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Research article

Relación de datos climáticos y de teledetección con la diversidad arbórea en un bosque templado

Relationship of climate and remote sensing data with tree diversity in a temperate forest

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Abstract

Quantifying biodiversity is key to natural resource conservation; however, data collection can be time-consuming and costly. Given that climate and remote sensing data help in the prediction of species diversity, the objective of this study was to analyze the relationship of climate data and the Normalized Difference Vegetation Index (*NDVI*) with tree diversity in a temperate forest in Northern Mexico. Species richness (*S*), Simpson's (*1-D*) and Shannon's (*H*) diversity indices were calculated at 663 sampling sites. Subsequently, an exploratory regression analysis was performed to obtain regression models that would account for the relationship of tree diversity indices with the *NDVI*, climatic data, and the number of trees. The best model for each diversity index and its predictor variables was integrated into a Geographically Weighted Regression (GWR) model. The results showed that the relationship of diversity indices and predictor variables varies across the space. The variables showed greater predictive potential in the Northern and Northwestern part of the study area. The *NDVI* was the variable with the greatest relative influence in the explanation of the diversity indices; therefore, it can function as a proxy for factors associated with tree diversity.

Keywords: Spatial distribution, vegetation index, diversity indices, forest management, spatial regression, species richness.

Resumen

Cuantificar la biodiversidad es clave para la conservación de los recursos naturales; sin embargo, la recolección de datos puede llevar mucho tiempo y resultar costosa. Dado que los datos climáticos y de teledetección ayudan a la predicción de la diversidad de especies, el objetivo de este estudio fue analizar la relación entre datos climáticos y el Índice de Vegetación de Diferencia Normalizada (*IVDN*) con la diversidad arbórea, en un bosque templado del Norte de México. Se calculó la riqueza de especies (*S*), los índices de diversidad de *Simpson* (*1-D*) y de *Shannon* (*H*) en 663 sitios de muestreo. Posteriormente se realizó un análisis de regresión exploratoria para obtener modelos de regresión que expliquen la relación de los índices de diversidad de árboles con el *IVDN*, los datos climáticos y el número de árboles. El mejor modelo de cada índice de diversidad y sus variables predictoras se integró en un modelo de Regresión Ponderada Geográficamente (RGP). Los resultados mostraron que la relación de los índices de diversidad y las variables predictoras varía a través del espacio. Las variables registraron mayor potencial de predicción en la zona Norte y Noroeste del área de estudio. El *IVDN* fue la variable de mayor influencia relativa en la explicación de los índices de diversidad, por lo que puede funcionar como sustituto de factores asociados con la diversidad arbórea.

Palabras Clave: Distribución espacial, índice de vegetación, índices de diversidad, manejo forestal, regresión espacial, riqueza de especies.

Introduction

Biodiversity loss is increasingly evident and worrisome, mainly due to the deforestation resulting from agricultural activities (Leija *et al.*, 2021); consequently, interest in measuring and modeling it has increased (Gillespie *et al.*, 2008).

The most popular strategy has been to model individual species distributions one at a time (Miller, 2010; Aceves-Rangel *et al.*, 2018; Martínez-Sifuentes *et al.*, 2021). However, spatial modeling of species diversity at the community level can generate significant benefits, particularly if many of these taxa are infrequently recorded (Ferrier and Guisán, 2006).

Remote sensing is one of the main tools available for the study and monitoring of biodiversity patterns across different spatial scales (Sánchez-Díaz, 2018), given that it is possible to assess the spectral characteristics of communities (Arekhi *et al.*, 2017). Such monitoring and evaluation is based on establishing relationships between the spectral information in an image and the tree species diversity measured in the field (Madonsela *et al.*, 2018). Likewise, vegetation indices estimated thanks to remote sensing allow us to know the different plant elements located on the surface of the Earth (Sancha, 2010; Vela-Pelaez *et al.*, 2024).

