

SPATIAL PATTERNS IN PLANT STRUCTURAL DIVERSITY ACROSS A SHRUB
ENCROACHMENT–NATIVE GRASSLAND LANDSCAPE MOSAIC
IN THE NORTHERN CHIHUAHUAN DESERT.

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by

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THESIS

Presented to the Faculty of the Graduate School of

The University of Texas at El Paso

in Partial Fulfillment

of the Requirements

for the Degree of

MASTER OF SCIENCE

Department of Biological Sciences

THE UNIVERSITY OF TEXAS AT EL PASO

December 2025

Acknowledgements

Words cannot express my deep gratitude to my research advisor, Dr. Elizabeth LaRue, for guiding me, providing critical feedback, continuous support, and mentorship throughout the research journey. I wish to express my sincere gratitude to my committee members – Dr. Anthony Darrouzet-Nardi, Dr. Marguerite Mauritz-Tozer, and Dr. Richard P. Langford for their invaluable insights from my proposal defense through to thesis completion.

I would like to thank NEON (National Ecological Observatory Network) and the Jornada Experiment Range (JER) for providing essential data for my study. Many thanks to my lab mates—Kylie, Anna, Eli—and my classmates, Talveer and John, for their support and encouragement. Lastly, I am profoundly grateful to my family back in Nepal, whose faith in me has given me the strength to reach this far, and to my husband for his constant emotional support and encouragement throughout this academic journey.

Abstract

Drylands are heterogeneous landscapes that provide important ecosystem services, but they are threatened by global change factors that may influence aspects of their diversity and function. Environmental factors may influence the three-dimensional physical characteristics of vegetation structure (structural diversity) across spatial scales in arid ecosystems. This study investigated how environmental factors, including shrub cover, landform, and elevation, are related to vegetation structural diversity metrics across different spatial scales and scopes across the Jornada Experimental Range, a long-term ecological research site located in the northern Chihuahuan Desert. A canopy height model generated by Airborne Observation Platform (AOP) LiDAR data and collected by the National Ecological Observatory Network in 2022 were used to derive structural diversity metrics across the dryland landscape: mean height, maximum height, and top rugosity. Structural diversity metrics and environmental predictor rasters were aggregated to 10 m, 20 m, and 40 m spatial grain sizes and cut to spatial extents of 50 m, 100 m, and 200 m, respectively which produced two spatial scopes (extent-to-grain ratios) with two to three sets of absolute scale datasets (fixed grain size with different extent sizes). A total of 56 non-overlapping plots were randomly selected across the study area. Non-parametric tests, including Spearman's Rank Correlation and the Kruskal-Wallis test, were used to investigate how environmental variables -shrubs cover, elevation, and landform type - were associated with structural diversity at different scales, i.e., within similar scope (extent-to-grain ratios) or absolute scales (different grain and extent combinations). The proportion of shrub cover was a significant negative correlate of vegetation structure metrics in the Jornada dryland landscape, showing that denser shrub cover is associated with a decrease in structural diversity. However, models with shrub cover as a predictor of structural diversity only occurred at one scope value (Scope value = 100), while the other scope value of 25, did not display a similar significant trend. In contrast, elevation and landforms were not significantly associated with structural diversity, which was consistent across all spatial datasets (scope or absolute scale). My findings emphasize that ecological patterns do not act

uniformly across spatial scales in the landscape and that the absolute spatial scale and scope value require careful consideration when selecting the appropriate values for ecological studies in drylands.

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1. Introduction

Drylands are heterogeneous landscapes that cover a significant portion of the Earth's surface and support diverse plant communities (Maestre et al., 2021; Právělie, 2016). This heterogeneity arises from the dynamic interactions of both natural and anthropogenic factors (Reynolds et al., 2007). Geological aspects, including water distribution and landform morphology, act as the natural drivers of dryland heterogeneity (McAuliffe, 1994; Monger & Bestelmeyer, 2006). For instance, the increase in aridity and drought in drylands with soil erosion may exacerbate land degradation, affecting vegetation patterns, including the establishment of shrubs and the changes in grass cover (Ravi et al., 2010). Human activities, such as grazing, land-use change, and fire, further accelerate the dynamics of vegetation change (Archer 2017).

Drylands possess immense value in supporting human well-being and biodiversity (Hassan & Dregne, 1997; Mitsugi, 2019), but a major threat they face is shrub encroachment (Alvarez et al., 2011; Maestre et al., 2016). Shrub encroachment is common in arid and semiarid biomes (Alvarez et al., 2011; Eldridge et al., 2011; Huang et al., 2018; Turnbull & Wainwright, 2019) and is defined as an increase in the density, cover, and biomass of shrubs (Eldridge et al., 2011). Shrub encroachment causes shrubs to dominate, significantly affecting plant diversity. For instance, dense shrub cover reduces the number of plant species, decreasing overall diversity (Zehnder et al., 2020). While in the dryland ecosystems, shrub encroachment is a gradual process that is thought to be at least partially triggered by soil moisture redistribution, which shifts from a grass-dominated condition to a mixed-shrub stage and eventually to a shrub-dominated landscape, leading to loss of ecological functions (Cao et al., 2019). Grasslands are considered more valuable than shrublands in the context of pastoral production (Eldridge et al., 2011). However, these delicate ecosystems that cover 6.1 billion acres worldwide (Hassan & Dregne, 1997) have been destabilized and transformed into shrublands (Archer, 2009).

Water runoff due to elevational changes in arid and semi-arid regions, results in landform development that can also influence the vegetation structure of plant communities. Landforms tend

to determine the transition of plant communities across space (Wondzell et al., 1996). Complex landscapes such as alluvial fans, playas, and rocky uplands create a mosaic that influences the ecological zones and determines the types of plant structures that thrive (McAuliffe, 1994). For example, Rachal et al. (2012) indicated that landform-driven environmental variation influences long-term composition of plant communities. The research highlighted that sandy alluvial plains, bajadas, and sand sheets tended to have more shrub dominance, whereas low-lying playas and alluvial fan collars were more often grass-dominated. Elevation governs the composition of vegetation and the distribution of species with respect to the availability of moisture and temperature, as a change with altitude (Allen et al 1991). A study on small desert mountains (elevations < 500 m) by Mata-González et al. (2002) demonstrates diverse patterns; grasses diminish with increasing elevation on north and east aspects, while they increase on south and west aspects. Similarly, succulents prevail at lower elevations in south and west aspects but decline at higher elevations in desert mountains. Furthermore, research on the distribution patterns of plant diversity along elevation at the intersection of temperate grasslands and desert ecosystems (He et al., 2023) has shown that shrub and herb diversity increase from lower to mid-elevations and then decrease at higher elevations, due to changes in resource availability and climatic conditions. However, these studies focused on taxonomic diversity rather than other dimensions of diversity that might also be impacted by landform and elevation.

