MULTI-OBJECTIVE METHOD TO ASSESS THE QUALITY OF GRASSLANDS IN THE NORTHERN CHIHUAHUAN DESERT

MÉTODO MULTI-OBJETIVO PARA EVALUAR LA CALIDAD DE LOS PASTIZALES DEL DESIERTO CHIHUAHUENSE

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ABSTRACT

It has been demonstrated that conducting a landscape analysis using a single landscape metric yields data of limited predictive value. Therefore, a combination of selected metrics is more desirable. However, universal set of landscape variables that can effectively evaluate the quality of a particular landscape fragment does not exist. This study considered 14 patch-level landscape metrics and evaluated the best suited to estimate the quality of grasslands in an area of the Northern Chihuahuan Desert ecoregion. A principal component analysis was used to select the combination of metrics, while the multi-objective optimization on the basis of ratio analysis (MOORA) method was used to integrate these variables in addition to rank their quality as predictors. This study proposes that Area, Euclidean distance, Proximity index and Similarity index as the best landscape metrics when characterizing the quality of Chihuahuan Desert grasslands.

RESUMEN

Los análisis que utilizan una sola métrica de paisaje poseen un valor predictivo limitado para la toma de decisiones en el manejo de los ecosistemas, por lo que es deseable seleccionar múltiples indicadores simultáneamente. Sin embargo, actualmente no existe un conjunto universal de variables que puedan evaluar efectivamente la calidad de un fragmento dentro de un paisaje determinado. El presente estudio considera 14 métricas con el fin de evaluar cuáles son las mejores para describir la calidad de fragmentos de pastizal natural dentro de la ecoregión del Desierto Chihuahuense. La selección de la combinación de variables se realizó a través de un análisis de componentes principales, mientras que el método de optimización multi-objetivo basado en el análisis de radios (MOORA) fue utilizado para la integración de las variables seleccionadas al mismo tiempo de ponderar la influencia de cada variable. En este estudio se concluye que el área, la distancia euclidiana, el índice de proximidad y el índice de similitud son las métricas de paisaje que mejor caracterizan la calidad de los pastizales en el Desierto Chihuahuense.

INTRODUCTION

Human-dominated landscapes are actually increasing their presence throughout the planet (Foley et al., 2005; Haila, 2002; Lepczyk et al., 2008). Human induced changes in landscape structure are transforming extensive natural areas into habitat patches that are often surrounded by developed land. This type of disturbance is potentially hostile to biodiversity and their processes (Mossman et al., 2015). Although the overall landscape quality has an important influence on wildlife populations, patch attributes determine the distribution of quality among habitat patches giving rise to source-sink dynamics (Heinrichs et al., 2015). If the premise of habitat degradation is listed as the main cause of wildlife population declining, patch-level assessment plans for wildlife management and conservation are needed. Mortelliti et al. (2012) showed that the omission of patch quality in a fragmentation analysis could carry substantial risk in conservation of landscapes where significant variation across the patches exists.

Landscape structure refers to the patterns found within its elements, which are defined as discrete entities or patches (Kupfer, 2012; Tscharntke et al., 2012; Uuemaa et al., 2013). Quantifying landscape structure can be assessed under two approaches: the species-oriented and the pattern-oriented (Fischer and Lindenmayer, 2007). Pattern-oriented approach originated from the island biogeography theory (MacArthur and Wilson, 1967) is the strongest hold on landscape ecology research (Fischer and Lindenmayer, 2007; Haila, 2002).

The patch matrix model (PMM) describes landscape structure as a mosaic of homogeneous areas discretely delineated, with three principal elements, i.e., patches, corridor and matrix (Forman and Gordon, 1986; Forman, 1995). This model can be addressed through landscape composition, which represents the proportion of fragment types and landscape configuration that describes the spatial aspects of the patch mosaic (e.g. size, shape and arrangement). Although the PMM has been heavily criticized due to the oversimplification of the landscape features, Lausch et al. (2015) suggested that this approach should be used in landscapes under severe pressure (e.g. urban and agricultural areas) because they tend to fix vegetation patterns, creating landscapes dominated by homogeneous areas with very distinct boundaries. PMM has been the prevailing model used due to its simplicity, compatibility with data models in geographic information systems, and the availability of remotely sensed data (Fischer and Lindenmayer, 2007).

Landscape metrics characterize quantitatively the landscape structure based on maps or remotely sensed images (Kupfer, 2012; Símová and Gdulová, 2012; Uuemaa et al., 2009). Several dozens of landscape metrics have been proposed to describe landscape structure creating an enormous confusion to which metrics are appropriate in effectively characterizing relevant landscape components (Fan and Myint, 2014; McGarigal, 2015; Schindler et al., 2014; Símová and Gdulová, 2012). To avoid including a large list of redundant variables a pre-selection of metrics is often required. This selection can be based on theoretical consideration, expert knowledge, previously published studies and statistical approaches (Riitters et al., 1995; Schindler et al., 2014). However, there are no universally appropriate indicator variables, because their performance depends mainly on each landscape context (Schindler et al., 2014; Walz, 2011). In the absence of prior knowledge for a specific study system, a pre-selection of landscape metrics is a challenging task for conservationists and policy-makers interested in identifying appropriate indicators (Walz, 2011).