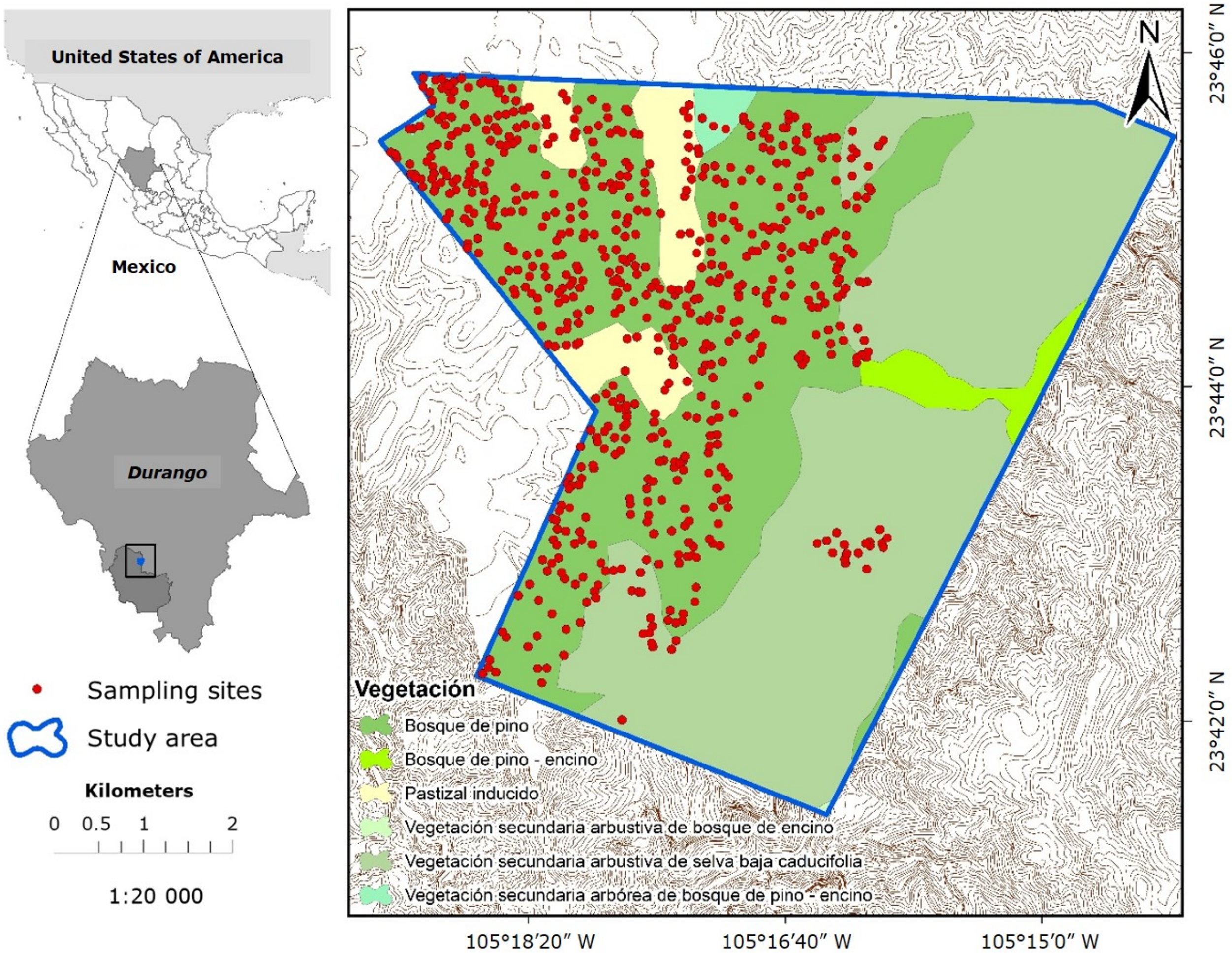
Globally, several studies have used the Normalized Difference Vegetation Index (*NDVI*) to estimate tree diversity, based on its sensitivity to primary productivity, that defines the spatial variation in plant diversity (Madonsela *et al.*, 2018). Given that such spatial variation or heterogeneity is an important driver of species richness, population structure, and complexity (Amatulli *et al.*, 2018), it is of great interest to use techniques that may help understand such variation and, consequently, in due course, make better decisions.

The main objective of this study was to reveal the spatial relationship between tree diversity, *NDVI*, and certain environmental variables according to the Geographically Weighted Regression model. The hypothesis is that the relationship between tree diversity, the *NDVI*, and environmental variables vary across space.

Materials and Methods

Study area

The study area included the *Adolfo Ruiz Cortines ejido*, located in *Pueblo Nuevo* municipality, in the Southwestern region of the state of *Durango*, within the Western *Sierra Madre* (Figure 1). The climates present are temperate sub-humid C(w_2) and semi-warm sub-humid (A)C(w_2), with an average annual precipitation of 1 000 mm. The altitude above the sea level varies between 2 063 and 2 670 m (Rosales, 2016). The main vegetation types are mixed forests composed of the genera *Pinus* L. and *Quercus* L., the most representative vegetation types being pine forest (P), pine-oak forest (Pq) and oak-pine forest (Qp) (Rosales, 2016).