To mitigate the impact of ecological degradation on drylands, it is crucial to understand how different aspects of diversity, including structural diversity, are related to landscape heterogeneity, such as shrub cover, landform, and elevation (Eldridge et al., 2011; LaRue et al., 2023; Maestre et al., 2016; Titulaer et al., 2024). Plant diversity is known to support ecosystem productivity through the unique niche-specific roles and efficient resource utilization of individual plants (Liang et al., 2015). Structural diversity is thought to provide more niche space than species diversity via the stratification of functional structural traits throughout the canopy (Forrester & Bausch, 2016), supporting various ecosystem functions (LaRue et al., 2023). Similar work shows that structural diversity is an essential predictor of forest ecosystem function and biodiversity (Ali,

2019; Ali et al., 2019; Gough et al., 2019; Hinsley et al., 2002; Jennings et al., 1999; Kovács et al., 2017; Michel & Winter, 2009; Zeller & Pretzsch, 2019), which may also extend to drylands, where vegetation cover, space, and patch size influence ecosystem stability to withstand environmental stress (Maestre et al., 2016). Structural diversity may, therefore, be an important dimension of diversity for promoting ecosystem function in drylands, but this is not well understood, especially with regards to its spatial patterns and potential landscape drivers.

Research on structural diversity has often been neglected in ecological studies, not because its environmental importance is not recognized, but because it involves technological measurement constraints. Traditional field tools, such as measuring tapes and calipers, are limited to a small extent (Atkins et al., 2023). However, recent remote sensing technological advancements, such as airborne lidar, have provided new insights into data collection by integrating data across large scales and expanding our understanding of ecological phenomena. These technologies can directly measure vegetation height and canopies in three dimensions (Getzin et al., 2017; Zhang et al., 2017) including in shrublands. Understanding the landscape patterns and associated drivers of plant diversity patterns across spatial scales is crucial for developing practical management actions to better understand and protect dryland ecosystems (Jones et al., 2021). However, the landscape patterns of structural diversity in drylands have yet to be well investigated. Specifically, we do not know how they vary with factors such as shrub dominance (cover), elevation, and soil landform in the drylands of the northern Chihuahuan Desert.

By analyzing vegetation's spatial distribution, we can better understand plant community dynamics, but ecological patterns and processes can change across spatial scales (Wiens, 1989; Wu et al., 2003). Absolute scale is the relative size of the observation (i.e., the absolute value is the combine of the grain as the smallest spatial unit and extent as the overall spatial area of a study) or overall study area (Frazier et al., 2023; Wiens, 1989). The effect of changing the spatial scale (grain and extent) on pattern analysis, especially on landscape metrics (Turner et al., 1989), landscape genetics (Cushman & Landguth, 2010), and surface metrics (Frazier, 2016), have been well documented. Both grain and extent provide valuable spatial information on their own, but

Frazier (2023) argued that to ensure the maximum ability to capture relevant data without losing information, that we should carefully set the grain and extent using the scope formula rather than randomly assigning their values. The scope formula is the dimensionless ratio of the measurement's range (extent) to its resolution (grain) (Frazier, 2023; Schneider et al., 1997). In ecological studies, the spatial scope is defined as a quantitative measure that shows the ratio between the extent and the grain (Frazier, 2023). By reporting the scope, researchers can determine if specific structural diversity metrics behave predictably across different scales in drylands. As such, the use of scope might help advance the science of scaling in landscape ecology, create the study's robustness, and facilitate replications and comparisons (Frazier, 2023; Schneider, 2001), but further testing is required with landscape heterogeneity in dimensions of diversity, such as structural diversity in drylands.

Environmental factors can have a complex impact on ecosystem structures, and it is essential to understand how structural diversity might be related to it and its spatial patterns. This research aims to estimate how spatial patterns in plant structural diversity vary with shrub encroachment, elevation, and landform type in a dryland landscape in the northern Chihuahuan Desert at the Jornada Experimental Range, New Mexico, USA (Figure 1.1). Furthermore, it will test whether these patterns of structural diversity and relationships with shrub cover, elevation, and landform change with the absolute scale and spatial scope of the dataset.

Objective 1: Determine if the structural diversity of plant height varies with shrub cover, elevation, and landform within the Jornada Experimental Range, New Mexico, USA.

Prediction and Hypothesis 1.1: Structural diversity will be higher in areas of medium shrub cover because it may indicate that mixed shrub-grass communities have a greater variety of plant growth forms (architecture) compared to an area with high shrub cover that is dominated by a single growth form.

Prediction and Hypothesis 1.2: Structural diversity will increase with elevation in the Jornada landscape, because higher elevation will indicate areas of greater slope that may influence

a structurally more complex landscape that supports a structurally complex plant community than the flatter valley of Jornada.

Prediction and Hypothesis 1.3: I expect that landform type and shrub cover may interact to influence structural diversity. Some landforms, such as sand sheets alluvial plains, may facilitate shrub establishment due to their loose texture. In contrast, wind-worked alluvial plains and eroded plains may limit shrub growth, resulting in different structural diversity variations across landform types.

Objective 2: Assess the influence of absolute scale and spatial scope on the value and the relationships of structural diversity with environmental drivers across the Jornada Experiment Range.

Prediction and Hypothesis 2.1: Structural diversity and its relationship to landscape drivers will exhibit similar model results within the same spatial scope despite having different grain/extent because resolution will be more important than absolute scale values in capturing the same landscape patterns of variation in structural diversity and its environmental drivers.

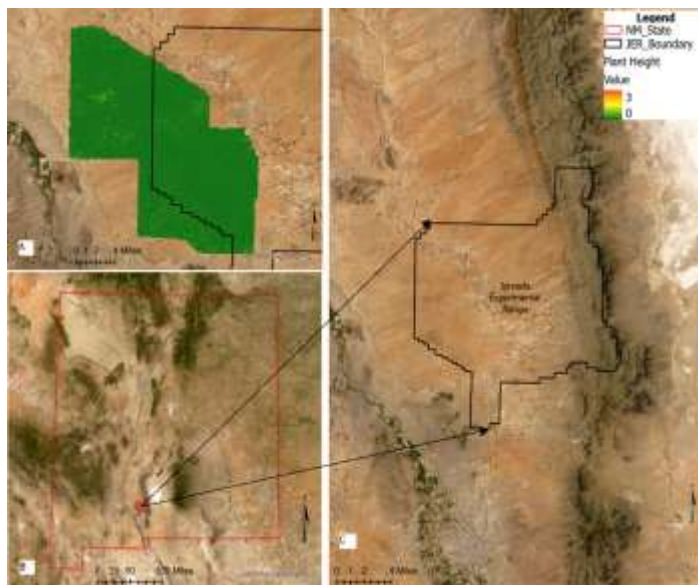


Figure 1.1: Extent of the study area in the Jornada Experimental Range, NM (a-c) and the plant height data of year 2022 (a) obtained from the NEONAOP to generate structural diversity metrics from (NEON 2025a).