Environmental decision-making process is often complex because it relies on experimental results or computational models that assess human health and ecological risk associated with environmental stressors. The interpretation of these results is extremely difficult because there are many emerging risks for which information is not available and decisions should be made under significant uncertainty. Multi-criteria decision analyses (MCDA) constitutes a set of useful tools for decision-making problems in environmental sciences because it allows the combination of a set of weighted variables to rank the different alternatives under consideration. The use of MCDA as a tool to support decision-making in environmental research has increased mainly due to the recognition of the complexity of environmental problems and the need for transparency from stakeholders throughout the process. When selecting a particular MCDA approach, it is important to consider the complexity of the decision in terms of scientific, social and technical factors as well as understanding the processes needs and the level of available knowledge about the problem (Huang et al., 2011).

The multi-objective optimization, also known as multi-criteria or multi-attribute optimization (MOORA), is a process of simultaneously optimizing two or more conflicting attributes (objectives) subject to certain constraints (Chakraborty, 2011; Gadakh, 2011; Karande and Chakraborty, 2012). This method was first introduced like a multi-objective optimization technique that can be successfully applied to solve various types of complex decision making problems (Brauers et al., 2008; Brauers and Zavadskas, 2006; Karande and Chakraborty, 2012). Thus the aim of this study is identify the set of landscape metrics that best characterize the quality of grassland patches in the Northern Chihuahuan Desert ecoregion trough MOORA approach.

MATERIALS AND METHODS

Study area.- The Chihuahuan Desert encompasses one of the most biologically diverse arid regions on earth. It covers nearly 630 000 km^2, covering from eastern Arizona, southern New Mexico, and western Texas, USA to the edge on Mexico's Meseta Central (Figure 1). Most of the ecoregion lies between 900 and 1500 m.a.s.l., although foothill areas and some isolated mountains in Meseta Central may rise more than 3000 m.a.s.l. (Dinerstein et al., 2000). The climate is relatively uniform with hot summers and cool to cold, dry winters; precipitation is monsoonal during the summer months ranging from 150 to 500 mm annually (Schmidt, 1986).