Vegetación = Vegetation; *Bosque de pino* = Pine forest; *Bosque de pino-encino* = Pine-oak forest; *Pastizal inducido* = Induced grassland; *Vegetación secundaria arbustiva de bosque de encino* = Shrub secondary vegetation of oak forest; *Vegetación secundaria arbustiva de selva baja caducifolia* = Shrub secondary vegetation of low deciduous rainforest; *Vegetación secundaria arbórea de bosque de pino-encino* = Tree secondary vegetation of pine-oak forest.

Figure 1. Location of the study area, main vegetation types, and distribution of sampling sites.

Dasometric data

Based on information from the *ejido*'s Forest Management Program, the authors analyzed dasometric data of a total of 41 928 trees belonging to 20 species from 663 sampling sites circular in shape with a surface area of 1 000 m^2 (Table 1).

Table 1. Analyzed species and number of trees.

Species	Number of trees
Pinus cooperi C. E. Blanco	561
Pinus durangensis Martínez	4 150
Pinus leiophylla Schiede *ex* Schltdl. & Cham.	7 532
Pinus teocote Schltdl. & Cham.	2 645
Pinus engelmannii Carrière	2 138
Pinus lumholtzii B. L. Rob. & Fernald	54
Pinus ayacahuite C. Ehrenb. *ex* Schltdl.	52
Pinus chihuahuana Engelm.	1
Juniperus deppeana Steud.	1 813
Cupressus spp.	1
Quercus sideroxyla Bonpl.	7 211
Quercus durifolia Seemen	1 253
Quercus laeta Liebm.	257
Quercus eduardii Trelease	195
Quercus crassifolia Bonpl.	21
Quercus splendens Née	132

Quercus rugosa Née	9 963
Alnus acuminata Kunth	3
Alnus spp.	10
Arbutus xalapensis Kunth	3 936

As indicators of alpha diversity, the total number of species (species richness *S*) and Simpson's Diversity Index (*1*) (Equation 1) (Simpson, 1949; Peet, 1974) were measured at each site, and, given that their value is inverse to the evenness (Equation 2) (Lande, 1996), diversity can be calculated as follows:

$$1 - D \qquad (1)$$

$$D = \sum\left(\frac{n}{N}\right)^2 = \sum(pi)^2 \qquad (2)$$

Where:

n = Number of trees of a particular species

N = Number of trees of all the species

pi = Proportional abundance of the species

Also utilized was the Shannon Index (Equation 3), which measures the average degree of uncertainty in predicting to which species a tree chosen at random from a collection will belong (Peet, 1974; Magurran, 1988). It acquires values between 0, when there is only one species, and the logarithm of *S*, when all the species are represented by the same number of trees (Magurran, 1988).

$$H^{´} = -\Sigma\, pilnpi \qquad (3)$$

Where:

$H^{´}$ = Shannon's Index

pi = Proportional abundance of the species

ln = Natural logarithm

NDVI and climate data

The *NVDI* was computed monthly and annually, using the Landsat 8 Surface Reflectance Tier 1 image set (30 m spatial resolution) in the Google Earth Engine® platform. These data have been atmospherically corrected using the LaSRC algorithm and include a cloud, shadow, water, and snow mask produced with CFMask and a per-pixel saturation mask. The images used correspond to the period from January 1, 2020 to December 31, 2020. One image was used for each month of the year with the least amount of clouds, and for the annual *NDVI* data, an average of the 12 images was calculated. Subsequently, the images were cropped to fit the study area.

In addition, data were obtained on mean annual precipitation and minimum, mean and maximum temperatures. These data were recorded in raster format (600 m spatial resolution) through the Digital Climate Atlas of Mexico and represent the average for the period 1902-2011 (Instituto de Ciencias de la Atmósfera y Cambio Climático, 2009).

Geoprocessing

Sampling sites were georeferenced and linked to the diversity index in a point-type shapefile. To match the diversity index data for each sampling site with the *NDVI* and climate information, a data extraction process was performed in ArcGIS 10.8® (ESRI, 2020), which consisted of extracting cell values from a raster based on a set of coordinate points. The resulting file was a point-type shapefile with attributes of coordinates, sampling site number, total number of trees per site, number of trees per species, diversity index values, monthly and annual average *NDVI* values, and climatic data of mean annual precipitation and minimum, mean and maximum temperatures.

Statistical analysis

An Exploratory Regression analysis was carried out using the ArcGIS 10.8® (ESRI, 2020) software to generate regression models that would explain the relationship between tree diversity and the *NDVI* and climate data. The dependent variables were the values of tree diversity indices, and the independent variables were the values of the *NDVI*, climate data, and the number of trees in each sampling site. In this analysis, all possible combinations of the candidate independent variables were evaluated. Unlike Stepwise Regression, which looks for models with high adjusted R^2 values, Exploratory Regression tracks models that meet all the requirements and assumptions of the Ordinary Least Squares (OLS) method (ESRI, 2024).

