THE INFLUENCE OF SPATIAL EXTENT SHAPE ON LST-NDVI PATTERNS: A MULTI-SCALE PERSPECTIVE

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ABSTRACT

Understanding the relationship between vegetation cover and land surface temperature is vital for analyzing landscape structure and addressing climate-related challenges. While extensive research has focused on the scale of effect in multi-scale analyses, the impact of spatial extent shape on LST-vegetation correlations remains largely unexplored, representing a global knowledge gap. Most studies rely on circular or square shapes, overlooking how different geometries may alter analytical outcomes. This study aims to investigate how spatial extent shapes influence the correlation between LST and the Normalized Difference Vegetation Index. Using data from western Iran, we analyzed five geometric shapes—circular, square, elliptical, hexagonal, and diamond—at multiple spatial extents ranging from 90 to 990 meters, applying Pearson's correlation and statistical tests. Our findings reveal that while circular, square, and elliptical shapes yield similar results, hexagonal and diamond shapes introduce significant variations, particularly at smaller extents, with p-values as low as 0.00. Additionally, we observed that the correlation between land surface temperature and the Normalized Difference Vegetation Index strengthens as the spatial extent increases, peaking at 990 meters. These results demonstrate that the choice of spatial extent shape can significantly impact the interpretation of LST-vegetation relationships, highlighting the need to move beyond traditional circular or square extents. This study provides novel insights into spatial data aggregation methods and offers a framework for enhancing landscape analysis globally. By emphasizing the importance of spatial geometry in ecological studies, the findings hold relevance for landscape ecologists, urban planners, and environmental researchers seeking to refine multi-scale analyses and improve landscape-scale decision-making worldwide.

Keywords: Landscape ecology, LST- NDVI relationship, the scale of effect, spatial extent.

INTRODUCTION

Landscape ecologists often seek to understand how environmental factors influence biological responses, such as species abundance, within a given spatial context (Newman *et al*., 2019). This relationship hinges on the spatial scale or extent at which environmental variables are measured, as it directly affects the strength and significance of the observed effects (Carpentier & Martin, 2021; Jackson & Fahrig, 2012; Newman *et al*., 2019). The "scale of effect," or the spatial extent at which the relationship between an environmental variable and a biological response is most pronounced, is a fundamental concept in landscape ecology (Miguet *et al*., 2016). However, identifying the optimal scale for a given ecological process remains a challenge, as it often depends on a complex interplay of species traits, landscape structure, and methodological approaches (Gabriel *et al.*, 2010; Mayer & Cameron, 2003).

In landscape ecology, grain and extent are fundamental concepts that define the spatial scale at which ecological patterns and processes are analyzed (Turner, 1989a). Grain refers to the smallest spatial unit of measurement or resolution, such as the pixel size in raster data, and determines the level of detail captured in the analysis. Fine-grained data provide detailed insights into small-scale features and spatial heterogeneity, often showing higher levels of fragmentation and complexity, while coarse-grained data aggregate details into broader patterns, simplifying the landscape (Lin *et al.*, 2021). The choice of grain size significantly influences landscape metrics like patch density and edge density, which tend to vary with resolution, requiring careful selection to match the ecological question (Alhamad *et al.*, 2011).

Extent, on the other hand, refers to the total area or spatial coverage of the study, ranging from small local areas to entire regions (Turner, 1989a). Larger extents encompass greater landscape variability and reveal broader ecological trends, such as habitat connectivity or species dispersal patterns, while smaller extents focus on localized processes. The interaction between grain and extent shapes the overall scale of analysis, influencing the ability to detect ecological relationships and patterns (Šímová & Gdulová, 2012). Fine grains combined with large extents offer comprehensive analyses but demand high computational resources, whereas coarse grains and small extents risk losing critical details. The relationships between environmental variables and biological responses are often scale-dependent (Agrawal, 2020), with variations occurring across both grain and extent, making their careful selection essential for robust analyses. Together, grain and extent serve as the spatial framework for understanding and modeling landscape structure and ecological dynamics, influencing the generalizability and comparability of findings in landscape ecology (Suárez-Castro *et al.*, 2018).