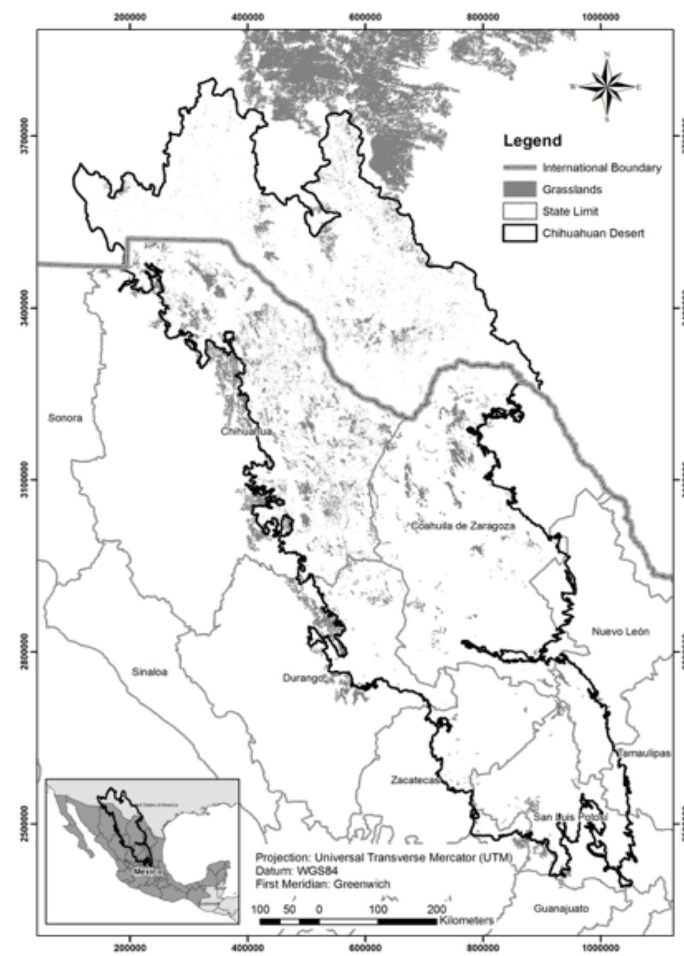

Figure 1. Location of the Chihuahuan desert grasslands

The Chihuahuan Desert is composed mainly of two types of vegetation. One dominated by shrubs, which currently covers more than 85% of its surface and the other dominated by grasses, which covers less than 15% (PMARP, 2012). Chihuahuan desert grasslands were formerly characterized by extensive areas of tobosagrass (*Pleuraphis mutica*) and black gramma (*Bouteloua eriopoda*). However, grassland areas across this ecoregion are undergoing a large-scale transformation mainly due to expanding agriculture, urbanization, energy development, desertification (Pool et al., 2014) and shrub invasion attributed to climate change, over grazing, fire suppression, distribution of shrub seeds by domestic livestock and the removal of native herbivores (Desmond and Montoya, 2006; Manzano-Fischer et al., 2006).

Data sources and processing.- The data used in this study consists of two categorical maps and one raster. The first categorical map was the 1:50,000 Land Use and Vegetation of the state of Chihuahua, Mexico (CONAFOR, 2013). The second categorical map was the 1:250,000 Land Use and Vegetation covered by the rest of the Mexican states within the Chihuahuan Desert (INEGI, 2015). The raster was the land cover of North America at a scale of 1:10,000,000 with a resolution of 250 meters (CEC, 2013). Of the resulting map, patches classified as natural grassland were identified and together with their neighbors polygons were selected to create a raster file with a resolution of 200 meters in ArcGIS 10.0.

Landscape structure analysis.- This study computed 14 metrics at patch level, available in FRAGSTATS software package (McGarigal et al., 2002) as follows: area (AREA), perimeter (PERIM), radius of gyration (GYRATE), perimeter-area ratio (PARA), shape index (SHAPE), fractal dimension index (FRAC), related circumscribing circle (CIRCLE), contiguity index (CONTIG), core area (CORE), number of core areas (NCA), core area index (CAI) Euclidean nearest neighbor distance (ENN), proximity index (PROX) and similarity index (SIMI) (Table 1).

Multi-objective optimization on the basis of ratio analysis (MOORA) method.- The MOORA method (Brauers and Zavadskas, 2006) starts with a decision matrix showing the response of different alternatives with respect to various objectives (attributes):

$$(x_{ij}) \qquad (1)$$

Where *xij* is the response of alternative *j* to objective *i*, *i* 0 1,2,…, *n* are the objectives, *j*= 1,2,… *m* are the alternatives.

The MOORA method is based on a ratio system in which the response of each alternative is compared to a denominator which is representative for all the alternatives concerning that objective. For this denominator the square root of the sum of squares of each alternative per objective is chosen. This ratio can be expressed as:

$$Nx_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{m} x_{ij}^2}} \qquad (2)$$

Where x_{ij} = response of alternative *j* to objective *i*, *j* = 1, 2,…, *m*; *m* the number of alternatives, *i* = 1, 2,…, *n*; *n* being the number of objectives,
Nx_{ij} = a dimensionless number representing the normalized response of alternative *j* to objective *i*; these normalized responses of the alternatives to the objectives belong to the interval [0;1].

For the multi-objective optimization, these normalized responses of each alternative are added in case of maximization (beneficial attributes) and subtracted in case of minimization (non beneficial attributes) as outlined below:

$$Ny_j = \sum_{i=1}^{i=g} Nx_{ij} - \sum_{1=g+1}^{i=n} Nx_{ij} \qquad (3)$$

with:
i = 1, 2,…, g for the objectives to be maximized, *i* = *g* + 1, *g* + 2,…, *n* for the objectives to be minimized,
Ny_i = the normalized assessment of alternative *j* with respect to all objectives.

In this formula linearity concerns dimensionless measure in the interval [0;1]. An ordinal ranking of the shows the final preference.
In some cases, it is observed that some objectives are more important than others. In order to give more importance to an attribute, it could be multiplied by its corresponding weight.

$$Ny_j = \sum_{i=1}^{i=g} WjNx_{ij} - \sum_{1=g+1}^{i=n} WjNx_{ij\,(j=1,2,\ldots,n)} \qquad (4)$$

Where *Wj*=the weight of *jth* attribute

The Ny_i value can be positive or negative depending of the totals of its maximized (beneficial attributes) and minimized (non-beneficial attributes) in the decision matrix. An ordinal ranking of Ny_i shows the final preference. Thus, the best alternative has the highest Ny_i value, while the worst alternative has the lowest Ny_i value.

