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EVALUATING THE FOREST LANDSCAPE PERFORMANCE EFFICIENCY FOR FOREST UTILIZATION IN ZAKHO POPLAR STANDS

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Abstract

This study employs a Multiple Regression Analysis using SPSS software to explore the diverse factors influencing landscape performance efficiency at recreational amenity sites (Y), depending on Structural equation modelling (SEM) using the Travel Cost Method (TCM) in Zakho Poplar stands. The landscape attributes were meticulously collected through field surveys conducted on May 5, 2023, utilizing Garmin GPS S62. The model integrates various predictors, including independent variables, such as: poplar coverage extent, agricultural land usage area, proportions of different elements within the site, underlying topological structure, and visitor-related metrics. The results highlight a substantial and significant relationship between these predictors and the dependent variable, shedding light on the complex interplay between landscape attributes and site performance. The model's robustness is underscored by its high r-squared adjusted value of 0.91, indicating strong explanatory power. Additionally, ANOVA analysis confirms the collective significance of the predictors. The coefficients within the model elucidate the nature and strength of each predictor's impact on the dependent variable. The study's findings emphasize the positive influence of factors such as poplar and agricultural coverage, as well as topological configuration, all contributing positively to site performance. Conversely, a higher ratio of elements within the area is linked to reduced performance. Furthermore, visitor volume emerges as a pivotal and positive factor. Overall, this study provides valuable insights with actionable and potential to enhance the landscape performance of recreational amenity sites. Furthermore, it significantly advances the understanding of the intricate relationships between distinct landscape attributes and performance outcomes in this context.

Keywords: landscape performance, unobservable variables, Structural equation model (SED), Zakho stands, *Populus nigra* L

1. INTRODUCTION

In recent times, there has been a notable surge in deforestation and forest degradation on a global scale. This concerning trend has prompted both governmental and environmental advocates to take proactive measures aimed at managing, restoring, or preserving these vital ecosystems. However, traditional methods of forest restoration are proving inadequate, and largely relying on a limited array of tree species for regenerations, Dudley *et al.,* (2005). Unfortunately, yielded adverse effects such as diminished diversity, compromised quality, and reduced quantity of forest-based products and services. This situation has been exacerbated by ineffective resource allocation and a weakening of forest resilience in the face of climate change and other natural calamities Pellegrini *et al.,* (2017), Hamilton and Friess.(2018)

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Hence, the assessment of forest landscape performance has emerged as a critical imperative. This is essential to formulate restoration strategies that holistically address broader environmental, social, and economic objectives. Yet, the challenge remains in selecting priority restoration sites, requiring a delicate equilibrium between bolstering ecological services and optimizing resource input sources, Ribeiro *et al.,* (2009), Rudnick *et al.,* (2012).

In the realm of natural landscapes, recreational amenity sites play a vital role in creating spaces for relaxation, leisure, and fostering a deep connection with the natural world. Understanding the intricate factors that influence the effectiveness of these sites is essential for effective landscape management and strategic planning. This study adopts a comprehensive approach, utilizing multiple regression analysis to explore the complex relationships between landscape characteristics and the performance efficiency of recreational amenity sites. Among the variables under scrutiny are the size of areas covered by poplar trees, the extent of agricultural coverage, the proportion of specific elements within the area, the underlying topological structure, and various metrics related to visitor numbers and visits.

Through a rigorous quantification of how these variables impact site performance, this research provides valuable insights for crafting strategies that have the potential to enhance the overall quality and attractiveness of recreational amenity sites in Poplar Stands in Zakho.

The European Landscape Convention (Council of Europe, 2000) defines a landscape as an area shaped by the interplay of natural and human factors, yielding a distinct character as perceived by people. Additionally, according to The Millennium Ecosystem Assessment (M E A, 2005), landscapes serve as regions offering society various goods and services, including ecosystem services, such as natural areas, and landscapes are rich sources of multiple societal benefits.