Therefore, the selection of grain size and spatial extent plays a pivotal role in landscape ecology. Both can significantly influence landscape metrics, with finer-grained data often appearing more fragmented and complex than coarser-grained data (Francis & Klopatek, 2000; Šímová & Gdulová, 2012). Despite advancements in remote sensing and computational tools, variability in scale choices across studies has limited the comparability of findings and hindered the development of general scaling laws. For example, Mayer & Cameron (2003) found that only 61 % of studies explicitly reported their chosen grain size and extent, with decisions often driven by pragmatic considerations rather than methodological appropriateness. This inconsistency underscores the need for more structured and standardized approaches to scale selection in landscape studies to advance the field. Adding to the complexity, recent research has demonstrated that the thematic resolution of data—how landscape categories are defined—also affects the values of landscape metrics. Šímová & Gdulová (2012) emphasize that simple, interpretable metrics such as the number of patches (NP), patch density (PD), and edge density (ED) are the most robust for analyzing landscape structure across varying scales. However, the integration of thematic resolution with spatial scaling remains underexplored, leaving significant gaps in understanding how these factors interact to shape ecological patterns.

Beyond issues of grain size and extent, the concept of extent shape has received limited attention. While circular and square buffers are commonly used for landscape analyses, their influence on landscape metrics and ecological interpretations remains poorly understood. Extent shape can affect the aggregation of spatial data, altering metrics like patch density, edge length, and connectivity, which are critical for assessing ecological processes (Francis

& Klopatek, 2000; Šímová & Gdulová, 2012). This knowledge gap is particularly relevant when examining relationships such as those between land surface temperature (LST) and vegetation cover, represented by the normalized difference vegetation index (NDVI). Although studies like Rahimi *et al*. (2021), Rahimi & Jung (2025) and Zhou & Cao (2020) have explored the LST-NDVI relationship across varying spatial extents, they primarily focus on extent size rather than shape, leaving an opportunity to further investigate how extent shape influences these correlations.

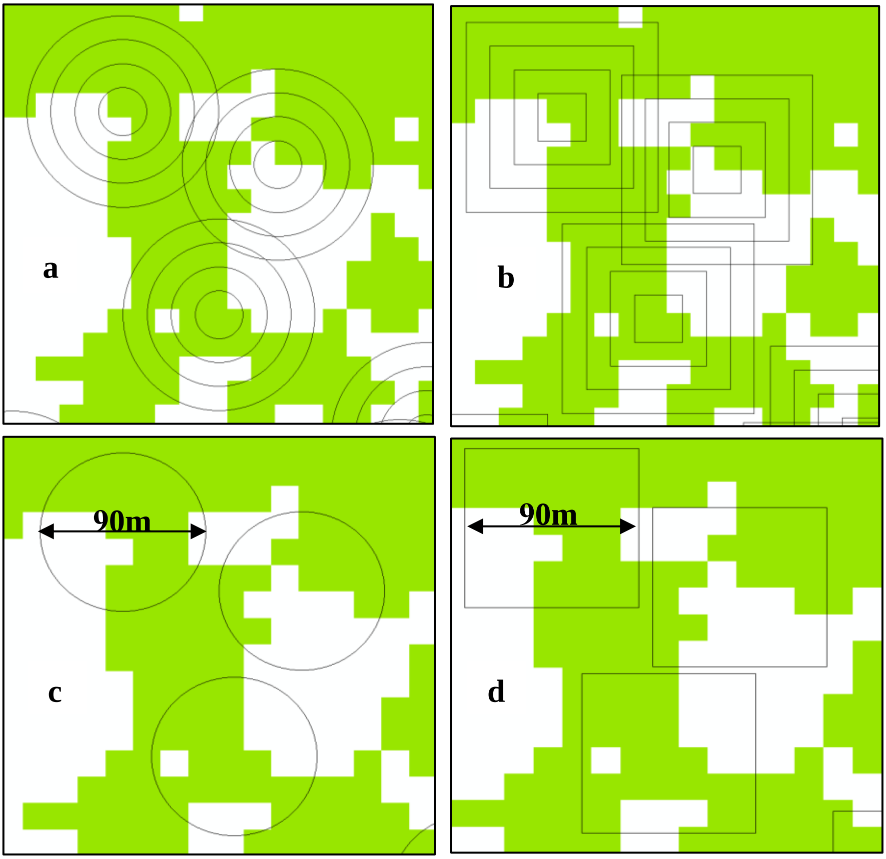
Determining the optimal scale for a specific environmental variable and biological or non-biological response is typically not straightforward (Newman *et al*., 2019; Turner, 1989b). One method to identify the scale of effect involves empirical data analysis in a multi-scale study (Frazier, 2023; Lechner & Rhodes, 2016; Wu & Qi, 2000) (Fig. 1). Here, the environmental variable is assessed across various spatial extents surrounding each sampled location of the dependent variable. Usually, circular (Fig. 1-A) or square (Fig. 1-B) buffers are commonly used for calculating landscape variables due to a lack of prior knowledge about more complex shapes (Peng *et al*., 2010; Saura & Martinez-Millan, 2001; Wu *et al*., 2002). Subsequently, a statistical model, often employing linear regression, is applied for each spatial extent to relate the environmental variable to the biological response (Jackson & Fahrig, 2015). The scale of the effect is then determined as the spatial extent that yields the most optimal model based on a predefined criterion, such as Pearson's correlation coefficient (r) (Miguet *et al*., 2016).