Statistical analysis.- To select the landscape structure variables that were used to build the different MOORA combinations, a principal component analysis (PCA) was used, which was performed in SPSS (IBM SPSS, 2013). Pearson correlation analysis allowed detecting redundancy between landscape metrics that helped establishing the number of MOORA and their variable combinations. Eigenvalues of the PCA were used to weight each landscape metric in every MOORA set. The similarity of the results of each MOORA set was evaluated with a dendrogram built with the Euclidean distances using SPSS (IBM SPSS, 2013). The first dendrogram was created using the 30 best patches selected by each MOORA set. The second one was the result of using the 30 worst patches selected by each MOORA set. To evaluate the precision of the quality established by each MOORA set a Kappa analysis was conducted, which provides a quantitative measure of agreement between categorical variables. Kappa is calculated from the difference between how much agreement is actually present (observed agreement) compared to how much agreement would be expected to be present by chance alone (expected agreement) (Viera and Garrett, 2005). Kappa value is standardized to lie on a -1 to 1 scale, where 1 is perfect agreement, 0 is exactly what would be expected by chance. Negative values indicate agreement less than chance.

RESULTS

A total of 22,045 patches of natural grassland were identified in the Chihuahuan Desert Ecoregion. The 14 landscape metrics calculated to assess the quality of each of these fragments are summarized in Table 2. In order to select the variables that constitute each MOORA set a PCA analysis was conducted. Cross-correlation between variables showed a variety of complex relationships (Table 3). AREA-CORE was completely redundant, while AREA-PERIM, AREA-NCORE, PERIM-CORE, and GYRATE-NCORE were strongly correlated in a positive way. While PARA-CONTIG showed a strong and positive correlation, PROX, SIMI, and ENN did not correlate with other metrics.

Nine MOORA sets were built based on the performance of landscape metrics of Chihuahuan Desert grasslands through a PCA and literature review where theoretical relations were established between variables (Table 4). Using the 30 best and 30 worst quality patches with each MOORA combination, it was determined that sets 5, 7, 8 and 9 were most similar when selecting the best grassland patches (Figure 2).

While the MOORA combinations 2, 6, 7, 8 and 9 were similar in the selection of the worst grassland patches (Figure 3). MOORA sets 7, 8 and 9 are consistent in discriminating between patches that have good landscape features and those who do not have them.

The level of agreement between all possible pairs of MOORA set combinations, using the Kappa statistic value showed that 5.55% of them had an almost perfect agreement, 8.3% had a substantial agreement, 16.66% had a moderate agreement, 47.22% had a fair agreement, while 22.22% had a slight agreement (Table 5).

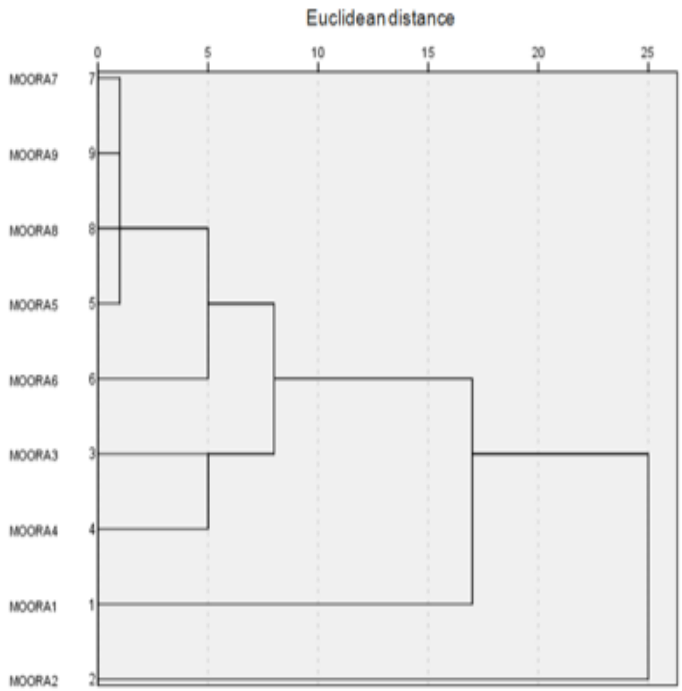

Figure 2. Euclidean distance dendogram of the 30 best grassland fragments selected by each MOORA combination