2. Method

2.1. STUDY AREA

The study area was conducted using open-source datasets from the Jornada Experimental Range (JER). The Jornada is part of the Long-Term Ecological Research Network (LTER), which is situated in North America's largest desert, the Chihuahuan Desert. Typically, the vegetation of Jornada includes black grama, mesa dropseed, three-awn, honey mesquite, four-wing saltbush, broom snakeweed, and soap tree yucca, but many areas of the landscape have experienced shrub encroachment (Havstad et al., 2000). It has an arid climate with an average of 243 mm of precipitation (Wainwright 2006). The Jornada Experimental ranges from approximately 1,186m to 2,833m west of the Rio Grande flood plain and the San Andres mountains in the east, respectively (Havstad et al., 2000). Most of the study area lies at elevations (1,314-1,339 m) based on the available data from the National Ecological Observatory Network (NEON, 2025b). The landscape consists of sandy alluvial plains, alluvial fans/bajadas, sand sheets, mountain uplands, and playas, which represent the various geomorphic processes of river basin floor geomorphology in the Chihuahuan Desert (Monger & Bestelmeyer, 2006; Rachal et al., 2012) .

2.2. STRUCTURAL DIVERSITY AND ITS PREDICTOR VARIABLES ACROSS THE JORNADA EXPERIMENT RANGE

2.2.1. Structural Diversity

Plant height data from 2022 was downloaded from the National Ecological Observatory Network ecosystem structure data product from the Airborne Observation Platform (canopy height model), which is collected over the western portion of the Jornada Experimental Range (hereafter referred to as Jornada). The data is provided in a 1 km² raster tile format with a grain of 1 m (NEON, 2025a) . Plant height files were analyzed using the R terra package (Hijmans, 2024) for

geospatial analysis of rasters. The raster tiles were combined into one raster file with the `terra mosaic()` function. The resulting mosaiced raster data was further processed to filter out outlier pixels greater than or equal to 3 meters that were unlikely to represent shrubs or would be outliers due to features such as powerlines or buildings. Three structural diversity metrics were calculated using filtered data from the year of 2022, adopted by LaRue et al. (2022) (Table 1). These metrics were aggregated as the mean using the `aggregate` function across all of the 1 x 1 m pixels with each grain size (10 m, 20 m, 40 m).

Table 1.1: Structural diversity metrics of height and external heterogeneity (definitions from LaRue et al. 2022).

Category	Metric	Description
Height	MOCH (Mean of maximum height)	Mean of maximum height (in meters) in a specified area
	Maximum canopy height	Maximum canopy height (in meters) within a specified area
External heterogeneity	Top rugosity	SD (in meters) of outer canopy heights in a specified area

2.2.2. Elevation

Elevation data was obtained from the NEON portal (NEON 2025b), which includes bare earth elevation surface (DTM) in GeoTIFF format. The dataset has a spatial resolution of 1 m with 1 km x 1 km tiles. The downloaded elevation raster files were combined using the `mosaic ()` function of the `terra` package (Hijmans, 2024). The downloaded data was also aggregated with R software using the `aggregate` function at each grain size (10 m, 20 m, 40 m).

2.2.3. Shrub Cover

A high-resolution shrub cover raster map was utilized, which had a 1m resolution and shrub cover was coded as a binary variable, where 1 indicated shrub presence, 0 indicated shrub absence, and 2 represented masked areas, as published by Ji and Niall (2020). The shrub cover raster map was clipped to the extents of the structural diversity raster originally set by NEON's

AOP, after being reprojected to WGS 1984 UTM Zone 13 N using ArcGIS Pro. Cells with the 2 no data value was excluded and masked from further analysis by treating them as No Data. The cleaned clipped shrub raster data was aggregated using the aggregate function using mean to get a proportion of shrub cover across each grain size (10 m, 20 m, 40 m), resulting in a continuous raster, using R software.

2.2.4. Landform

Landform data in a KMZ layer were downloaded from the Jornada website for the landform type data (Jornada Basin LTER, 2025; Monger & Bestelmeyer, 2006). The KMZ layer was first converted into a polygon feature class. Then, the landform code field was added to the attribute table. The list consists of 26 unique landform names with each unique integer landform code was created using the summarized function. The table is then joined to the original polygon layer so that all polygon layers sharing the same landform type have the same integer value. Next, the polygon layers were converted to raster layers using landform code as the value field with 1m resolution to maintain consistency with other datasets. Then the converted raster was projected to the WGS 1984 UTM Zone 13N, clipped to the structural diversity data extent, and saved in the .tiff format for further analysis. After clipping to the structural diversity data extent, only 6 landform types remained. Due to the low representation of some categories, such as Alluvial flat, Alluvial plain, Sand sheets over Gypsiferous Landforms, were removed, resulting in a final set of three dominant landform types: Alluvial plain eroded, Alluvial plain Reddish Brown Sand Sheet, and Alluvial plain wind worked. Since the landform data are categorical, I aggregated a 1m landform raster to each grain size (10 m, 20 m, 40 m) using the aggregate () function with modal function in R software from the terra package to ensure that aggregated cells represent the dominant landform type.





2.3. GENERATING COMPARABLE DATASETS VARYING IN SCALE AND SCOPE

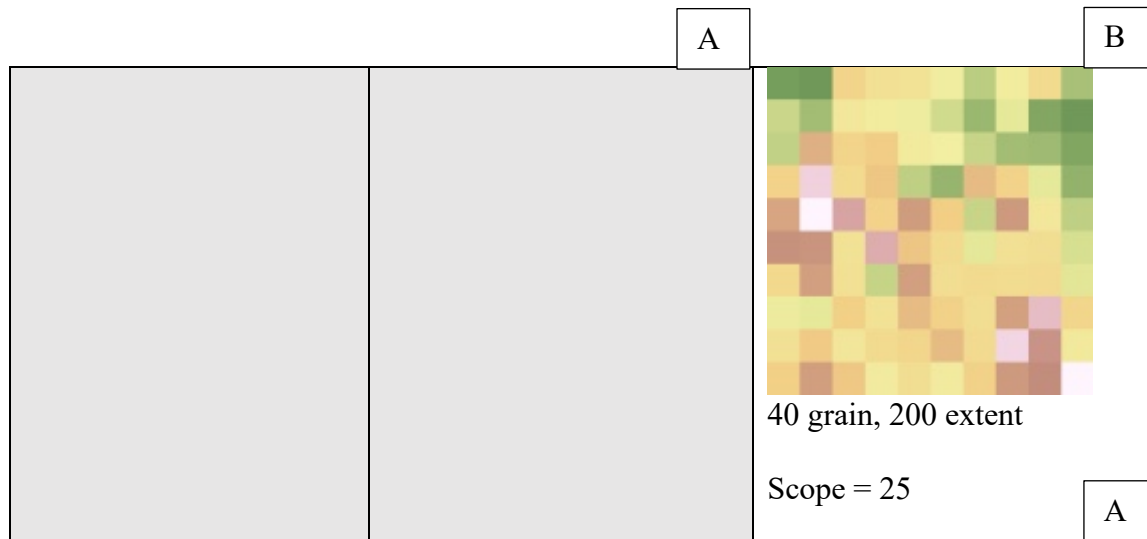
The scope is defined as the dimensionless ratio of the extent to the grain (Schneider, 2001). To assess the influence of scope on the structural diversity matrix (plant height), different extents and grain sizes with similar scope values were selected as in Figure 2. The resolution (cell size) of all variables packaged as rasters was 1m, whereas landform was a polygon that was split into the appropriate grains. Therefore, for this research, scopes with similar scope values (25,100) and grain sizes (10 m, 20 m, and 40 m) and extent sizes (50 m, 100 m, and 200 m) were used (Table 1.2). The same scope with different grains and extents was set following Frazier's (2023) concept. The absolute scale in this study is defined by the combination of grain and extent sizes (e.g., combination of 10 grain, i.e., 10 grain, 50 extent, and 10 grain, 100 extent; combination of 20 grain, i.e., 20 grain, 100 extent, and 20 grain, 200 extent).