The term "landscape" pertains to a specific expanse encompassing diverse ecosystems, both untouched by humans and those influenced by human activities. In contrast, "cultural landscape" refers to regions with significant human presence, although no precise literature-based definition exists for this term. Notably, the International Tropical Timber Organization (ITTO, 2002) defines a landscape as an amalgamation of interacting ecosystem types.

Furthermore, the landscape approach presents a holistic framework that integrates policies and practices spanning various land uses within a specific area. This approach aims to ensure sustainable and equitable land utilization while also addressing climate change mitigation and adaptation (Reed *et al.,* 2014). A central focus of this approach is balancing conservation and development trade-offs within defined geographical regions (Sayer, 2009). The Food and Agriculture Organization (FAO, 2012) emphasizes that the landscape approach encompasses comprehensive, large-scale management of natural resources, factoring in environmental, social, and economic aspects, including livelihood considerations.

In a recent study by Hou B. *et al.,* (2023), a novel technique was proposed to assess forest landscape stability by modifying characteristics of forest landscape patterns. The Toeplitz Inverse Covariance-based Clustering (TICC) method was employed to analyze the interplay between landscape indices—forest Cover Area (CA), Patch Density (PD), to identify short-term processes such as degradation, restoration, and stability between 1987 and 2021. The

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study established four long-term indicators for landscape stability: no change, increase, reduction, and wave, based on the temporal distribution of short-term change processes. The results show diverse forest change processes in the short term, with restoration being predominant, constituting 46% of the overall subsequence and existing in 75% of landscape units. Additionally, the study revealed that 57% of landscape units demonstrated stability, while 6.7% displayed instability. These findings offer a novel outlook on dynamic landscape pattern analysis, with implications for refining ecological restoration techniques.

Another avenue to gauge the value of landscapes is through non-market valuation studies, wherein the influence of landscape elements on market prices is examined. Hedonic pricing, for instance, involves assessing the impact of landscape features on prices of goods such as restaurants, hotels, and package deals. Key landscape attributes, as identified by Monty and Skidmore (2003), include proximity to urban centers, beaches, the presence of open coasts and dikes (Hamilton, 2007), and rural settings (Mangion *et al.,* 2005).

Structural Equation Modelling (SEM) emerges as a valuable tool for exploring intricate relationships within landscapes. It employs equations and digital analysis to address variables not directly measurable, transforming observable aspects of landscape performance into latent factors. SEM allows the simultaneous analysis of multiple dependent variables, accounting for measurement errors and transcending limitations of traditional statistics. By incorporating latent variables, SEM investigates causal relationships and strengths between abstract variables, unveiling mathematical patterns and quantification principles underlying spatial dynamics in the built environment. Noteworthy research by Zhe Li *et al.,* (2020) exemplifies this innovative approach, showcasing its precision in extracting and analyzing landscape environmental information.

On a global scale, studies have explored the interplay between Forest Landscape Restoration (FLR) and biodiversity (Bremer & Farley, 2010), examined the adopted goals (Hallett et al., 2013), and elucidated key methodologies employed in Family-Based Livelihood Approaches (Meli *et al.,* 2017).

Conversely, according to Zhang *et al.,* (2019), unobservable factors within landscape performance are those that cannot be directly measured or are prohibitively expensive to observe. In contrast, observable factors are quantifiable using explicit indices. In the realm of statistics, latent variables serve as unobservable factors capable of reducing data dimensionality, with latent concepts often influenced by numerous observable factors. Consequently, the relationship between unobservable factors can be inferred from the relationship between observable ones (Li and Cheng, 2019).

Zigmars (2015) employed quantitative techniques like spatial analysis and landscape metrics in their research. The results highlighted how factors influencing clearcut spatial patterns shifted over time, and private forest management practices leaned more towards natural afforestation compared to state and municipal management. Moreover, Zigmars (2015) harnessed GIS methods to study forested landscapes across various scales, drawing from sources such as the State Forest Register and supplementary data from topographical and

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orthophoto maps.

