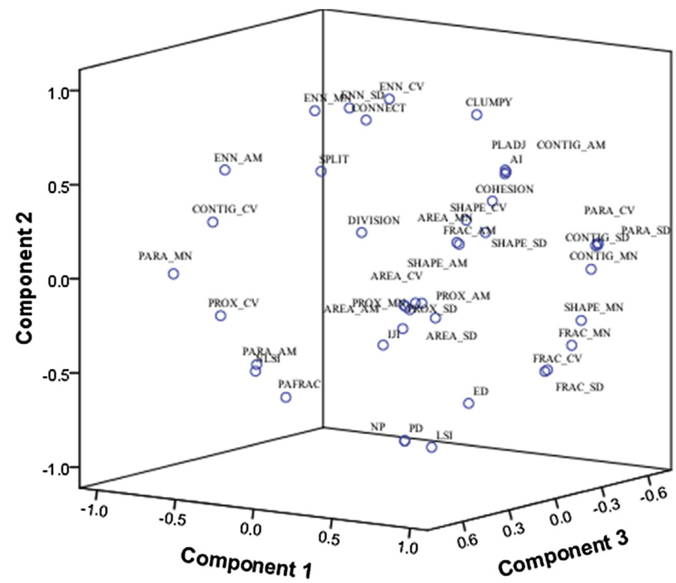

Fig. 3. Ordination plot from a principal components analysis (PCA) of landscape metric and classification accuracy data in the plane of principal component 1, 2 and principle component 3. Principle components 1, 2 and 3 describe 93.1% of the total variation.

for DCCA ordinations of 2610 grid windows are shown in Fig. 4. In the DCCA ordination, the first axis was positively correlated with the average annual temperature, NDVI, and land use type. It also had strong negative correlations with altitude, average annual precipitation, curvature, and slope degree. The second DCCA axis was positively correlated with the intensity of human disturbances. The arrows for ecological variables in Fig. 4 accounted for 76.7% of the variance in the weighted average of the 11 landscape metrics, with respect to the 9 influence variables.

Although there were large differences in land use type among individual sites, the vector lengths in Figs. 3 and 4 indicated that land use variables were not the most important in explaining the variation in landscape metrics formation of these 2610 grid windows. Rather the site conditions and microclimate, especially temperature, altitude and precipitation, appeared to play greater roles in determining the landscape metrics formation. As shown in Fig. 4, shape metrics ENN-MN and AI were greatly influenced by temperature, while PAFRAC and PROX-CV were positively influenced by NDVI and land use. Alternatively, ED, PARA-AM, and LSI had stronger relationships with altitude and precipitation, and on average, CONTIG-MN, SHDI and PD were influenced by multiple ecological factors.

3.5. Correlation between the studied variables

Appendix 4 (electronic version only) outlines the correlation coefficient found among landscape metrics and ecological factors. In general, landform slope and curvature have stronger correlations with landscape metrics than other ecological factors. Weaker correlations were found for site altitude, average annual temperature, and average annual precipitation. Surprisingly, the contribution of human disturbance, vegetation index and site aspect was minimal.

The patch density (PD) showed a significant positive correlation with altitude, slope and precipitation, yet a negative correlation with temperature. The patch shape (PAFRAC) had a significant positive relationship with altitude and precipitation, but a negative relationship with temperature and human disturbance. The metric CONTIG (shape metric) showed significant positive relations ($p < 0.05$) with curvature and precipitation, but negative relations