2.4. SAMPLING METHODS OF RANDOM POINTS

The structural diversity raster was clipped to the JER extent. Then, 250 random points were generated at least 1000 m away from the edge. Each point was buffered by 250 m around each point. Shrub cover with greater than two or missing values from plant height was removed. Finally, 60 random points were retained after applying a 300 m buffer to avoid overlapping points that might vary in their extent in clipping data extents in the next steps. During the data cleaning process, the soil category with fewer than four data points was excluded, resulting in a final dataset of 56 random points for all subsequent analysis.

Table 1.2: Representative raster of structural diversity metric top rugosity at one randomly selected location (325561 easting, 3609754 northing) for which three different grain sizes (10 m, 20 m, and 30 m grain) and three different extents were extracted to create two different scope values (25, 100). Extremely high (e.g., 400) and low (e.g., 6.25 and 1.56) ratios from the possible combinations of grains and extents in the table were excluded due to it being unfeasible to aggregate to those values or a lack of replicates across different grain/extent values for the same scope. Scope A is 25 and B is 100. The absolute scale was selected by combining the different grain and extent sizes (e.g., 10 grain, 50 extent and 10 grain, 100 extent, 20 grain, 100 extent and 20 grain, 200 extent)

 10 grain, 50 extent Scope = 25 <div>A</div>	 10 grain, 100 extent Scope = 100 <div>B</div>	
	 20 grain, 100 extent Scope = 25	 20 grain, 200 extent Scope = 100



2.4.1. Grains

Using the “terra” Raster package, the structural diversity metrics, shrub cover, and elevation were aggregated to 10 m, 20 m, and 40 m grain sizes. Since the landform data was categorical, they were aggregated at each grain size (10 m, 20 m, 40 m) using the modal function to ensure that the aggregated cells represented the dominant landform type.

2.4.2. Extents

For the continuous variables - structural diversity metrics, shrub cover, and elevation, aggregated grain size of 10 m, 20 m, and 40 m were used to extract around 56 random sampling points. Each point was then buffered by 50 m, 100 m, and 200 m using square buffers from the sf package in R (Pebesma & Bivand, 2023). The values were then extracted and combined with the original data and exported in .csv format using R software.

Aggregated landform data with 10 m, 20 m, and 40 m grain sizes were converted into integer raster using INT geoprocessing tools, as ArcGIS does not treat floating-point values as categorical data. Then, 56 random points were added and converted to points in ArcGIS. A buffer of 50 m around random points was created. Aggregated 10 m landform data was extracted using zonal statistics as a table with statistics type majority. After that, the extracted 10 m landform data

was joined to the 50 m buffer point, and the table was exported in .csv format. The same method was applied to different extents and grain values, creating unique combinations of grain and extent.

2.5. STATISTICAL ANALYSIS

The statistical analyses were executed using R software (version 4.4.2). Spatial preprocessing was conducted in ArcGIS Pro to generate variables at different scales. Histograms, Q-Q plots, and the Shapiro-Wilk test were utilized to assess the normality of response variables. However, the response variable did not meet the assumptions of normality even after the transformation in the initial parametric models.

Given the issues, Spearman's rank correlation was performed to predict the relationship between structural diversity with shrub cover or elevation. Furthermore, a Kruskal-Wallis test was used to evaluate the differences in landform types. Specifically, for the landform as the categorical variable, Kruskal-Wallis was utilized to investigate differences in structural diversity among landform types. Each scope and absolute scale (grain/extent combo) was run as a separate model for each of the above tests. These tests assessed how structural diversity was related to environmental predictors and evaluated whether the relationships remained consistent across datasets with varying scopes and scales.

3. Results

3.1. DISTRIBUTION OF STRUCTURAL DIVERSITY METRIC VALUES ACROSS SCOPE AND ABSOLUTE SCALE DATASETS ON THE JORNADA EXPERIMENTAL RANGE LANDSCAPE

Ridgeline graphs for the three structural diversity metrics: maximum height, mean height, and top rugosity, were examined to evaluate the distribution of values of sampling locations across the Jornada landscape between scope (extent-to-grain ratio) and absolute scale datasets for each structural diversity metric. The distribution of structural diversity metrics across different absolute scales and scope combinations were similar for mean height and top rugosity but showed more variation among datasets for maximum height (Fig. 1.2). Maximum height displayed a slightly higher and bimodal distribution at larger extents (40g_200e, 20g_200e, 20g_100e), transitioning to a unimodal form as extent decreased (10g_50e, 10g_100e). However, the distributions did not distinctly separate by scope. Mean height and top rugosity exhibited comparable distributions across a closer absolute scale and scope range.