Subsequently, to analyze the spatial pattern of the relationship between tree diversity and the *NDVI*, climate data, and number of trees, the models obtained using the Exploratory Regression were integrated into the Geographically Weighted Regression (GWR) model (Equation 4); *i. e.*, the same models were utilized, but the spatial component (location) was incorporated in their structure. The method fits a regression model for each observation (in this case for each sampling site) based on data from close neighbors and, under a concept of distance (bandwidth), gives more weight to the closest neighbor and vice versa (Brunsdon *et al.*, 1996). The optimal bandwidth for each model was identified using an adaptive kernel function that was evaluated by minimizing the Akaike Information Criterion (*AIC*) (Fotheringham *et al.*, 2002). According to Fotheringham *et al.* (2002), the model can be expressed as follows:

$$yi = \beta_0(ui, vi) + \sum_{k=1}^{n} \beta_k(ui, vi)x_{ik} + ei \qquad (4)$$

Where:

yi = Dependent variable

β_0 = Intercept

(u, v) = Coordinates the i^{th} observation

k = Number of independent variables

β_k = Slope

x_{ik} = Independent variables

e = Model error

The Geographically Weighted Regression model was fitted in GWR 4.0.90 software (Nakaya, 2015), which also fits the Ordinary Least Squares (OLS) regression model and through an *F*-test compares the improvements of the GWR model about the OLS model (Nakaya, 2016).

Results

Exploratory Regression Analysis

An Exploratory Regression analysis indicated the combination of independent variables that best met the assumptions of the OLS method for each model. The independent variables for the regression model explaining species richness (*S*) were the *NDVI* values for the month of March ($NDVI_{March}$), the number of trees present at each site, and the mean annual rainfall. For the Simpson (*1-D*) and Shannon (*H*) index models, the independent variables were the values of the January *NDVI*

($NDVI_{January}$) and the number of trees. All variables were statistically significant ($p \leq 0.05$).

OLS regression models

The regression equations adjusted for the diversity indices and their explanatory variables through OLS showed a low explanation of the observed variation (R^2). The values of the variance inflation factor (VIF) of the explanatory variables of the diversity indexes did not show multicollinearity issues, as in all cases the values were lower than the reference value (7.5). In addition, the regression coefficients indicated that, in all cases, the *NDVI* was the variable of greatest relative importance, followed by the number of trees. In the case of species richness (*S*), the variable of least relative importance was precipitation (Table 2).

Table 2. Regression coefficients of OLS models adjusted for diversity indices.

Index	Variable	Regression coefficient (*β*)	*P* value	Standard error	*AIC*	R^2
Species richness (*S*)	Intercept	9.1347	0.000	2.09	2 239.05	0.15
	$NDVI_{March}$	2.0978	0.002	0.68		
	Number of trees	0.0178	0.000	0.002		
	Rainfall	-0.0055	0.033	0.002		
Simpson (*1-D*)	Intercept	0.6621	0.000	0.02	-921.9	0.005
	$NDVI_{January}$	0.1617	0.045	0.08		
	Number of trees	0.00005	0.007	0.0001		
Shannon (*H*)	Intercept	1.3146	0.000	0.05	286.09	0.01
	$NDVI_{January}$	0.4071	0.048	0.2		
	Number of trees	0.0009	0.033	0.0004		

AIC = Akaike Information Criterion.