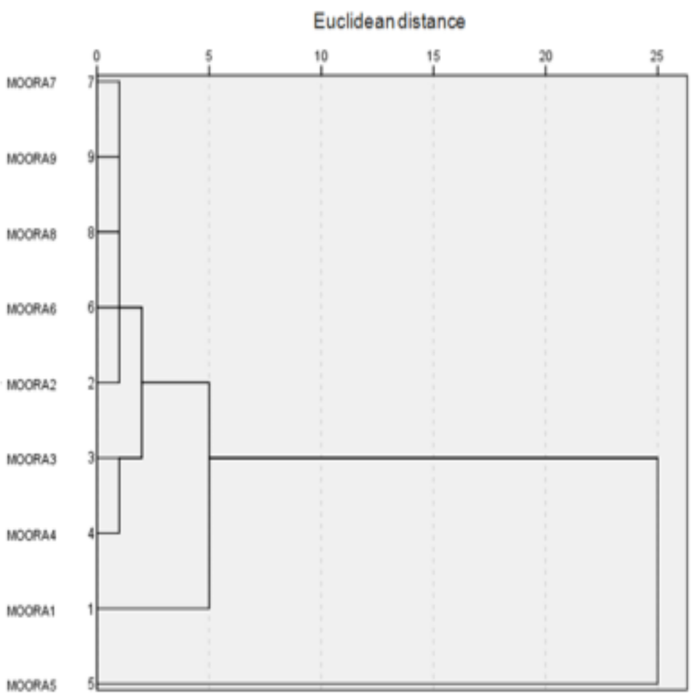

Figure 3. Euclidean distance dendogram of the 30 worst grassland fragments selected by each MOORA combination

DISCUSSION

The values of the landscape metrics estimated for the 22,045 grassland patches confirmed the high fragmentation of the Chihuahuan Desert grasslands described in many studies (Curtin et al., 2002; Manzano-Fischer and Cruzado, 2010; Manzano-Fischer et al., 2006; Pidgeon et al., 2001; Pool et al., 2014). The AREA, PERIM, and GYRATE metrics reveled that the extent of grassland patches is highly variable. The SHAPE, FRAC, and CIRCLE metrics showed that despite the extent of the patch, most grassland patches tend to have simple perimeters with very little convolutions. The CONTIG metric indicates that the spatial connectedness of most grassland patches is limited and the PROX, SIMI, and ENN metrics showed that the aggregation of grassland patches is highly variable throughout the ecoregion. The ambiguity about how far the edge effect influences the patches is a species specific attribute (Helzer and Jelinski, 1999). Therefore, the use of CORE, NCORE and CAI metrics seems not appropriate for general fragmentation models.

The redundancy found between AREA with CORE, PERIM, NCORE, and GYRATE was consistent with previous studies (Szabó et al., 2014). This is mainly because these metrics represent patch extent and therefore polygon area has a very strong influence on their formulation. The strong and positive correlation found between PARA and CONTIG is because both metrics incorporate the extent and shape to address patch complexity (Helzer and Jelinski, 1999). However, Szabó et al. (2014) found a strong negative correlation between these metrics. PROX, SIMI, and ENN did not correlate with other metrics. Consequently, they can be regarded as the ones providing unique information when selecting indices to characterize a particular fragment. Szabó et al. (2014) found that the only non-correlated metrics were PROX and ENN.

It has been established that landscape metrics are very difficult to interpret and associate to ecological patterns and processes (Cushman et al., 2008). Therefore, we thoroughly analyzed each landscape metric both theoretically and empirically to establish the MOORA decision for maximizing (positive influence) or minimizing (negative influence). The MOORA method was chosen to integrate the landscape metrics and build the fragmentation model, because we considered that it is the most robust of all the multi-objective optimization techniques. This method is the only one that fulfills the seven conditions of robustness used to evaluate the performance of MCDA. It includes all stakeholders, evaluation objectives, response alternatives, it is based on cardinal numbers, it uses only non-subjective estimators, it uses the latest information available, and it uses two different methods of multi objective optimization (the ratio system and the reference point approach) (Brauers and Zavadskas, 2009, 2012).

In addition to the mathematical robustness, the operation of this method is very simple. Chakraborty (2011) compared the MOORA to other multi-objective methods (AHP, TOPSIS, ELECTRE, VIKOR, PROMETHEE, and GRA) and demonstrated that the MOORA method besides being mathematically robust, is very simple to comprehend and easy to implement because it involves the least amount of mathematical calculations and minimal computational skills are required. Therefore, the MOORA method is highly recommended to assist during any complex decision-making process, such as the determination of the quality of grassland patches of the Chihuahua Desert.

Landscape metric combination established in MOORA 7, MOORA 8, and MOORA 9 were consistent in selecting the same patches of good quality and poor quality. The four metrics used in MOORA 7 (AREA, ENN, PROX and SIMI) were the least correlated between themselves. While the MOORA 8 uses the AREA and PERIM which are highly correlated. The effect of the PERIM was absorbed by the AREA because it was minimized. Therefore, AREA, ENN, PROX and SIMI were again the important indicators. Finally, in MOORA 9, PARA was used instead of AREA and/or PERIM. PARA equals to the ratio of the patch perimeter to its area and it has been established that PARA is strongly influenced by patch area (McGarigal et al., 2002).

The KAPPA value showed that MOORA 7 and MOORA 8 had an almost perfect agreement when assigning patch quality. Cushman et al. (2008) noted that it is desirable that a smaller number of independent variables be included when describing landscape structure (Cushman et al., 2008). Therefore, we propose that MOORA 7 (AREA, ENN, PROX and SIMI) includes the patch metrics that best describe the grassland patches of the Chihuahuan Desert Ecoregion.