The circular or square nature of this shape can impact the correlation between the response variable and the independent variable. As depicted schematically in Figure 1, assuming our landscape comprises vegetation (green cells), the choice between circular and square buffers results in varying vegetation areas, even when maintaining equal diameters (Fig. 1-C) or widths (Fig. 1-D). This discrepancy can influence factors like the number of patches, the distance between them, and overall landscape composition and configuration within each buffer. Consequently, the shape of the spatial extent holds the potential to alter our perception of the relationship between dependent and independent variables, particularly in multi-scale analyses.

Given these gaps, our study aims to explore the underexamined influence of spatial extent shape on the relationship between LST and NDVI. We hypothesize that extent shape—whether circular, square, or more complex geometries—significantly affects the interpretation of landscape metrics and their correlations with ecological variables. Specifically, our first hypothesis proposes that the shape of the spatial extent has a measurable impact on the correlation between LST and NDVI, with non-circular shapes (e.g., hexagonal, diamond) yielding distinct patterns compared to standard shapes like circular and square extents. Furthermore, the second hypothesis posits that as the spatial extent size increases, the correlation between LST and NDVI strengthens consistently across all extent shapes, although the differences between shapes diminish at larger scales.

By analyzing LST and NDVI relationships across multiple spatial extents and shapes, we seek to advance the understanding of how spatial geometry influences landscape dynamics. Our findings will contribute to the broader goal of integrating spatial, temporal, and thematic dimensions into landscape ecology, ultimately improving the field's ability to address pressing conservation challenges.

Fig. 1: A theoretical multi-scale study setup:
(a) and (b) assessing landscape structure across various spatial extents using different shapes. (c) and (d) the proportion of vegetation cover varies based on the chosen shape of the spatial extent.