GWR models

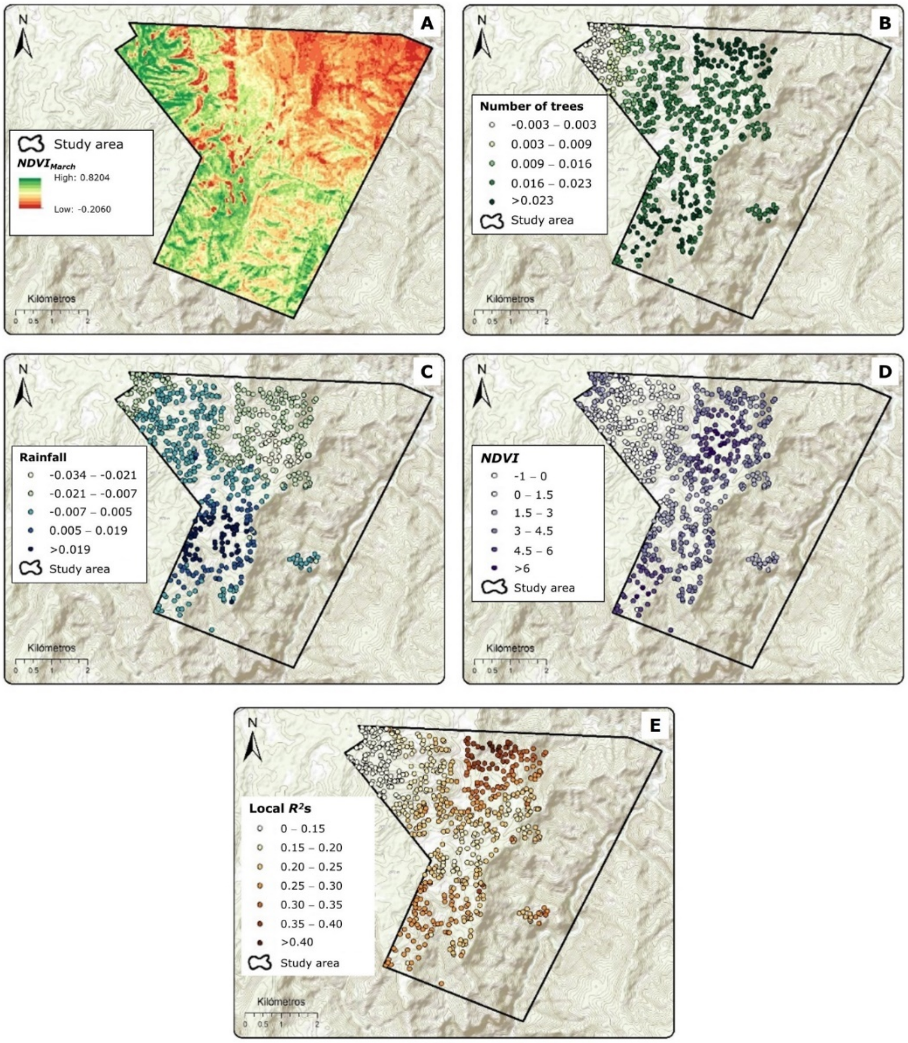
The number of spatial units (sampling sites) considered for the fit of the GWR models was 663, the bandwidth was defined as 48 neighbors for the species richness (*S*) model and 46 for the Simpson and Shannon index models. The fitted GWR models showed lower *AIC* values than those obtained with the OLS models. These *AIC* values were 2 174.42 for the species richness (*S*) explanatory model, -1 000.37 for the Simpson's Index model, and 195.72 for the Shannon Index model. The above indicated that the GWR models had an improvement in error reduction, concerning the OLS models. In addition, based on the *F*-tests, the reduction in the sum of squares of GWR was determined to be significant ($p<0.05$) in all cases. This suggests that the GWR models are statistically different from the OLS models. Regarding the regression coefficients of the GWR model, it was also observed that the variable with the highest relative importance was the *NDVI* in all cases (Table 3).

Table 3. Summary statistics of the regression coefficients of the fitted GWR models for the diversity indices.

Index	Variable	Mean	Standard deviation	Minimum	Maximum	Average *t*-value
Species richness (*S*)	Intercept	6.8749	12.4785	-26.6498	33.518	1.4216
	$NVDI_{March}$	2.3361	2.1847	-1.9417	6.4714	1.4187
	Number of	0.0183	0.0076	-0.0038	0.0307	3.8003

	trees					
	Rainfall	-0.0031	0.0136	-0.0344	0.0325	-0.5272
Simpson (*1-D*)	Intercept	0.5869	0.0683	0.4305	0.7446	12.1779
	$NDVI_{January}$	0.6939	0.5533	-0.1278	2.3567	2.0044
	Number of trees	-0.00005	0.0008	-0.0024	0.001	-0.1102
Shannon (*H*)	Intercept	1.1338	0.1859	0.6952	1.5882	9.6453
	$NDVI_{January}$	1.7722	1.5229	-0.9463	5.8945	2.0255
	Number of trees	0.0005	0.0019	-0.0049	0.0028	0.5003