Quoting Gustafson (1998) and Turner *et al.,* (2001), it's pivotal to note that quantitative evaluation of landscape patterns plays a vital role in landscape ecological studies, with landscape metrics offering a standardized method for measuring and comparing spatial patterns.

In a study published in Science Direct, Zhe Li *et al.,* (2020) scrutinized landscape efficacy and quantified landscape performance. They discovered that topological depth significantly influenced landscape performance, suggesting a potential link between topological structures and performance efficiency. Additionally, a study in Renqiu City by Zang Y. *et al.,* (2022) explored the relationships between forest ecosystem service capacity and landscape patterns. The study identified indices like PLAND, LSI, and CONTAG as having polynomial relationships with various forest ecosystem service functions, highlighting the impact of specific landscape patterns.

Aligned with the topic, Robert's study in 2009 identified five key components of the landscape approach: the area or landscape, partner collaboration, sustainable development, knowledge production, and sharing of experiences and knowledge. These components were categorized based on their relevance to stakeholders and actors.

2. METHODOLOGY

2.1 The Technical Route

Depending on the Structural Equation Model, SEM, is a statistical method used to examine the relationship between hidden or latent variables and observable or explicit variables in a dataset. In the context of landscape efficacy, this approach is employed to study the connections between factors such as ecosystem services, biodiversity, and human well-being, as well as elements such as land use, soil quality, and air quality.

The fundamental tenet of SEM is to determine the coefficient of linear regression between the explicit variables and then use this estimate to determine the appropriateness of the proposed model. If the model is found to be suitable, it implies that the relationship between the latent variables is plausible.

The literature review and theoretical modeling helped to identify five factors that impact landscape performance efficacy. It needs to collect data from various sources, transform and processes for using depth map X 0.5, Grasshopper, and SPSS 26.0, and normalized it for analysis. Next, fitted the established model on SPSS Amos 24, assess and correct it based on the results, and use it to analyze the collected data. The analysis revealed insights into the connections between the unobservable factors and landscape performance.

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2.2 Theoretical Modeling

The theoretical model for landscape performance efficacy in Poplar Stands in Zakho, was developed based on the following hypothesis:

All independent variables such as Poplar coverage area, Agricultural coverage area, the ratio of elements, Topographical formation and the number of visitors/visits has a direct and significant positive effect on landscape performance efficacy. And the Figure 1, illustrates the theoretical model for landscape performance efficacy.