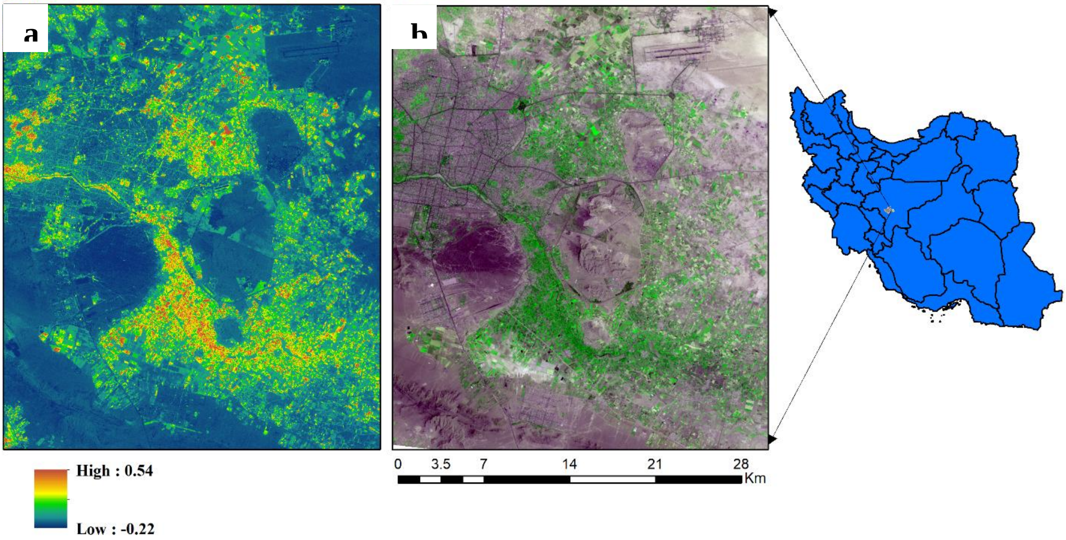


METHODS

Study area

We selected the western regions of Isfahan City, including Najaf Abad, Qahdrijan, and Flowerjan, for their diverse vegetation cover, ranging from dense to sparse. This variation provides an ideal setting to investigate correlations between NDVI and LST.

Fig. 2: Study area location in Iran.
(a) NDVI, and (b) color composite of bands 4,3,2 in August 2009 (Landsat 5 TM).



Spatial data

NDVI calculation

When assessing landscape patterns within a continuous framework, it's imperative to utilize indices that accurately portray landscape characteristics. In our study, we opted to use the Normalized Difference Vegetation Index (NDVI) as an alternative indicator of landscape attributes. NDVI proves particularly effective in delineating green vegetation biomass, owing to its capability to detect strong absorption in the red region (Band 3) and robust reflection in the near-infrared band (Band 4)) (Fan & Myint, 2014). Recognized and utilized extensively, NDVI stands as the most prevalent index across a spectrum of applications, spanning from vegetation monitoring to urban sprawl analysis (Nolè *et al*., 2014).

$$\mathrm{NDVI} = \frac{NIR-RED}{NIR+RED} \tag{1}$$

Where Red and NIR stand for the spectral reflectance measurements acquired in the red (visible) and near-infrared regions, respectively.

LST calculation

Objects with temperatures above absolute zero Kelvin emit thermal electromagnetic energy. The signals captured by the thermal sensors of Landsat TM are recorded and expressed as digital numbers (DN). Equation (2) is employed to transform these digital numbers into space-reaching radiance or top-of-atmosphere (TOA) radiance, which is measured by the instrument (Oguz, 2013).

$$L_\lambda = \frac{(L_{max} - L_{min})}{(QCAL_{max} - QCAL_{min})}(DN - QCAL_{min}) + L_{min} \tag{2}$$

Where λ is TIR band 6; $L_\lambda$is the Top of-Atmosphere (TOA) radiance at the sensor's aperture in W m−2 sr−1μm−1; $QCAL_{min} = 1$, the least value in the range of rescaled radiance in DN; $QCAL_{max}$ = 255, the highest value in the range of rescaled radiance in DN; L_{max}= 15.303; L_{min}= 1.238.

Spectral Radiance (L) to Temperature in Kelvin can be expressed as:

$$T_B = \frac{K_2}{ln\left(\frac{K_1}{L} + 1\right)}$$

Where, K_1 = Calibration Constant 1 (607.76), K_2 = Calibration Constant 1 (1260.56), TB = Surface Temperature.

Extent Shape effects on the LST-NDVI relationship

To test the first hypothesis, which posits that the shape of the spatial extent significantly influences the correlation between LST and NDVI, we began by generating 30,000 random points across the study area using ArcGIS software. Around each point, we created buffers in five distinct geometric shapes—circular, square, elliptical, hexagonal, and diamond—chosen to represent varying degrees of complexity in spatial aggregation. Circular buffers were defined by a fixed radius, creating symmetrical areas around the points, while square buffers aligned with raster grids to examine square-shaped extents. Elliptical buffers extended the concept of circular buffers by varying radii along two axes to incorporate directional variation. Hexagonal buffers provided six-sided polygons that are often more natural in spatial representation, and diamond buffers, constructed using Manhattan distances, formed distinct diamond-shaped geometries. For each buffer, we extracted mean LST and NDVI values from the raster datasets, which served as the basis for calculating correlations between the two variables.