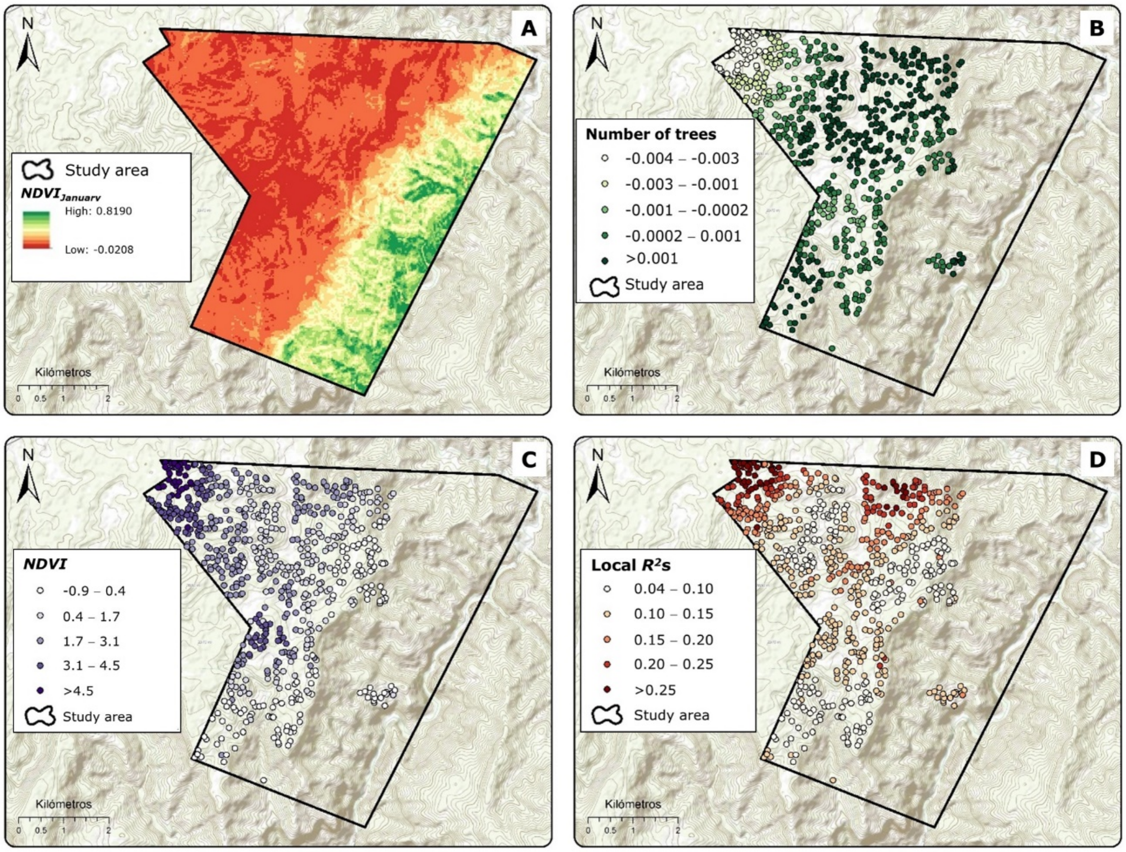
The GWR approach allowed the mapping of model statistics and the analysis of their spatial variability. Figure 2A shows the spatial distribution of the $NDVI_{March}$ that corresponded to the one with the highest association with the species richness. The highest values of the regression coefficients of the number of trees tend to be distributed in the Northern part of the property (Figure 2B). Rainfall had a positive relationship with species richness in some spatial units, while in others it had a negative relationship (Figure 2C). The highest values for the regression coefficients of $NDVI_{March}$ were distributed in the Central-Northern part of the property, and the lowest, in the Northwestern portion (Figure 2D). Regarding the spatial variation of the coefficients of determination (local R^2s), the highest values were registered in the Northern part of the property (Figure 2E). This variability in the local R^2s indicates the locations where the variables explain the diversity indices to a greater or lesser extent.



A = Regression coefficient; B = Regression coefficients associated with a number of trees; C = Regression coefficients associated with rainfall; D = Regression coefficients associated with the *NDVI*$_{March}$; E = Local R^2s. *Kilómetros* = Kilometers.

Figure 2. Spatial distribution of GWR statistics for species richness.