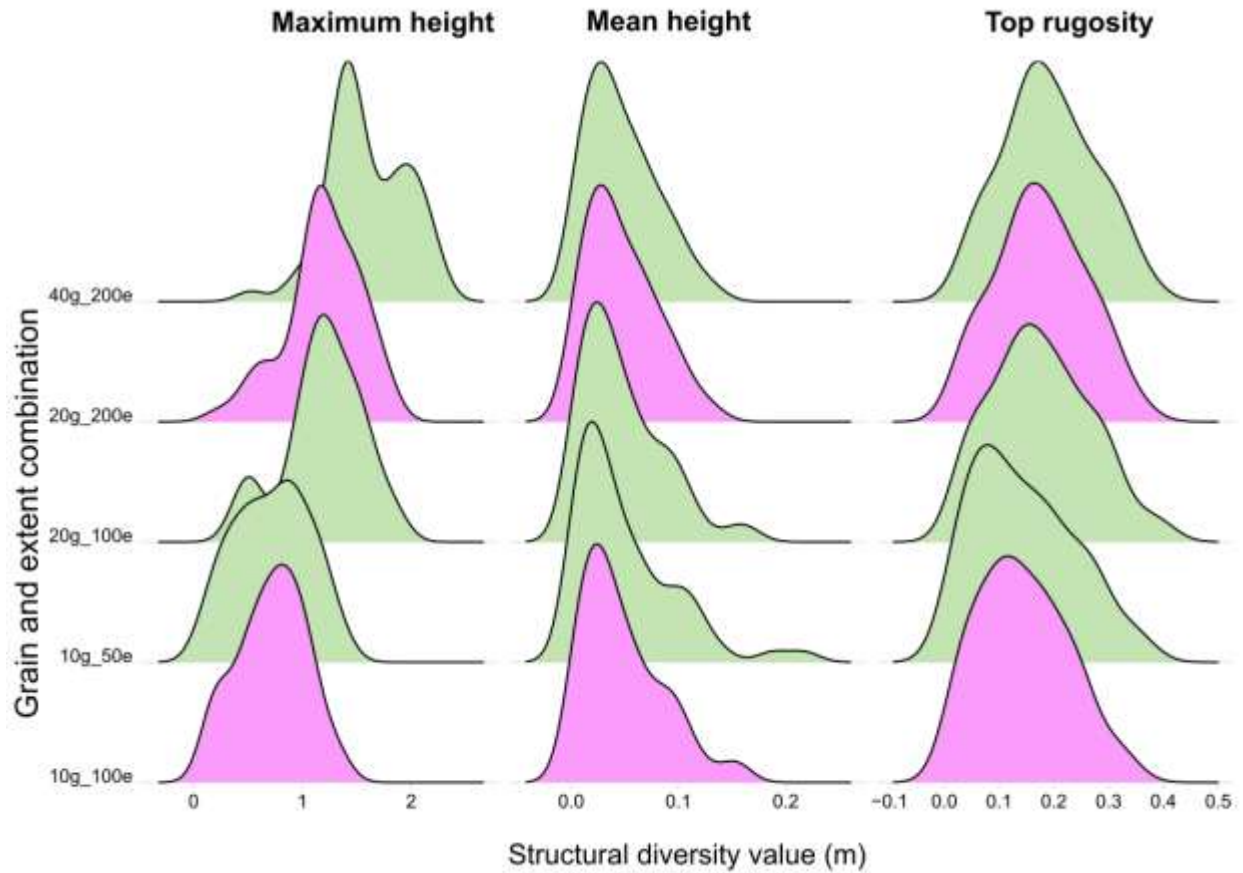


Figure 1.2: Ridgeline Graphs of Structural Diversity Metrics Across Grain Sizes/Extents combination for multiple scope value datasets. The combination of 40g_200e, 20g_100e, and 10g_50e represents the same scope value as A (green in color), while 20g_200e and 10g_100e represent the same scope as B (pink in color), as shown in Table 1.2.

3.2. ENVIRONMENTAL PREDICTOR AND STRUCTURAL DIVERSITY RELATIONSHIPS

3.2.1. Shrub Cover as a Predictor of Structural Diversity across scope and scale datasets

Shrub cover generally had a negative relationship with structural diversity metrics, including top rugosity, mean height, and maximum height (Figure 1.3). Higher shrub cover was

associated with lower structural diversity metrics. These patterns were supported by significant Spearman's rank correlation analysis (Table 1.3), where most of the models showed negative slopes and statistically significant values ($p < 0.05$).

Generally, shrub cover was a significant predictor of structural diversity across all scope values and absolute datasets, except at the finest grain and extent dataset (10g_50e). Shrub cover was statistically significant ($p < 0.05$) across different scale combinations, whereas the 10g_50e model did not produce statistically significant ($p > 0.05$) results in any of the three structural diversity metrics. For top rugosity significant correlation was observed at 10g_100e ($\rho = -0.37$, $p = 0.005$), 20g_100e ($\rho = -0.38$, $p = 0.003$), 20g_200e ($\rho = -0.43$, $p = 0.001$), 40g_200e ($\rho = -0.46$, $p < 0.001$). A similar significant negative correlation was observed for mean height at 10g_100e ($\rho = -0.36$), 20g_100e ($\rho = -0.33$), 20g_200e ($\rho = -0.38$), 40g_200e ($\rho = -0.38$). For the maximum height, results were significant at 10g_100e through 40g_200e ($p < 0.001$ or $p < 0.001$) as shown in Table 1.3.

When considering the influence of the absolute scale (10g_50e, 10g_100e, 20g_100e, and 20g_200e), it resulted in stronger negative Spearman's ρ values. For instance, from 10g_50e ($\rho = -0.24$, $p = 0.068$) to 10g_100e ($\rho = -0.37$, $p = 0.05$) and from 20g_100e ($\rho = -0.38$) to 20g_200e ($\rho = -0.43$, $p = 0.001$). Similarly, mean height decreased from $\rho = -0.33$ to $\rho = -0.38$ at the 20-grain combination with a greater extent. Maximum height also displayed similar significant patterns.

Within the scope of 25 (10g_50e, 20g_100e, 40g_200e), the correlation of top rugosity shifted from $\rho = -0.24$ to $\rho = -0.38$ to $\rho = -0.46$, with mean height changing from $\rho = -0.25$ to $\rho = -0.33$ to $\rho = -0.38$, and maximum height varying from $\rho = -0.23$ to $\rho = -0.53$ to $\rho = -0.64$. Similarly, for the scope of 100 (10g_100e and 20g_200e), the correlation of the top rugosity reduced from $\rho = -0.37$ to $\rho = -0.43$, with mean height showing $\rho = -0.36$ and $\rho = -0.38$, and maximum height at $\rho = -0.37$ and $\rho = -0.55$, respectively