To assess the first hypothesis statistically, we calculated Pearson's correlation coefficients for each buffer shape, quantifying the strength of the LST-NDVI relationship for every geometric configuration. To determine whether buffer shape significantly affected these correlations, paired t-tests were conducted between all combinations of shapes. For instance, we compared circular buffers with square buffers or hexagonal buffers with diamond buffers to identify significant differences in the resulting correlations. The null hypothesis for these tests was that the mean difference in correlation values between two shapes was greater than or equal to zero, suggesting no significant difference. The alternative hypothesis proposed that the mean difference was less than zero, indicating a significant difference between shapes. The statistical significance of these comparisons was determined using p-values, with a threshold of 0.05. If the p-values fell below this threshold, the differences in correlation values between the shapes were considered statistically significant, thereby supporting the hypothesis that buffer shape influences the LST-NDVI relationship.

The second hypothesis suggested that as the spatial extent size increases, the correlation between LST and NDVI strengthens consistently across all extent shapes, and the differences between shapes diminish at larger scales. To test this hypothesis, we generated buffers for each shape at 31 spatial extents ranging from 90 meters to 990 meters, with increments of 30 meters. For circular buffers, extent size was defined by the radius, while for square buffers it was defined by the side length. Equivalent measures were applied for elliptical, hexagonal, and diamond shapes. For each extent size, mean LST and NDVI values were extracted, and Pearson's correlation coefficients were calculated for each buffer shape and size. This provided a comprehensive dataset to examine how scaling influenced the strength of the LST-NDVI relationship.

To evaluate the scaling effects described in the second hypothesis, we performed a trend analysis by plotting correlation coefficients for each buffer shape across all extent sizes. This allowed us to observe whether correlations consistently strengthened with increasing spatial extent. Cross-scale comparisons were then conducted to determine whether differences in correlations between shapes diminished at larger extents. To ensure consistency and reproducibility, the entire workflow, including buffer generation, data extraction, and statistical analysis, was automated using a Python script. The script efficiently processed the raster datasets to generate buffers of all shapes and sizes, calculated mean LST and NDVI values, and conducted the necessary statistical tests. This automation reduced manual errors and allowed for consistent application of the methodology across the extensive dataset.

RESULTS

Correlation Between LST and NDVI Across Buffer Shapes

The results demonstrate that the correlation between LST and NDVI varies significantly depending on the spatial extent shape and size. As depicted in Fig. 3, areas with sparse vegetation correspond to higher LST values, confirming the expected inverse relationship between vegetation density and temperature. Fig. 4 highlights that the correlation between LST and NDVI becomes more negative with increasing spatial extent size across all buffer shapes, indicating a stronger inverse relationship as the spatial scale grows. This trend was consistent across circular, square, elliptical, hexagonal, and diamond buffers, though distinct differences emerged at smaller extents (90 to 270 meters). For instance, hexagonal and diamond buffers displayed more pronounced deviations from circular and square buffers, suggesting that the choice of buffer shape influences spatial data aggregation.

Statistical Evaluation of Buffer Shapes

Paired t-tests were conducted to assess the statistical significance of differences in LST-NDVI correlations among the five buffer shapes. As shown in Table 1, comparisons involving square and circular or elliptical buffers yielded no statistically significant differences, with p-values above 0.05. This suggests that these shapes tend to produce similar mean correlation values, indicating limited influence of buffer shape on the results when using standard geometries. For example, the square versus circle comparison resulted in a p-value of 0.08, while square versus elliptical produced a p-value of 0.19.