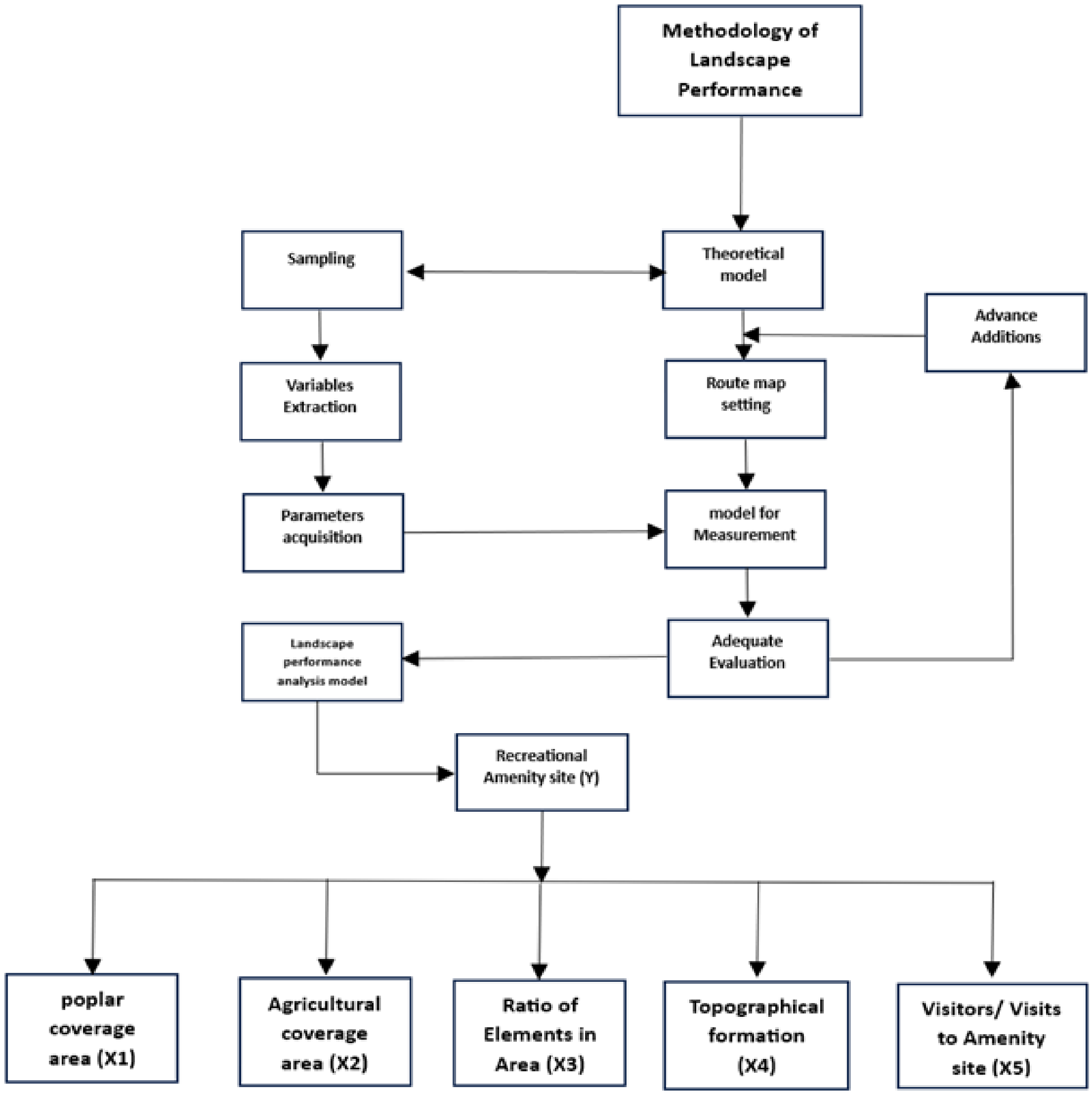

Fig 1: Technical Procedure for Structural Equation Modelling of the Landscape Performance for Poplar Stand in Zakho.

Source: Prepared by the researchers.

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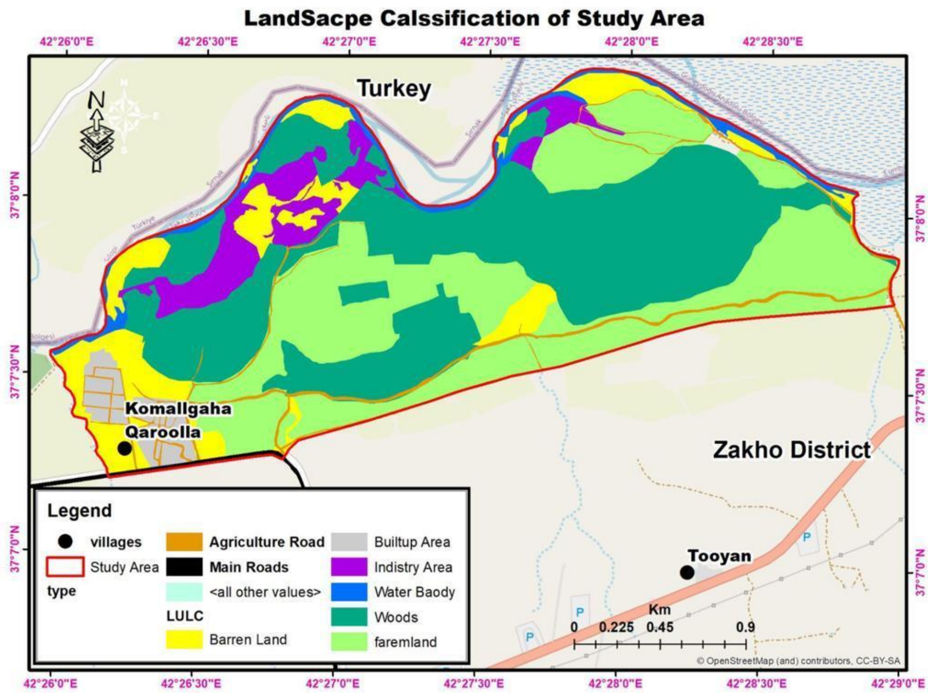
The following points are key hypotheses in the theoretical model for landscape performance efficacy:

- The validity of the relationship between the unobservable variable (Xi) and landscape performance was tested through multiple regression analysis, a widely used statistical technique for evaluating the accuracy of a model.
- It's important to note that all hypotheses were supported by the analysis, indicating that unobservable variables such as Poplar coverage area, Agricultural coverage area, the ratio of elements in the area, topographical formation, and the number of visitors/visits to the area have a considerable impact on landscape performance.
- This research can provide valuable insights for policymakers, urban planners, and environmental managers to create effective strategies to enhance landscape performance efficiency and sustainability in Poplar Stands in Zakho.

2.3 Sampling Construction:

The area of research study has been determined by field observation, with using Global Positioning System (GPS) and satellite image, the necessary map of study area prepared. Depended on the map the independent variables selected for the ($X_{1...}X_{5}$) as it shows in figure (1) above, the map (1) below. While the table (1) below refers to the information of all element types of the research area study.



The Map 1: study area in zakho, including the classification of the Landscape elements.

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Table 1: The spatial and relative distribution of landscape types in the study area.

Class	Area/ hectares	Area %
Woods	208.365	39.38
farmland	178.704	33.78
Built-up Area	16.313	3.08
Constr. Industry Area	34.071	6.44
Barren Land	58.669	11.09
Water Body	16.227	3.07
Main Roads	1.916	0.36
Agriculture Road	14.828	2.80
Total	**529.093**	**100**

2.4 Data Collection

The data for the both dependent variable (Y) and independent variables (Xi... X5) that impact landscape performances were collected. Along with, the quantitative information for these unobservable variables was obtained through the translation of observable variables into data. The specific meaning and formula for each variable are as follows:

1) Recreational Amenity site (Y)

This variable represents the relationship between the amenity site and the population zone's visits, which is determined by the value of the asset based on the travel cost method, as follows:

$$V = ((T \times w) + (D \times v) + Ca) \times Va$$

Where: T = travel time (in hours), w = average wage rate (ID/hour), D = distance (in km), v = marginal vehicle operating costs, Ca = cost of admission to the asset, Va = average number of visits per year.

2) Poplar Coverage Area (X_1)

The relationship between the area covered by poplar trees and the research area (measured in hectares) is represented by this variable.

$X_1 = PCA/ RA$ Where, PCA is area covered by poplar trees and RA is research area.

3) Agricultural Coverage Area (X_2)

The variable that represents the relationship between the area covered by agriculture and the research area (measured in hectares) is as follows:

$X_2 = Agr/ RA$ Where, Agr is area covered by Agricultural and RA is research area.

4) Ratio of Elements in Research Area (X_3)

This variable represents the relationship between the area elements in research area to the research area (hectares) as follows:

$X_3 = A_{elements} / RA$ Where, $A_{elements}$ is area covered elements in research area and RA is research area.