CONCLUSIONS

The values of the patch metrics confirmed the intense fragmentation that they are undergoing of the Chihuahuan Desert landscape and demonstrate that grasslands ecosystem are in a state of vulnerability. The enormous structural variation of grassland patches (e.g. area, shape and isolation) within the ecoregion and the redundancy of this fragmentation indices make difficult to identify which attributes were the best descriptors to identify grasslands remnants that have a higher quality and thus can be selected as priorities for conservation.
The MCDA MOORA method used in this study proved to be simple, easy to understand, and mathematically robust to discriminate different sets of landscape metrics. This tool allows to simultaneously considering any number of attributes with their relative importance and offering a more objective and logical attribute selection approach.

Finally, it is possible to conclude that the best set of landscape metrics to describe the quality of Chihuahuan Desert Grassland patches includes the area, Euclidean nearest-neighbor distance, and proximity and similarity coefficients.

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Table I. Description of patch-base metrics for the raster image integrated with grassland patch of the Chihuahuan Desert calculated in FRAGSTAT 4.1 Software package (Mcgarigal, 2015).

Indicator	Description	Units	Range
AREA	Equals the area (m^2) of the patch, divided by 10 000. The area of each patch comprising a landscape mosaic is perhaps the single most important and useful piece of information contained in the landscape.	Hectares	AREA > 0, without limit
PERIM	Equals the perimeter (m) of the patch, including any internal holes in the patch. The perimeter of a patch is treated as an edge, and the intensity and distribution of edges constitutes a major aspect of landscape pattern	Meters	PERIM > 0, without limit
GYRATE	Equals the mean distance (m) between each cell in the patch and the patch centroid. Radius of gyration is a measure of patch extent	Meters	Gyrate ≥ 0, without limit
PARA	Equals the ratio of the patch perimeter (m) to area (m^2). Perimeter-area ratio is a simple measure of shape complexity, but without standardization to a simple Euclidean shape.	None	PARA > 0, without limit
SHAPE	Equals patch perimeter (m) divided by the square root of patch area (m2), adjusted by a constant to adjust for a square standard. Shape index corrects for the size problem of the perimeter-area ratio index by adjusting for a square standard and, as a result, is the simplest and perhaps most straightforward measure of shape complexity.	None	SHAPE ≥ 1, without limit SHAPE = 1 when the patch is a square and increase whitout limit as patch shape becomes more irregular.
FRAC	Equals the logarithm of patch perimeter (m) divided by the logarithm of patch area (m^2); the perimeter is adjusted to correct for the raster bias in perimeter. Fractal dimension index is appealing because it reflects shape complexity across a range of spatial scales.	None	1 ≤ FRAC ≤ 2
CIRCLE	Equals 1 minus patch area (m^2) divided by the area (m^2) of the smallest circumscribing circle. This index is not influenced by patch size.	None	0 ≤ CIRCLE < 1 CIRCLE = 0 for square patches and approaches 1 for elongated, linear patches one cell wide
CONTIG	Equals the average contiguity value for the cells in a patch minus 1, divided by the sum of the template values minus 1. Contiguity index assesses the spatial connectedness, or contiguity of cells within a grid-cell patch to provide an index on patch boundary configuration and thus patch shape	None	0 ≤ CONTIG ≤ 1 CONTIG equals 0 for a one-pixel patch and increases to a limit of 1 as patch congruity, or connectedness, increases.
CORE	Equals the area (m2) within the patch that is further than the specified depth-of-edge distance from the patch perimeter, divided by 10,000. Core area index is a relative index that quantifies core area as a percentage of patch area	Hectares	CORE ≥ 0, without limit CORE = 0 when every location within the patch is within the specified depth-of edge distance from the patch perimeter. CORE approaches AREA as the specified depth-of-edge distance decreases and as patch shape is simplified
NCORE	Equals the number of disjunctive core areas contained within the patch boundary. A disjunction core is a spatially contiguous (and therefore distinct) core area. Depending on the size and shapes of the patch and the specified depth-of-edge distance(s), a single patch may actually contain several disjunctive core areas.	None	CORE ≥ 0, without limit NCORE = 0 when CORE = 0 (every location within the patch is within the specified depth-of-edge distance from the patch perimeter) NCORE > 1 when, because of shape, the patch contains disjunctive core areas
CAI	Equals the patch core area (m2) divided by total patch area (m2), multiplied by 100 (to convert to a percentage); in other words, CAI equals the percentage of a patch that is core area. Core area index is a relative index that quantifies core area as a percentage of patch area.	Percent	0 ≤ CAI < 100 CAI approaches 100 when the patch, because of size, shape, and edge width, conns mostly core area
ENN	Equals the distance (m) to the nearest neighboring patch of the same type, based on shorts edge-to-edge distance. Note that the edge to edge distances are from cell center to cell center. Euclidean nearest-neighbor distance is perhaps the simplest measure of patch context and has been used extensively to quantify patch isolation.	Meters	ENN > 0, without limit ENN approaches) as the distance to the nearest neighbor decreases
PROX	Equals the sum of patch area (m2) divided by the nearest edge to edge distance squared (m2) 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.	None	PROX ≥ 0 PROX =) if a patch has no neighbors of the same patch type within the specified radius. PROX increases as the neighborhood is increasingly occupied by patches of the same type and as this patches become closer and more contiguous in distribution
SIMI	Equals the sum, over all neighboring patches with edges within a specified distance the focal patch type and the class of the neighboring patch (0-1), divided by the nearest edge-to edge distance squares (m^2) between the focal patch and the neighboring patch.	None	SMI ≥ 0 SIMI = 0 if all the patches within the specified neighborhood have a 0 similarity coefficient. SIMI increases as the neighborhood is increasingly occupied by patches with greater similarity coefficients and as this similar patches become closer and more contiguous and less fragmented in distribution