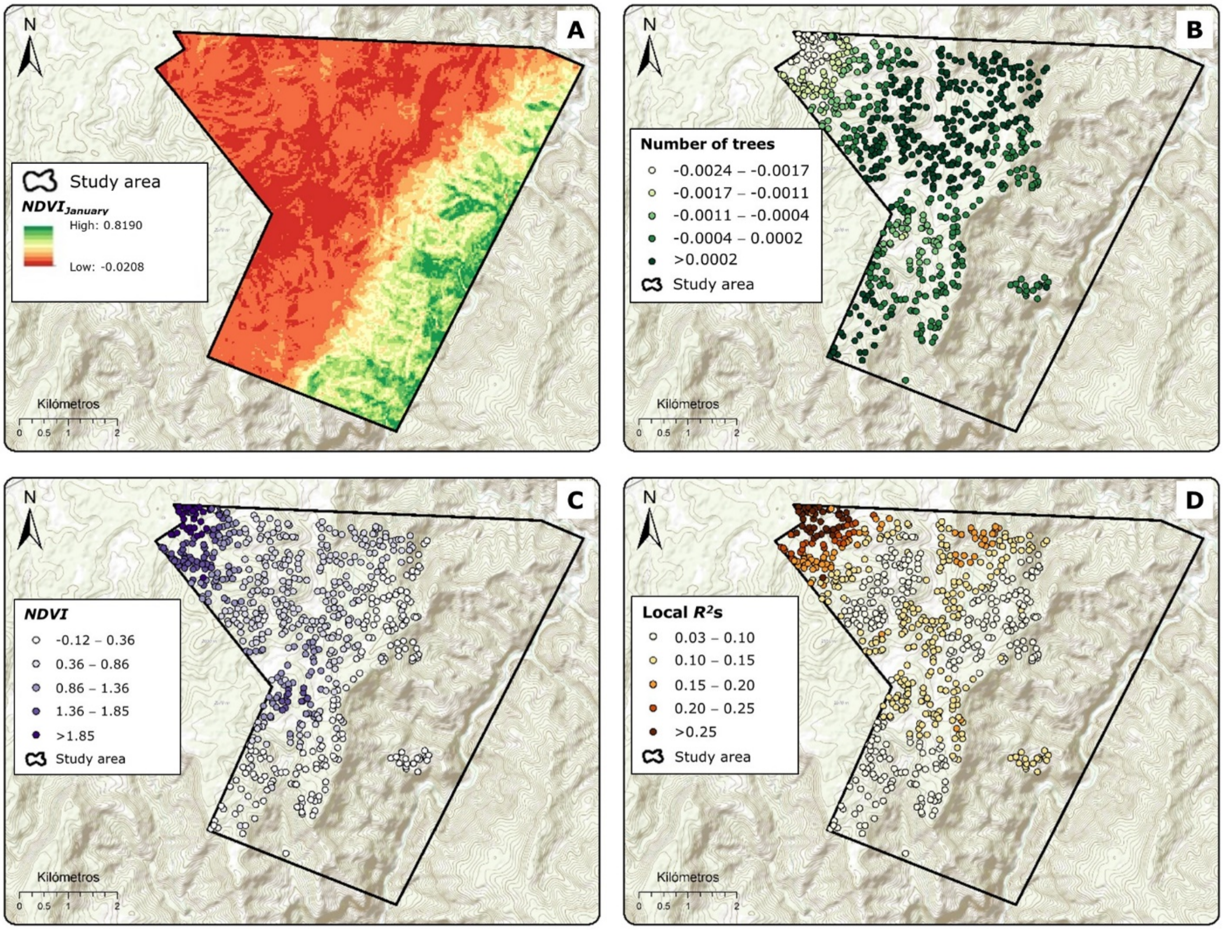
Figure 3A shows the spatial distribution of the *NDVI January*, which exhibited the highest association with the Shannon index. The Regression coefficient of the number of trees had the lowest relative importance of the analyzed variables (Figure 3B). The highest values of relative importance for a number of trees showed a tendency to be distributed in the Northern part of the property. The Regression coefficient of the $NDVI_{January}$ registered the highest relative importance, with the highest values distributed toward the Northwest of the property, while the lowest values were for the Northeast to Southwest area (Figure 3C). Finally, the local R^2s had the highest values in the Northwest of the site, where the $NDVI_{January}$ showed the highest relative importance. The lowest values were distributed in most of the analyzed samples (Figure 3D).



A = $NDVI_{January}$; B = Regression coefficient associated with a number of trees; C = Regression coefficients associated with $NDVI_{January}$; D = Local R^2s. *Kilómetros* = Kilometers.

Figure 3. Spatial distribution of GWR statistics for Shannon index.

The spatial distribution of $NDVI_{January}$ showed the strongest association with Simpson's index (Figure 4A). The Regression coefficient of the number of trees registered the lowest relative importance of all the variables analyzed (Figure 4B); the highest values for the relative importance of number of trees were distributed in the Northern, Central, and Southern parts of the total distribution of the sites within the property. The lowest values were clustered to the Northwest of the property boundary and shared this distribution zone with the highest *January* values. The lowest values of the *January regression* coefficient were recorded from Northeast to East and South (Figure 4C). The local R^2 values followed the same distribution pattern (Figure 4D).



A = $NDVI_{January}$; B = Regression coefficient associated with a number of trees; C = Regression coefficients associated with $NDVI_{January}$; D = Local R^2s. *Kilómetros* = Kilometers.

Figure 4. Spatial distribution of GWR statistics for Simpson's index.