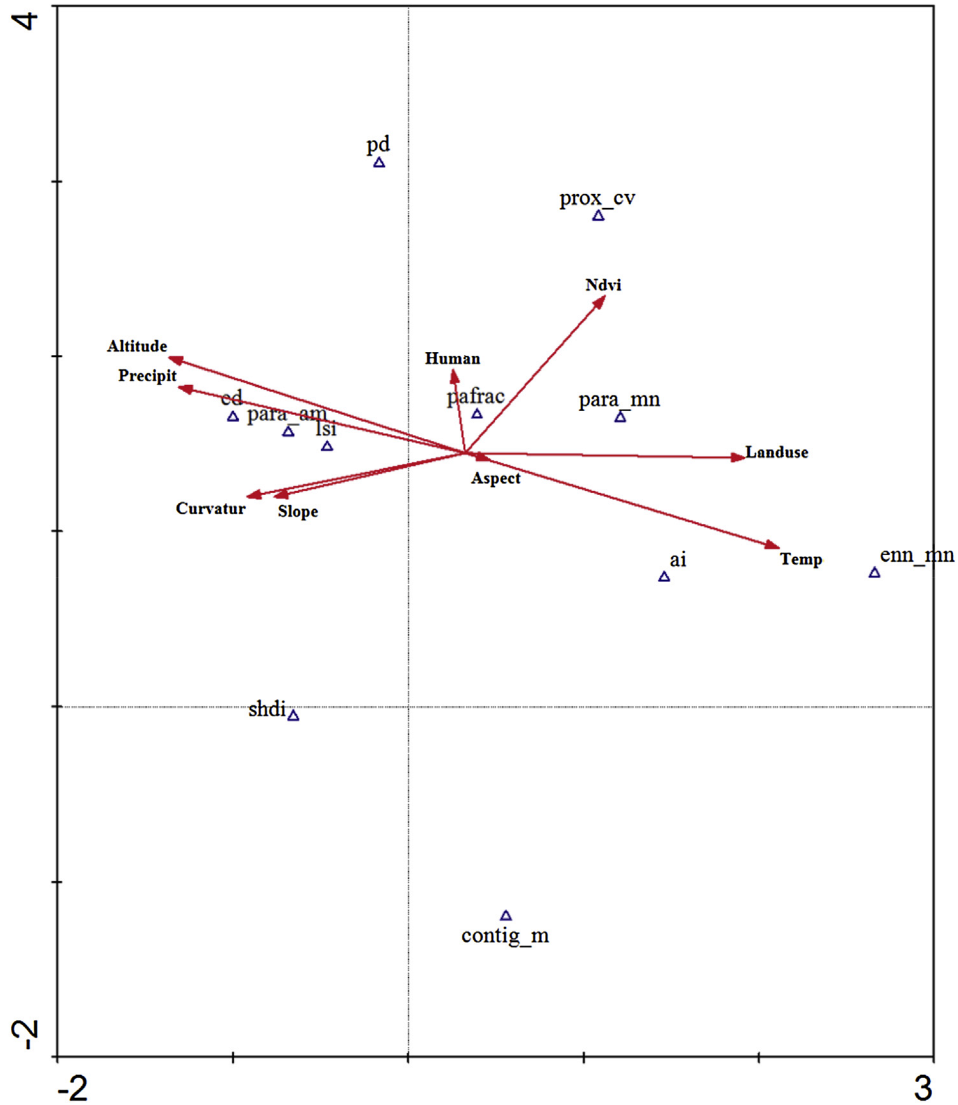

Fig. 4. DCCA ordination diagram of 2610 quadrates from Helin County with respect to landscape metrics. Arrows represent quantitative and ordinal variables. Small triangles represent landscape metrics; vectors represent ecological factors. Landscape metrics as in Table 2. Ecological factors as in Appendix 1 (electronic version only).

with human disturbance and NDVI. The patch isolation indices ENN-MN and PROX-CV showed a similar tendency, being mainly influenced by temperature, precipitation and human disturbance. The patch shape indices (PARA-MN) were mostly influenced by human disturbance and NDVI. Thus, patch shape indices were differentially influenced compared to the other landscape metrics.

4. Discussion

4.1. Scale effect and optional scale selection

Previous studies (Wu and Hobbs, 2002; Castilla et al., 2009) have reported the existence of scale effects on landscape metrics, not only for patch density but also for landscape shape, connectivity, configuration and fragmentation. Scale effect refers to the variation in the results of statistical analysis caused by the changing spatial extent and grain resolution of imagery data (Rocchini, 2007). Consideration of different scales in grain size and spatial extent is necessary for the assessment of landscape metrics (Castilla et al., 2009; Renetzeder et al., 2010). In a small scale, with minimal mapping units, almost every cell is completely dominated by a single class and results in diversity metrics equal to 1 and over-simplified metrics indices. With the increase of scale where the landscape unit covers more class, patch shape index becomes more complicated and variation among different metric indices increases. Enhancement of scale also appears to diminish the contagion with increasing extent. In general, the moderate scale, where the landscape metrics reach stabilized values, will always be selected as an optional scale to make further analysis on landscape metrics. For example, in the Trikala Prefecture, central Greece, after selecting the scale (600 ha) where metrics values stabilized, it was shown that metrics were more greatly correlated at the small scale of 60 ha (Plexida et al., 2014). Likewise, the size of 1 km^2 turned out to be useful for landscape analysis at the national level in Austria (Wrbka et al., 2008). Similarly, the UK Countryside Survey concluded that for a Europe-wide analysis 1 km × 1 km squares are a satisfying pragmatic solution (Bunce et al., 2008).