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5) Topological Formation (X_4)

This value is calculated as the difference in elevation between the highest point in the research area and all other points as follow:

X_4 = Highest ps - Other ps

6) Number of Visitors/ Visits to Area (X_5)

This value represents the total number of visits to the Zakho Poplar Stands research area over the course of one year, from January 6th, 2022 to January 6th, 2023.

3. MATERIALS AND METHODS

This study was carried out in the stands of *Populus nigra* L. stands in Zakho, located in the Duhok/Kurdistan Region of Iraq, with a latitude of 42° 28' 22.00" E and a longitude of 37° 8' 0" N, and an altitude of 433.5 m above sea level. The region is characterized by its mountainous terrain and is situated near the Heizl rivers, known for their fertile soil and high agricultural productivity. The study area spanned approximately 208.365 hectares, with the Populus Nigra plantation Stands situated on the eastern bank of the Heizl river, located approximately 15 km from the center of the town of Zakho.

4. RESULTS AND DISCUSSION

In the below is the Equation of the Multiple Regression Analysis, which was prepared depending on the collected data:

(Y) = -2028142 + 704397210 (X1) ha + 754567056 (X2) - 763329080 (X3) ha + 53430 (X4) m + 10174 (X5)

The standard error of the estimate stands at 1408712.56235, reflecting the inherent uncertainty associated with the estimation process. In totality, this model summary underlines the appropriateness of the multiple regression analysis in effectively capturing the underlying patterns within the data.

Table 2: The ANOVA table in the study area.

ANOVA [a]						
Model		Sum of Squares	d.f	Mean Square	F	Sig.
1	Regression	1768494609994930.800	5	353698921998986.100	178.233	.000[b]
	Residual	164711099916851.500	83	1984471083335.560		
	Total	1933205709911782.200	88			
a. Dependent Variable: Recreational Amenity site						
b. Predictors: (Constant), Visitors Visits, Topological formation, Agricultural Coverage Area, Element Ratio in Area, Poplar Coverage Area						

From the ANOVA Table for Multiple Regression Analysis, in the realm of multiple regression analysis, the ANOVA (analysis of variance) table (2), serves as a tool to assess the significance of predictors within the model. This table offers crucial insights into the total sum of squares, degrees of freedom, mean squares, F-statistics, and p-values associated with the

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model.

In the specific ANOVA table at hand, the focal point is the dependent variable termed **"Recreational Amenity Site,"** while the predictors encompass a range of factors: (Constant), Visitors/Visits, Topological formation, Agricultural Coverage Area, Element Ratio in Area, Poplar Coverage Area, and Forest Coverage Area.

Delving into the details, the table unveils a total sum of squares amounting to 19332057099117 82.200, paired with 88 degrees of freedom. Calculated by dividing the sum of squares of predictors by their degrees of freedom, the mean square holds significance. Meanwhile, the F-statistic, a pivotal ratio, is determined by the mean square divided by the residual sum of squares. The latter, referred to as the residual sum of squares, is derived from the disparity between the total sum of squares and the mean square. Lastly, the p-value assumes prominence by signifying the probability of obtaining a test statistic as extreme as, or more extreme than, the F-statistic under the assumption that the null hypothesis holds true.

In this specific instance, the F-statistic emerges as 178.233, while the p-value dwindles significantly below 0.000. This outcome underscores the rejection of the null hypothesis, which posits no connection between predictors and the dependent variable. In essence, the findings point toward the significant association of at least one predictor with the dependent variable.