In contrast, comparisons involving hexagonal and diamond buffers revealed significant differences. The square versus hexagonal comparison yielded a p-value of 0.00, and the square versus diamond comparison produced a p-value of 0.001, indicating that hexagonal and diamond buffers generate distinct correlation patterns compared to standard shapes. Similar trends were observed when circular buffers were compared with hexagonal ($p = 0.016$) and diamond ($p = 0.046$) buffers. These findings highlight that hexagonal and diamond buffers lead to more variable interpretations of spatial relationships, particularly at smaller extents. Additionally, elliptical buffers showed significant differences when compared to hexagonal ($p = 0.005$) and diamond ($p = 0.015$) buffers, further supporting the hypothesis that shape influences spatial data aggregation.

Fig. 3: Output maps of (a) NDVI, (b) LST

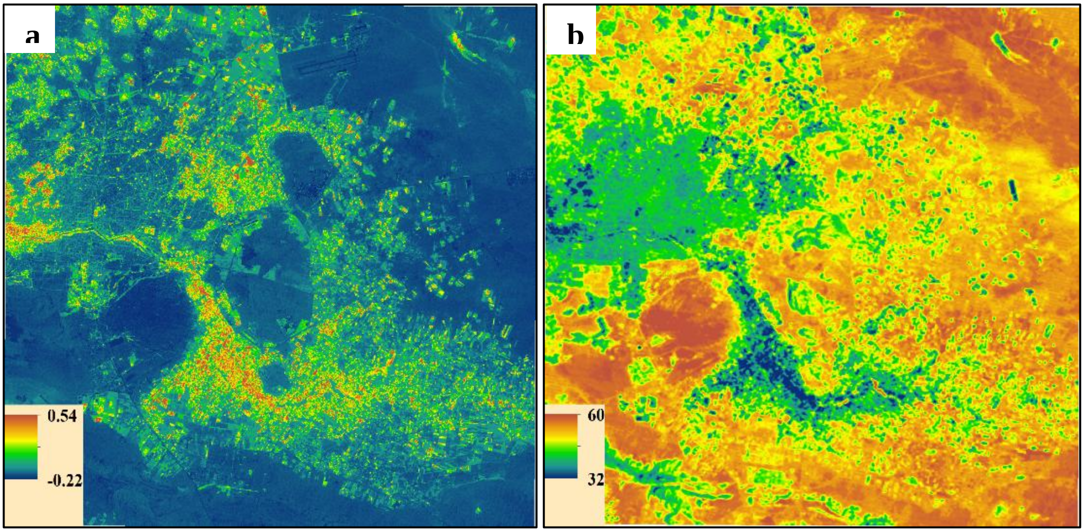


Fig. 4: The correlation between LST and NDVI across various spatial extent sizes and shapes