Discussion

Understanding how species diversity varies across space and exploring the processes and driving mechanisms involved have been fundamental goals of ecology (Balvanera and Aguirre, 2006) and have contributed to the development of different estimation methods that make it possible to improve the traditional classification methods (Hernández-Stefanoni *et al.*, 2012).

In this study, the spatial variation of the relationship of tree diversity indices with *NDVI* values, climate data, and number of trees was analyzed using the GWR model. The use of spatially adjusted regression models, such as the GWR, improves the estimation of the statistics in comparison with OLS (Mallick *et al.*, 2021; Cabral-Alemán *et al.*, 2022; Lu *et al.*, 2022); this was also observed in the present study. In addition, the use of GWR allowed the visualization of the predictive power of the independent variables analyzed, as well as the spatial distribution of the statistics and their respective mapping.

Notably, it was determined that the relationship of tree diversity indices with *NDVI* values, climatic data, and number of trees varied across space. Likewise, the explanatory power of each adjusted GWR model showed a tendency to vary in space; that is, there are areas where the R^2 was higher: for example, in the Northern and Northwestern part of the study area. It should be noted that these areas coincide with the most productive areas of the property in terms of biomass and carbon (Cartus *et al.*, 2014; Vargas-Larreta *et al.*, 2017). In addition, in these areas, a higher relationship between the *NDVI* and tree diversity was observed; this can be explained by the direct relationship between the biomass and structural variables and the *NDVI* (Meng *et al.*, 2016). Thus, the relaionship between IVDN and tree diversity supports the positive productivity-diversity assumption, which states that the relationship between productivity and species diversity follows an environmental gradient (Madonsela et al., 2017). Another important finding was the relationship of the diversity indices with the *NDVI* of different months; that is, species richness was more closely related to the $NDVI_{March}$, while the Simpson's and Shannon's indices showed a closer relationship with the $NDVI_{January}$. These results are consistent with some precedents indicating that diversity indices tend to relate mostly to monthly *NDVI* values rather than to annual values (Meng *et al.*, 2016; Madonsela *et al.*, 2017); this has been directly related to the beginning of the growing season, as the onset of leaf senescence in trees marks an increase in *NDVI* values (Lu *et al.*, 2022). For the study area, the growing season begins after cold conditions (January-March), characterized by low evaporation and greater soil moisture (Chávez-Gándara *et al.*, 2017), agreeing with the period when the *NDVI*-diversity ratio was higher.

As for the relative influence of the explanatory variables of diversity, the *NDVI* was the most influential in explaining diversity indices; thus, it is an important predictor of tree diversity (Arekhi *et al.*, 2017; Madonsela *et al.*, 2018), and functions as a surrogate for factors associated with species diversity (Hernández-Stefanoni *et al.*, 2023).

Another variable that helped explain the variability in the values of the diversity indices was the number of trees, which is the second variable in relative importance. This relationship is logical, given that diversity indices are a function of the relative distribution of individuals among species (Salami *et al.*, 2021).

On the other hand, many other factors influence species diversity, mainly climate, topography, and soil properties (Song *et al.*, 2021). However, the relative contribution of each variable may vary from one region to another (Song *et al.*, 2021). Particularly, in the present study, no significant relationships were obtained between certain diversity indices and climate data. However, it was determined that rainfall may be a predictor of species richness in the study area, although this relationship has been more evident at larger scales (Xu *et al.*, 2019).

Finally, as mentioned in similar studies, these types of results should be restricted to the working area, as they may be modified depending on the species examined, the environment, or the overall community members (Kiran and Mudaliar, 2012).

Conclusions

The relationship of diversity indices with *NVDI*, climate data, and a number of trees varies across space. The independent variables show greater predictive potential in the Northern and Northwestern parts of the study area; these results support the research hypothesis. *NDVI* has a high predictive power; therefore, it can function as a proxy for factors associated with tree diversity.

GWR is an effective method for analyzing the relationship between tree diversity and associated factors; in addition to being a technique that improves the results, it also contributes to the explanation of the spatial distribution of tree diversity.

Finally, these results serve as a basis for similar research in the region, and the use of statistical models that include the spatial component is recommended for a better understanding of diversity patterns and associated factors.

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Conflict of interest

The authors declare that they have no conflicts of interest.

Contribution by Author

Jesús Emmanuel Méndez-Zúñiga: planeación, levantamiento y análisis de datos, redacción del manuscrito; José Manuel Zúñiga-Vásquez: análisis de datos y revisión del manuscrito; José Guadalupe Colín: dirección, planeación, seguimiento del proyecto y revisión del manuscrito.

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