Table 3: The Coefficients of landscape types in the study area

Coefficients [a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-2028141.736	813572.434		-2.493	.015
	Poplar Coverage Area	704397176.899	279860627.341	.668	2.517	.014
	Agricultural Coverage Area	754567022.096	256553370.684	.989	2.941	.004
	Element Ratio in Area	-763329045.358	240584866.230	-.715	-3.173	.002
	Topological formation	53429.783	14449.672	.139	3.698	.000
	Visitors/ Visits	10173.627	829.391	1.104	12.266	.000
a. Dependent Variable: Recreational Amenity site						

The observations from Multiple Regression Analysis, As shown in the table (3), The coefficients derived from the multiple regression analysis offer insights into the anticipated impact of each independent variable on the dependent variable, "Recreational Amenity Site." The standardized coefficients (Beta) facilitate a comparison of variable significance, while t-values and p-values gauge the statistical significance of each coefficient.

Based on the outcomes of the multiple regression analysis, several key observations can be drawn regarding the interrelation between landscape performance efficiency and the included variables within the model.

The results of the multiple regression analysis yield a set of coefficients, standard errors, t-values, and p-values that collectively illuminate the strength and direction of the connection between each independent variable (X1, X2, X3, X4, and X5) and the dependent variable (Y).

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Notably, the constant term (-2028142) manifests significance at the 0.015 level, indicating a negative association between the dependent variable (Y) and the independent variable (X1).

The first noteworthy observation pertains to the negative value of the constant term, signifying an adverse link between overall landscape performance efficiency and the landscape's general performance. This might be attributed to the multifaceted influences affecting landscape performance, whereby a negative connection with one variable in the model can reverberate through overall performance.

The second observation highlights the positive coefficient of the variable "Poplar Coverage Area," indicating a favorable correlation between the expanse covered by poplar trees and overall landscape performance efficiency. Specifically, the first independent variable, Poplar coverage area (X1), exhibits a positive relationship with the dependent variable (Y), boasting a coefficient of 2.52 and a significance level of 0.014. This implies that as the coverage area of poplar trees expands, the visitor count increases at a swifter pace. This insight underscores that augmenting the poplar-covered area can bolster the landscape's overall performance. This observation is congruent with studies such as (Zhe Li *et al.,* 2021), (Vinter T. *et al.,* 2016), and (Oehri J. *et al.,* 2020).

The third finding emphasizes the affirmative coefficient associated with the variable "Agricultural Coverage Area," indicating a positive connection between the area enveloped by agricultural land and the landscape's overall performance efficiency. Correspondingly, the second independent variable, Agricultural coverage area (X2), displays a positive correlation with the dependent variable (Y), featuring a coefficient of 2.94 and a significance level of 0.004. In essence, an expansion of the agricultural land area corresponds to an accelerated increase in visitor numbers. This underscores that amplifying the agricultural coverage area can enhance the landscape's overall performance. This concurs with studies like (Estrada N. *et al.,* 2022), (Agrawal A. *et al.,* 2014), and (Kleeschulte S. *et al.,* 2023).

The fourth insight points to the negative coefficient attributed to the variable "Element Ratio in Area," indicating an unfavorable relationship between the ratio of elements in the area and the landscape's overall performance efficiency. Accordingly, the third independent variable, Element Ratio in Area (X3), exhibits a negative correlation with the dependent variable (Y), characterized by a coefficient of -3.17 and a significance level of 0.002. Thus, as the element ratio in the area decreases, the visitor count experiences a moderated growth. This underscores that a higher element ratio within the area can detrimentally affect the landscape's overall performance. This resonates with studies like (Estrada N. *et al.,* 2022), (Zhang Y. et al., 2022), and (Milheiras S. G. *et al.,* 2022).

The fifth observation underscores the positive coefficient linked to the variable "Topological formation," signifying a positive association between the topological structure and the landscape's overall performance efficiency. Consequently, the fourth independent variable, Topological formation (X4), establishes a positive link with the dependent variable (Y), showcasing a coefficient of 3.70 and a significance level of 0.000. In essence, an enhancement in topological formation leads to a more rapid increase in visitor numbers. This underscores

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that optimizing the topological structure can contribute to an improved landscape performance. This resonates with studies like (Zhe Li *et al.,* 2020) and (Zhang Y. *et al.,* 2022).