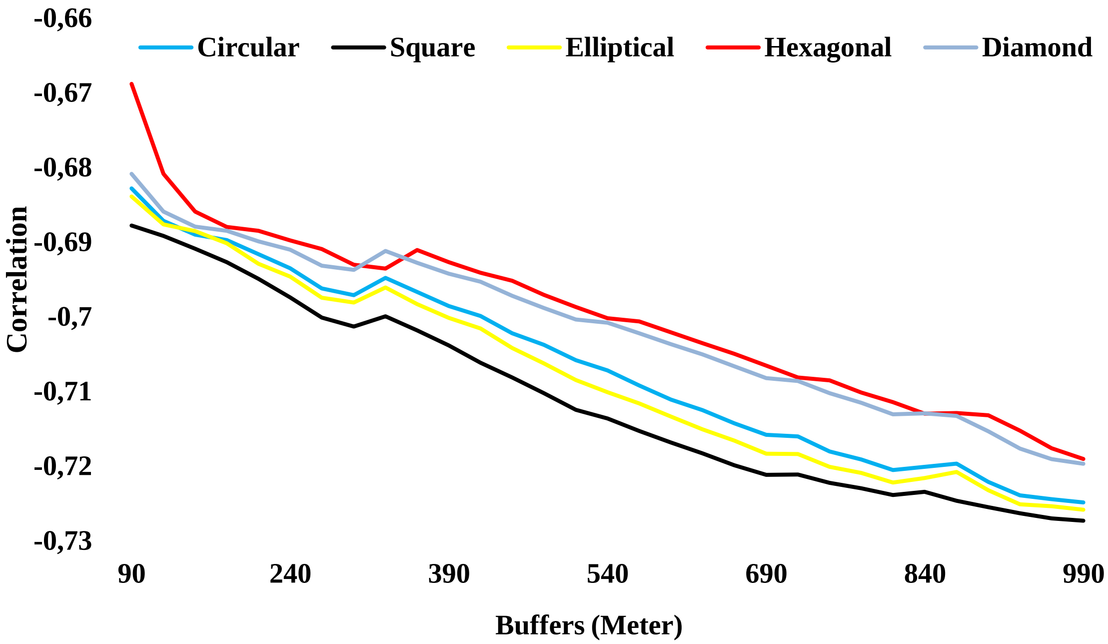


Table 1: The results of the equivalent t-test between the mean values of different extent shapes and sizes

Null hypothesis:	Mean (test sample) – Mean (reference sample) ≥ 0						
Alternative hypothesis:	Mean (test sample) – Mean (reference sample) < 0						
Variable	N	Mean	StDev	SE Mean	DF	T-Value	P-Value
Square	31	-0.71	0.012	0.002	59	-1.3	0.08
Circle	31	-0.70	0.012	0.002			
Square	31	-0.71	0.012	0.002	59	-0.88	0.19
Elliptical	31	-0.70	0.012	0.002			
Square	31	-0.71	0.012	0.002	59	-3.6	**0.00**
Hexagonal	31	-0.69	0.011	0.002			
Square	31	-0.71	0.012	0.002	58	-0.88	**0.00**
Diamond	31	-0.70	0.010	0.002			
Circle	31	-0.71	0.012	0.002	59	-2.2	**0.01**
Hexagonal	31	-0.69	0.011	0.002			
Circle	31	-0.70	0.012	0.002	58	-1.7	**0.04**
Diamond	31	-0.70	0.010	0.001			
Elliptical	31	-0.70	0.012	0.002	59	-2.6	**0.00**
Hexagonal	31	-0.69	0.011	0.001			
Elliptical	31	-0.70	0.012	0.002	58	-2.2	**0.01**
Diamond	31	-0.70	0.010	0.001			

DISCUSSION

This study aimed to investigate how variations in the shape of spatial extents influence the relationship between two key variables, LST and NDVI, and their effects on our understanding of landscape structure. The key findings are as follows: (1) The correlation between LST and NDVI varied based on the shape of the spatial extent. While these correlations showed differences, the observed variations were statistically significant. (2) When examining the relationship between NDVI and LST across different spatial extents, we found that the correlation increased with the size of the spatial extent, reaching its highest value at 990 meters. Our study highlights the significance of our findings on the influence of spatial extent shapes and sizes on the correlation between LST and NDVI, contributing to the broader field of landscape ecology.

Our results confirm that the shape of spatial extents significantly impacts spatial data aggregation and the observed relationships between ecological variables, with non-circular shapes like hexagonal and diamond buffers producing distinct patterns, especially at smaller extents. As extent size increases, the differences between shapes diminish, indicating that larger spatial extents may mitigate the influence of buffer geometry. This observation aligns with the hypothesis that spatial extent shape has a measurable effect on LST-NDVI correlations and that larger spatial scales offer more stable correlations across all buffer types. By emphasizing the importance of extent shape, our findings address a critical knowledge gap in multi-scale landscape analysis, a topic often overlooked in previous research that primarily focused on extent size alone.

From a methodological perspective, our study demonstrates a robust approach to testing hypotheses on spatial relationships. The use of multiple buffer shapes—circular, square, elliptical, hexagonal, and diamond—allowed for a nuanced understanding of how spatial geometry affects data interpretation. Statistical validation through paired t-tests provided clear evidence of significant differences between certain buffer types, especially hexagonal and diamond buffers compared to standard shapes. For example, the square versus hexagonal comparison yielded highly significant p-values, underscoring the unique patterns these non-standard shapes reveal. These results suggest that buffer shape considerations should be incorporated into future multi-scale analyses to enhance the accuracy and reliability of ecological interpretations. Such methodological advancements are critical for improving the rigor of landscape ecological studies and addressing the inherent variability introduced by scale-dependent factors.