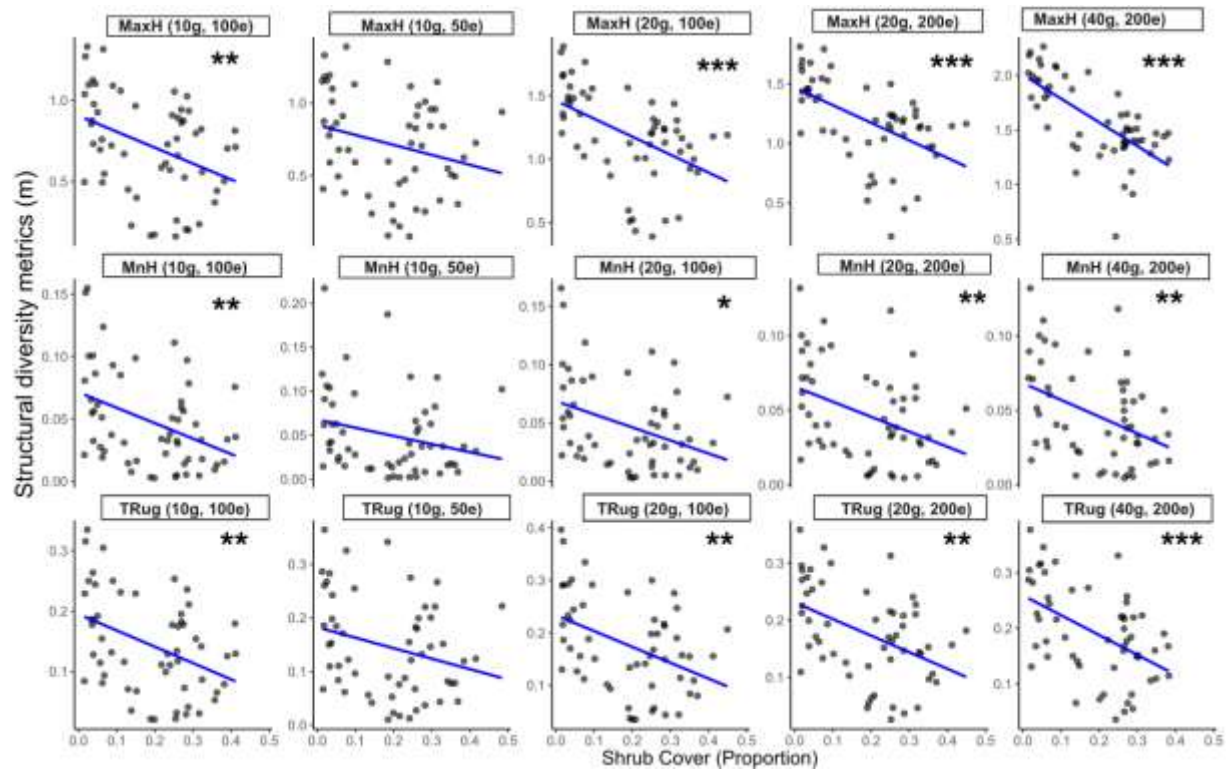


Figure 1.3: The linear relationship between shrub cover and structural diversity (top rugosity, maximum height, and mean height) metrics, and an asterisk (*) in the top right corner indicates the significance level. Trendline is shown for visualization purposes.

Table 1.3: Spearman correlation models between shrub cover and structural diversity across different grain sizes and extents, color-coded by scope value: Green = Scope 25 (A), Pink = Scope 100 (B)

Correlation Model	Grain extent	Spearman's rho	p-value	Significance
Top Rugosity~ Shrub cover	10g_50e	-0.24	0.068	N
	10g_100e	-0.37	0.005	Y
	20g_100e	-0.38	0.003	Y
	20g_200e	-0.43	0.001	Y
	40g_200e	-0.46	0.000	Y
Mean Height~ Shrub cover	10g_50e	-0.25	0.059	N
	10g_100e	-0.36	0.005	Y
	20g_100e	-0.33	0.012	Y
	20g_200e	-0.38	0.003	Y
	40g_200e	-0.38	0.003	Y
Maximum Height~ Shrub cover	10g_50e	-0.23	0.076	N
	10g_100e	-0.37	<0.01	Y
	20g_100e	-0.53	<0.001	Y
	20g_200e	-0.55	<0.001	Y
	40g_200e	-0.64	<0.001	Y

3.2.2. Elevation as a Predictor of Structural Diversity across scope and scale datasets

No significant relationship between elevation and any structural diversity metrics was observed. P-values in all models exceeded 0.05, and Spearman's rho values were insignificant for all metrics except 40g_200e, which had negative value ($\rho = -0.09$), as shown in Table 1.4. This indicates that the relationship between elevation and structural diversity metrics remained consistently insignificant across various scope and scale datasets.

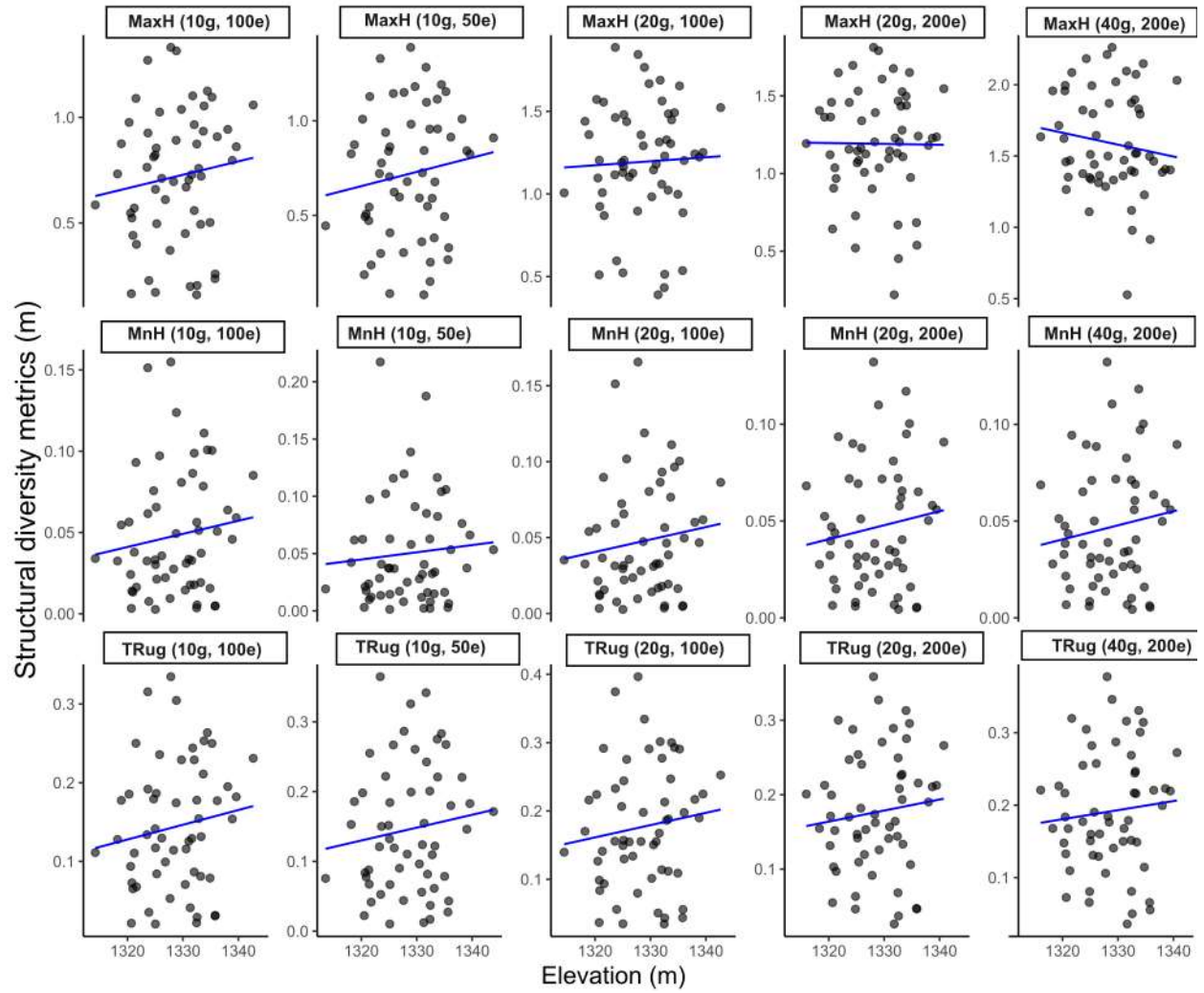


Figure 1.4: The linear relationship between elevation and structural diversity (top rugosity, maximum height, and mean height) metrics. Trendline is shown for visualization purposes.