Unlike previous studies of scaling effects in landscape metrics, the land use classification of our maps was derived from satellite imagery using a supervision classification method. The identification of categories in land use and cover were supported by spectral characteristics and field surveys. As shown previously, spectral data is a better proxy of ecological conditions than the land use classified maps (Palmer et al., 2002). The detailed land use information, which we gained from local the government, guarantees the accuracy of the analysis on different spatial extents. In this study, the scale series included a range of 100, to 5000 m, and landscape indices were stabilized by 1000 meters (m). Thus, 1000 m was chosen as an optimal scale, where the values of landscape metrics indices were minimally influenced by spatial scale changes.

4.2. Identification of key landscape metrics

There are more than 40 indices to characterize landscape pattern to describe area, shape, diversity and fragmentation. Since indices that refer to similar metrics were largely interrelated and contained redundant information, it was reasonable to reduce the number of indices to only those with key roles. Among the existing landscape metrics, we identified the average perimeter area ratio, contagion, standardized patch shape, patch perimeter-area scaling, large-patch density-area scaling, and patch classes to be the most effective indices to characterize for quantification of spatial features for landscape pattern (Liu and Weng, 2009; Peng et al., 2010).

Directly related to the degree of spatial shape are representative edge metrics (TE and ED) in landscapes (Plexida et al., 2014). Metrics such as PD, ENN, SHDI, ED, were used in previous studies due to the complexity of several components of spatial patterns and their effectiveness in quantifying them (Peng et al., 2010). Regarding landscape fractal dimension index, PAFRAC may reflect more characteristics of spatial heterogeneity than PARA or PROX (Farina, 2006). Diversity metrics (SHDI and SHEI) also include more information about patch class and its formation, which is regarded as an important indicator of landscape pattern (De Clercq et al., 2006). Although some indices are always used to represent all indicators for describing landscape metrics, these landscape indices may still behave differently in different areas. Despite the use of equivalent analysis methodology, typical landscape indices are likely influenced by different land use and land cover types across the different categories of land cover worldwide (Tscharntke et al., 2005; Peng et al., 2010; Zimmermann et al., 2010).

In our study, a principal component analysis (PCA) was conducted to ensure that the landscape metrics represented a wide range of explanatory variables in landscape configuration and formation. A large number of replicates (2610) allowed us to evaluate the robustness of the behavior of different landscape metrics. Consideration of the widespread indicators used in previous reports of landscape analyses and its effectiveness in quantifying spatial patterns, led us to choose ED, ENN_MN, PROX_CV, PD, PARA_MN, PARA_AM, LSI, SHDI, AI, PAFRAC and CONTIG_MN as the typical indices for further analysis. The ability of these indices to describe entirely different aspects of landscape pattern is supported by statistical analysis and previously reported findings.

4.3. Which factors to determine the formation of landscape metrics

In this study, we found that the main factors to determine landscape metrics are mean annual temperature, altitude and average annual precipitation. This was different to some previous studies that reported the main factors influencing landscape metric as human activities. Our study area was particularly favorable for exploring the key factors that determine landscape metrics. This area included rich spatial heterogeneity in landform (altitude, slope and aspect), weather conditions (temperature, precipitation and vegetation) and human activity (human settlements, agricultural and grazing activity, roads). The landscape comprised of plains, valleys, hills, and mountains, with an altitude that ranged from 1000 to 1977 m above sea level. The high landforms were accompanied by different severities of slopes ranging from 0 to 34°. High-elevation and southerly or easterly aspects were associated with higher moisture availability. Thus, across the study area, some locations possessed sandy soil, while others had fertilized land. In most cases, the different soil moisture, caused by different levels of precipitation, led to different types of vegetation. Particularly in sandy areas, vegetation cover depended heavily on the amount of precipitation, which was highly variable across the different landscapes (slopes, curvature and altitudes).