Our findings resonate with earlier studies that investigated scale effects in landscape metrics. For instance, Song *et al*. (2014) demonstrated that larger pixel sizes enhance correlations between LST and urban features, identifying optimal resolutions for assessing landscape-LST relationships. Similarly, Lu *et al*. (2020) noted peak correlations between NDVI and LST within specific cell sizes, reinforcing the idea that spatial scale plays a pivotal role in determining ecological relationships. However, our study extends these findings by highlighting the impact of shape in addition to size, offering a more comprehensive perspective on scale-related dynamics. This contribution is particularly relevant given the lack of empirical studies on the interplay between extent shape and landscape metrics (Miguet *et al*., 2016), as highlighted by

The implications of our results extend beyond methodological considerations to address broader conservation and land management challenges. Understanding how spatial geometry influences LST-NDVI relationships is crucial for designing effective conservation strategies, particularly in fragmented landscapes. For instance, the ability of hexagonal and diamond buffers to capture unique spatial patterns could be leveraged to refine habitat suitability models or identify microclimatic variations critical for biodiversity conservation. This aligns with calls for integrating landscape-scale processes with macroecological patterns, as emphasized by Teng *et al*. (2020). Such integration is essential for addressing the complex interactions between local landscape features and regional biodiversity trends, particularly in urban and agricultural settings where land-use intensity and fragmentation are pronounced.

Furthermore, the international importance of our findings lies in their applicability across diverse landscapes and ecological contexts. By demonstrating that spatial geometry significantly influences ecological relationships, our study provides a framework that can be adapted to various geographical settings, from urban areas to rural agricultural landscapes. For example, Norton *et al.* (2016) stressed the need for hierarchical, multi-scalar models to understand biodiversity dynamics in urban ecosystems. Similarly, Gabriel *et al*. (2010) highlighted the multi-scale dependencies of farmland biodiversity, advocating for policies that account for cross-scale interactions. Our results contribute to these discussions by providing a scalable and adaptable methodology for exploring spatial relationships in different ecological and geographical contexts.

In addition to spatial scale, temporal dimensions must also be considered to fully understand ecological processes. While our study focused on spatial relationships, it is important to acknowledge that temporal scales can also influence the LST-NDVI relationship. For instance, Ma *et al*. (2016), showed that temporal variations in LST and NDVI correlations could reveal historical legacies and long-term ecological trends. This highlights the need for future studies to incorporate temporal analyses alongside spatial dimensions to capture the full complexity of landscape dynamics. Overall, our study advances the field of landscape ecology by addressing critical gaps in understanding the role of spatial extent shape in ecological analyses. By integrating methodological rigor with practical relevance, our findings offer valuable insights for improving multi-scale landscape analyses and developing effective conservation strategies. The demonstrated impact of buffer shape and size on LST-NDVI correlations underscores the need for a nuanced approach to spatial analysis, one that considers both geometric and scale-related factors. These contributions not only enhance the theoretical foundations of landscape ecology but also provide practical tools for addressing pressing environmental challenges on a global scale.

CONCLUSION

This study provides novel insights into how spatial extent shape influences the relationship between LST and NDVI, addressing a critical gap in landscape ecology research. Our findings demonstrate that non-standard buffer shapes, such as hexagonal and diamond, yield distinct spatial patterns, especially at smaller extents, while differences diminish at larger scales. These results highlight the importance of incorporating spatial geometry into multi-scale analyses, advancing the methodological rigor in interpreting landscape-scale ecological relationships. This study is particularly significant for international readers as it presents a scalable and adaptable approach for ecological investigations across diverse landscapes. By emphasizing the interplay between spatial shape, scale, and ecological metrics, the findings contribute to the broader goal of improving the accuracy and applicability of landscape-scale analyses in addressing global environmental challenges. In the field of landscape ecology, these results underscore the need to consider not only spatial extent size but also shape when exploring ecological relationships, offering new directions for research and practical applications in conservation and land management.

CONFLICT OF INTEREST

The authors declare that they have no competing interests.

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