Table 1.4: Spearman's correlation (ρ) between elevation and structural diversity, different grain sizes and extents, color-coded by scope value: Green = Scope 25 (A), Pink = Scope 100 (B)

Correlation Model	Grain extent	Spearman's rho	p-value	Significance
Top Rugosity~ Elevation	10g_50e	0.11	0.359	N
	10g_100e	0.15	0.259	N
	20g_100e	0.14	0.271	N
	20g_200e	0.13	0.309	N
	40g_200e	0.10	0.429	N
Mean Height~ Elevation	10g_50e	0.10	0.459	N
	10g_100e	0.14	0.284	N
	20g_100e	0.15	0.242	N
	20g_200e	0.11	0.393	N
	40g_200e	0.11	0.381	N
Max Height~ Elevation	10g_50e	0.13	0.320	N
	10g_100e	0.14	0.278	N
	20g_100e	0.08	0.554	N
	20g_200e	0.06	0.639	N
	40g_200e	-0.09	0.483	N

3.2.3. Structural diversity differences among landform types by scope and scale datasets

Structural diversity metrics did not differ significantly across landforms of Jornada, such as alluvial plain eroded, alluvial plain reddish-brown sand sheet, and alluvial plain wind-worked (Figure 1.5). For instance, the landform alluvial plain wind-worked appeared to have slightly more structural diversity, followed by the alluvial plain eroded and reddish-brown sand sheet. However, Kruskal-Wallis test results indicated that these variations were not statistically significant for any structural diversity metrics ($p > 0.05$) at different scope and absolute scale datasets as depicted in Table 1.5.

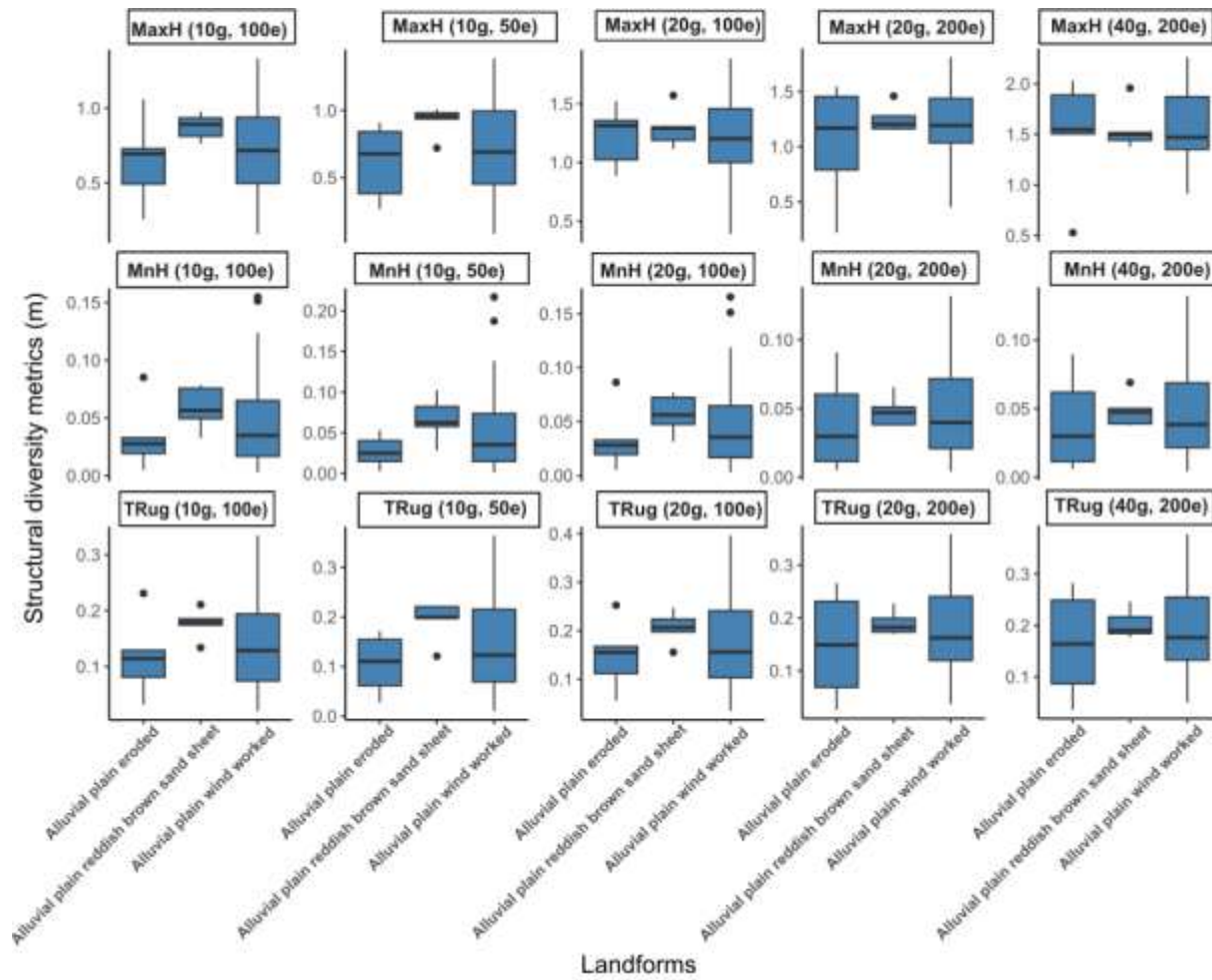


Figure 1.5: Boxplots showing variation in structural diversity metrics across different landform types.

Table 1.5: Kruskal-Wallis test-statistic table for differences in structural diversity metrics (top rugosity, mean height, and maximum height) by landform type, across different grain sizes and extents, color-coded by scope value: Green = Scope 25 (A), Pink = Scope 100 (B)

Kruskal-Wallis Test	Grain extent	Chi-square	p-value	Significance
Top Rugosity~ Landforms	10g_50e	2.98	0.225	N
	10g_100e	1.93	0.379	N
	20g_100e	1.51	0.468	N
	20g_200e	0.87	0.646	N
	40g_200e	0.84	0.656	N
Mean Height~ landforms	10g_50e	2.80	0.246	N
	10g_100e	1.87	0.391	N
	20g_100e	1.69	0.429	N
	20g_200e	0.82	0.664	N
	40g_200e	0.77	0.680	N
Maximum Height~ Landforms	10g_50e	2.75	0.292	N
	10g_100e	2.07	0.355	N
	20g_100e	0.44	0.800	N
	20g_200e	0.37	0.830	N
	40g_200e	0.15s	0.924	N