The maps we used in spatial and scale analysis were made from Landsat TM images collected in July, 2010, which corresponded to the peak of plant growth of the semi-arid region in Inner Mongolia, and gave us an accurate illustration of the characteristic vegetation of this area. Inter-annual variations in precipitation and temperature lead to either wet or dry years, and result in considerable changes to the landscape composition and configuration of patches. We recorded spatial distribution of precipitation and temperature in average annual values between 2000 and 2010 within the county, which reduced the influence of inter-annual variations on landscape configuration. These detailed accounts of spatial ecological heterogeneities can help to identify the factors that determine the formation of landscape metrics.

In addition to the diversity in natural ecological conditions, human activities, such as agricultural development, are dominant in this area. More than 80 human settlements (towns and villages) are located in this area. These settlements had a relatively even spatial distribution, and were connected by a complicated network of local roads and walking traces. This blend of natural ecological conditions and human disturbances created a desirable area in which to study landscape metrics and the factors that influence them.

Several studies have shown that human activity was the primary cause for large changes to landscape metrics, for example, alterations of land use in forest-steppe ecotone (Gowda et al., 2012). Livestock keeping and crop cultivation are the main agricultural activities in our study landscapes. Crop cultivating can have a large influence on landscape metrics by causing the land to become homogeneous and simple (Tscharntke et al., 2005; Gowda et al., 2012). In our study, landscape metrics were alternatively influenced more by natural ecological conditions than by human activities. This may be due to the semi-arid climate of the study area, it's more difficult to be cultivated largely in size or intensively grazed. Thus husbandry has much less impact on this type of landscapes than other human activities such as forest clearance and urban development, because structural ecological conditions are not much transformed. That's why ecological factors are the main drivers of landscape metrics, in our case. Similar cases can be found in the studies of Easdale and Domptail (2014). These are the common cases since there huge semi-arid areas across the globe, only a minimal amount of land is occupied by intensively human activities with urban or agriculture development. Distances to roads and human settlements were also considered in our study for their potential influence to landscape metrics. The sites with distance less than 30 m were regarded relatively stronger influence on landscape formation more than sites beyond 30 m. Distance to roads, which were more than 30 m were easily captured by the imagery grain resolution and so we were able to accurately identify the effects of roads on surrounding landscapes.

It has been previously demonstrated that the greater the landscape heterogeneity (in temperature and precipitation) the greater the species diversity, including both fine-scale and coarse-scale species richness (Honnay et al., 2003; Rocchini et al., 2005). Understandingly, human activity results in simplifying of land use and greater landscape homogeneity from agricultural development. As such, human activity will produce negative influences on plant diversity in comparison to that of natural ecological conditions (Poggio et al., 2010). From this point of view, landscape heterogeneity in regional management should be an important consideration. Even in cases that human activities have the primary influence on landscape metrics formation, natural ecological variation continues to play a prominent role. Due to this, we believe these relationships warrant further study.

5. Conclusions

This study demonstrated that natural ecological conditions, especially temperature, altitude and precipitation were the key factors in determining landscape metrics in semi-arid ecotones. Unexpectedly, our results also showed that the influence of human activity on landscape metrics was not as strong as expected when spatial scale effects were taken into account. This was despite the fact that agriculture development, which induces landscape homogeneity, is a common use of land in suburb and rural regions across the world. However, there are only small agricultural patches in the mountain regions far from human settlements, and so, had less land use intensity. Such effects, combined with natural ecological conditions, have shaped the land cover and in doing so determined the landscape metrics. We conclude that natural ecological factors, controlled by temperature, precipitation, and landforms defined by altitude and slope have determined the formation of landscape metrics. Given this, we believe future research should focus on the effects of natural ecological conditions on landscape metrics in areas surrounding, near and far from urban development, since this represents the majority of land across the world. In total, this study provides a theoretical case for the scaling effects and develops techniques for identifying the key ecological factors influencing on landscape metrics, so as to improve landscape management decisions in semi-arid regions and other ecotones.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jaridenv.2015.08.009.

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