Table II. Descriptive statistics of the metric landscape of the natural grassland found in the Chihuahuan Desert Ecoregion

	Mean	Standard deviation	Minimum	Maximum
AREA	671.45	71258.15	4	10572632
PERIM	11264.32	564066.34	800	83099600
GYRATE	334.59	1319.42	100	163609.98
PARA	133.73	49.89	7.53	200
SHAPE	1.4	0.97	1	63.88
FRAC	1.04	0.04	1	1.33
CIRCLE	0.47	0.27	0	0.96
CONTIG	0.29	0.23	0	0.95
CORE	530.25	63135.48	0	9370160
NCORE	0.69	13.52	0	1877
CAI	5.75	13.12	0	89.21
PROX	6433.59	60423.26	0	660828.25
SIMI	2434274.45	2846722.82	0	13113770.11
ENN	834.58	1832.57	400	117459.95

Table III. The Pearson correlation matrix between the 14 landscape variables calculated for the Chihuahuan Desert grasslands

	AREA	PERIM	GYRATE	PARA	SHAPE	FRAC	CIRCLE	CONTIG	CORE	NCORE	CAI	PROX	SIMI	ENN
AREA	*	0.996 p=0.000	0.850 p=0.000	-0.22 p=0.001	0.453 p=0.000	0.050 p=0.000	0.007 p=0.296	0.025 p=0.000	1 p=0.000	0.945 p=0.000	0.053 p=0.000	-0.001 0.923	0.014 p=0.042	-0.001 0.836
PERIM		*	0.881 p=0.000	-0.036 p=0.000	0.508 p=0.000	0.076 p=0.000	0.015 p=0.22	0.040 p=0.000	0.995 p=0.000	0.970 p=0.000	0.075 p=0.000	-0.001 p=0.885	0.015 p=0.026	-0.001 p=0.824
GYRATE			*	-0.247 p=0.000	0.791 p=0.000	0.350 p=0.000	0.153 p=0.000	0.269 p=0.000	0.846 p=0.000	0.926 p=0.000	0.377 p=0.000	0.002 p=0.821	0.063 p=0.000	0.028 p=0.000
PARA				*	-0.404 p=0.000	-0.603 p=0.000	0.694 p=0.000	0.987 p=0.000	-0.021 p=0.002	-0.087 p=0.000	-0.682 p=0.000	-0.063 p=0.000	0.432 p=0.000	0.126 p=0.000
SHAPE					*	0.731 p=0.000	0.355 p=0.000	0.449 p=0.000	0.447 p=0.000	0.646 p=0.000	0.499 p=0.000	-0.017 p=0.014	0.070 p=0.000	0.004 p=0.577
FRAC						*	0.721 p=0.000	0.668 p=0.000	0.047 p=0.000	0.155 p=0.000	0.517 p=0.000	-0.017 p=0.011	0.152 p=0.000	0.025 p=0.000
CIRCLE							*	0.688 p=0.000	0.006 p=0.361	0.044 p=0.000	0.287 p=0.000	0.031 p=0.000	0.247 p=0.000	0.057 p=0.000
CONTIG								*	0.023 p=0.001	0.096 p=0.000	0.738 p=0.000	0.056 p=0.000	0.427 p=0.000	0.130 p=0.000
CORE									*	0.942 p=0.000	0.050 p=0.000	-0.001 p=0.926	0.014 p=0.044	-0.001 p=0.835
NCORE										*	0.146 p=0.000	-0.001 p=0.848	0.025 p=0.000	-0.001 p=0.905
CAI											*	0.017 p=0.011	0.230 p=0.000	0.145 p=0.000
PROX												*	0.027 p=0.000	-0.024 p=0.000
SIMI													*	0.109 p=0.000
ENN														*