4. Discussion

Structural diversity has often been overlooked and underappreciated in biodiversity studies (LaRue et al., 2023; Willim et al., 2020), but as my research shows, there can be spatial heterogeneity in the structural diversity of dryland ecosystems. My research examined the effects of shrub cover, an important proxy for shrub encroachment status, on structural diversity metrics, including mean height, maximum height, and top rugosity within a southwestern USA shrubland-grassland dryland ecosystem. Indeed, I found that shrub cover may negatively influence the structural diversity of dryland ecosystems as the proportion of shrubs goes up. Specifically, I found a negative relationship between shrub cover and three structural diversity metrics, likely due to the similar type of shrub vegetation with similar sizes and architectures. This may decrease the layering or the vertical stratification of vegetation and thereby decreasing the heights and top rugosity (surface roughness of canopies). Research based on the Jornada Experiment range also found that sites with dense shrub cover exhibited greater root overlap and thus increased competition, limiting further shrub expansion creating die back and lower canopy cover over time (Wojcikiewicz et al., 2024). One study from savanna ecosystems (Sirami et al., 2009) reported a hump-shaped relationship between vegetation structural diversity and shrub cover, with diversity declining after reaching intermediate levels of shrub cover (e.g., 20-30%). Historically, shrub encroachment (e.g., mesquite) has replaced the native perennial grasses, such as black grama, which disappeared from 77% of the quadrats over a 64-year period in the Jornada Experiment Range (Gibbens & Reldon F Beck, 1987). These interaction dynamics between grasses and shrubs might explain the reduction in structural diversity metrics, as more shrub cover leads to decreased vertical variation in vegetation. Despite ecosystem differences, a similar response was noted in tropical and temperate grassy ecosystems, where shrub encroachment reduces herbaceous species such as graminoids and forbs, which helps contribute to the vertical complex structure, resulting in a more uniform and less structurally diverse environment community (Wieczorkowski & Lehmann, 2022). Consistent with this interpretation, a study conducted in semi-arid Australia also

addresses a decrease in understory and groundcover vegetation such as grass, forbs/herbs, with increased shrub cover (Freudenberger, 2001). Also, in alpine meadows, shrub cover affects the herbaceous community structure. This leads to a decline in lower-stature plants, and shade-tolerant species tend to start colonizing, primarily when shrub cover exceeds 60% (Zhang et al., 2022). However, in contrast with studies such as Yang et al. (2024), who reported the positive relationship between leguminous shrub encroachment and plant diversity in alpine meadows. This study reveals different outcomes. This difference with my study may stem from different biome-specific responses, particularly in nutrient-rich soil conditions and shrub traits, and how shrubs affect various grass types. For instance, leguminous shrubs in an alpine environment may enhance soil fertility and support the understory growth.

From a spatial perspective, the negative relationship between shrub maximum height and cover may have also resulted due to an artifact of data aggregation over larger spatial scales. In this research, at larger grain and extent sizes, the maximum height appears to have a negative relationship with the shrub cover, which may partially reflect a data aggregation or spatial artifact. As the analysis area increases, it is more likely to include taller shrubs, but simultaneously the shrub cover goes down with larger sampled area due to the presence of more bare-ground areas. It is also possible that non-shrub vegetation cover is changing with increased area but being misclassified as shrub cover. So, understanding these scale-dependent spatial dynamics is vital for interpreting the structural diversity from a data processing perspective and an ecological perspective.

In this study, elevation was not a significant predictor of structural diversity across the Jornada Experimental Range (JER). Similar patterns were observed from the (Zou et al., 2024) findings, which identified a neutral relationship between biodiversity and productivity in temperate forests while noting a negative relationship in subtropical forests that were more influenced by traits like maximum plant height and wood density. This suggests that elevation appeared to have a limited influence on structural diversity within the relatively narrow elevation range of the elevation of our sites. Due to moister conditions, lower elevations exhibit greater diversity,

whereas higher elevations, characterized by hotter and drier conditions, show lower tree diversity (Poulos & Camp, 2010). In my study area, which has limited topographic complexity and a narrow elevational range, primarily restricted in the northwestern part of the Jornada Experimental Range (away from the San Andres Mountain Range), it is likely that other environmental variables likely exert a decisively stronger influence than elevation in this system. Additionally, locations on the landscape where elevation might have an influence on vegetation in a relatively flat Chihuahuan Desert ecosystem, such as in arroyos or playas that receive more ephemeral water, might not have been well represented in my dataset due to the overall relatively flat landscape of Jornada.

Although previous studies at Jornada (Ji & Niall, 2020) reported variation in shrub size on sand sheets and moderate levels on wind-worked alluvial plains, in my study, a significant relationship was not found in structural diversity among the three dominant landform types. This may be due in part to different sample sizes or different landforms represented in the previous study, (i.e. alluvial plain eroded, alluvial plain wind-worked, and alluvial plain reddish-brown sand sheets versus no sand sheets represented in my dataset). In desert ecosystems, wind is vital for shaping the landscape through geomorphic processes such as wind erosion, sediment transport, and deposition, which create islands of fertility that can support a variety of vegetation growth (Ji & Niall, 2020; Puttock et al., 2014; Ridolfi et al., 2008; Schlesinger & Andrews, 2000). However, these trends were not statistically significant in my study, possibly due to the underrepresentation of certain landforms within my dataset. Ji & Niall (2020) had data that had a slightly different geographic coverage (i.e. more coverage toward the eastern piedmont area of the San Andres Mountains) than mine did that was more west towards the Rio Grande River.

Regarding my scaling hypothesis, this study's analysis revealed that the increasing grain and extent, rather than scope, may have been more influential on the strength of the relationships between structural diversity and environmental variable. Specifically, the mean height and top rugosity exhibited similar distribution patterns across the same scope value (Figure 1.2), suggesting that some metrics of structural diversity respond similarly across the same scope value. However, maximum height showed some differences within the same scope, as it would be

expected to be more sensitive to outliers. As plot size increases, the likelihood of capturing larger shrubs also increases. In contrast, mean height and top rugosity reflect canopy structure less affected by scale changes that would be averaged out in a bigger plot extent. Alternatively, the differences in significant relationships may be due to ecological processes influencing vegetation structural diversity at different scales (Frazier, 2023; Wu et al., 2003). Furthermore, these results imply that when assessing relationships with continuous variables like structural diversity metrics, absolute scales may capture subtle spatial heterogeneity than the grain-to-extent-ratio.

Ultimately, this research reveals that shrub cover in arid ecosystems is likely to be a potential driver of vegetation structural diversity of dryland plant communities, while elevation over a 20m gradient and the three landforms examined did not appear to be associated with structural diversity. By demonstrating that grain/extent in absolute scale of data clipping plays a more important role than scope in detecting the structural diversity patterns in arid ecosystems, this study provides a methodological foundation for landscape ecology researchers. As shrub traits impact vegetation diversity, research on species-specific shrubs may offer new insights into the response of structural diversity to shrub encroachment. Expanding research to include temporal dynamics can further help to track the long-term responses of shrub encroachment on structural diversity. Additionally, incorporating land use legacies, such as land use history and grazing, and a study area across an elevational and landform gradient will contribute to a more nuanced perspective on the structural-environmental relationship across spatial scales and resolutions.

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Vita

Bindu Poudel was born and raised in the Arghakhanchi district, Nepal. She earned her Bachelor of Science in Forestry from the Institute of Forestry, Tribhuvan University, Pokhara Campus, Nepal. In January 2023, she began her graduate studies in the Biological Sciences program at the University of Texas at El Paso (UTEP) in landscape, where she joined the Landscape ecology lab under the mentorship of Dr. Elizabeth LaRue. Her research focuses on spatial ecology, specifically evaluating the structural diversity of vegetation across shrub-encroached dryland ecosystems. During her graduate studies, Ms. Poudel served as a Teaching Assistant.

She is expected to graduate in December 2025. Following graduation, Ms. Poudel plans to pursue a career in the GIS and environmental data analysis industry, with a particular interest in applying spatial data science to support conservation planning, ecological decision-making, and natural resource management.

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