Table IV. Number of principal component of each set of landscape metrics with the weight and MOORA decision of each landscape metric in all MOORA combinations

	Eigenvalues of PCA	Landscape metrics	Weight	MOORA Decision
MOORA 1	43.89	AREA	7.35	Maximize
		PERIM	7.35	Minimize
		GYRATE	7.35	Maximize
		SHAPE	7.35	Minimize
		CORE	7.35	Maximize
		NCORE	7.35	Minimize
	30.91	PARA	6.18	Minimize
		FRACC	6.18	Minimize
		CIRCLE	6.18	Minimize
		CONTIG	6.18	Maximize
		CAI	6.18	Maximize
	8.68	ENN	8.68	Minimize
	8.54	PROX	8.54	Maximize
	7.97	SIMI	7.97	Maximize
MOORA 2	32.30	CONTIG	16.15	Maximize
		SIMI	16.15	Maximize
	23.55	PROX	23.55	Maximize
	22.29	ENN	22.29	Minimize
	21.87	GYRATE	21.87	Maximize
MOORA 3	45.30	PARA	9.06	Minimize
		SHAPE	9.06	Minimize
		FRAC	9.06	Minimize
		CIRCLE	9.06	Minimize
		CONTIG	9.06	Maximize
	31.36	AREA	10.45	Maximize
		PERIM	10.45	Minimize
		GYRATE	10.45	Maximize
	11.65	PROX	5.82	Maximize
		ENN	5.82	Minimize
	11.65	SIMI	11.65	Maximize
MOORA 4	58.97	AREA	29.48	Maximize
		SHAPE	29.48	Minimize
	41.02	SIMI	20.51	Maximize
		ENN	20.51	Minimize
MOORA 5	41.84	AREA	20.92	Maximize
		SHAPE	20.92	Minimize
	29.27	ENN	29.27	Minimize
	28.87	PROX	14.43	Maximize
		SIMI	14.43	Maximize
MOORA 6	45.04	GYRATE	22.52	Maximize
		SHAPE	22.52	Minimize
	27.65	ENN	27.65	Minimize
	27.29	SIMI	13.64	Maximize
		PROX	13.64	Maximize
MOORA 7	24.73	AREA	24.73	Maximize
	25.57	ENN	25.57	Minimize
	25.97	PROX	25.97	Maximize
	23.71	SIMI	23.71	Maximize
MOORA 8	48.73	AREA	24.36	Maximize
		PERIM	24.36	Minimize
	25.79	ENN	25.79	Minimize
	25.47	PROX	12.73	Maximize
		SIMI	12.73	Maximize

MOORA 9	40.19	PARA	20.09	Minimize
		SIMI	20.09	Maximize
	30.80	PROX	30.80	Maximize
	28.99	ENN	28.99	Minimize

Table V. Agreement analysis and correlation analysis between the different MOORA combinations. Above the diagonal is the agreement Kappa value and below the diagonal is the Kappa value interpretation of the level of agreement

	MOORA 1	MOORA 2	MOORA 3	MOORA 4	MOORA 5	MOORA 6	MOORA 7	MOORA 8	MOORA 9
MOORA 1	*	0.2818 p=0.00	0.7973 p=0.00	0.1067 p=0.11	0.1315 p=0.05	0.2815 p=0.00	0.3939 p=0.00	0.3451 p=0.00	0.3790 p=0.00
MOORA 2	Fair	*	0.1711 p=0.00	0.1335 p=0.06	0.1870 p=0.00	0.2188 p=0.00	0.2732 p=0.00	0.2199 p=0.00	0.5951 p=0.00
MOORA 3	Substantial	Slight	*	0.1797 p=0.00	0.2016 p=0.00	0.3250 p=0.00	0.4859 p=0.00	0.3639 p=0.00	0.4533 p=0.000
MOORA 4	Slight	Slight	Slight	*	0.8960 p=0.00	0.6632 p=0.00	0.2765 p=0.00	0.3905 p=0.00	0.1331 p=0.27
MOORA 5	Slight	Slight	Fair	Almost perfect	*	0.7649 p=0.00	0.3473 p=0.00	0.4534 p=0.00	0.1828 p=0.01
MOORA 6	Fair	Fair	Fair	Substantial	Substantial	*	0.4241 p=0.00	0.5209 p=0.00	0.2606 p=0.00
MOORA 7	Fair	Fair	Moderate	Fair	Fair	Moderate	*	0.8113 p=0.00	0.3893 p=0.00
MOORA 8	Fair	Fair	Fair	Fair	Moderate	Moderate	Almost perfect	*	0.2872 p=0.00
MOORA 9	Fair	Moderate	Moderate	Slight	Slight	Fair	Fair	Fair	*