Lastly, the variable "Visitors Visits" exhibits a positive coefficient, highlighting a favorable connection between the number of visitors to the recreational amenity site and its overall performance efficiency. In turn, the fifth independent variable, Visitors/Visits (X5), showcases a positive association with the dependent variable (Y), demonstrating a coefficient of 12.27 and a significance level of 0.000. Consequently, an escalation in visitor numbers directly corresponds to an accelerated increase in performance efficiency. This underscores that augmenting the visitor count can heighten the site's performance. The implications of this variable on forest landscape performance efficiency are consistent with studies by (Zhe Li *et al.,* 2020) and (Zhang Y. *et al.,* 2022) .In summary, these observations affirm the substantial impact of certain variables within the model on the overall landscape performance efficiency, suggesting their utility in enhancing landscape performance. Nonetheless, it's imperative to acknowledge that this model is just one facet, and other models or factors may similarly influence landscape performance.

To encapsulate, the results of the multiple regression analysis underscore the positive correlations between the independent variables Poplar coverage area (X1), Agricultural coverage area (X2), Element Ratio in Area (X3), Topological formation (X4), and Visitors/Visits (X5) with the dependent variable (Y). Additionally, the significance of the constant term at the 0.015 level underscores a negative relationship between the dependent variable (Y) and the independent variable (X1). Collectively, these findings denote that an increase in poplar coverage area, agricultural coverage area, topological formation, and visitor count correspondingly boosts the overall landscape performance efficiency, whereas a decrease in the element ratio in the area leads to improved performance.

Table 4: The correlation of landscape types in the study area.

Correlations							
		Recreational Amenity site	**Poplar Coverage Area**	**Agricultural Coverage Area**	**Element Ratio in Area**	**Topologic l formation**	**Visitors / Visits**
Recreational Amenity site	Pearson Correlation	1	-.411**	-.236*	-.524**	.076	.941**
Poplar Coverage Area	Pearson Correlation	**-.411****	1	-.607**	.094	.465**	-.432**
Agricultural Coverage Area	Pearson Correlation	**-.236***	**-.607****	1	.709**	-.343**	-.241*
Element Ratio in Area	Pearson Correlation	**-.524****	**.094**	**.709****	1	-.016	-.517**
Topological formation	Pearson Correlation	**.076**	**.465****	**-.343****	**-.016**	1	-.042
Visitors/ Visits	Pearson Correlation	**.941****	**-.432****	**-.241***	**-.517****	**-.042**	1
**. Correlation is significant at the 0.01 level (2-tailed).							
*. Correlation is significant at the 0.05 level (2-tailed).							

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The Correlation Analysis Results, depending on the table (4), illustrated the outcomes of the multiple regression analysis are succinctly displayed within a table, which comprehensively illustrates the Pearson correlation coefficients between various pairs of variables. Alongside these coefficients, the table also provides their corresponding significance levels. The Pearson correlation coefficient serves as a metric for gauging the magnitude and orientation of the linear connection between two continuous variables. A correlation coefficient of 1 signifies a perfect positive correlation, while a score of -1 denotes a perfect negative correlation. An index of 0 denotes the absence of correlation between the variables.

The table showcases several notable correlations with statistical significance:

- A significant negative correlation (-0.411) emerges between the "Recreational Amenity site" variable and the "Poplar Coverage Area" variable. This suggests that as the Poplar Coverage Area increases, the Recreational Amenity Site variable is inclined to decrease.
- Likewise, a significant negative correlation (-0.236) is observed between the "Recreational Amenity Site" variable and the "Agricultural Coverage Area" variable. As the Agricultural Coverage Area grows, the Recreational Amenity Site variable is prone to diminish.
- A substantial negative correlation (-0.524) is identified between the "Recreational Amenity site" variable and the "Element Ratio in Area" variable. An augmentation in the element ratio in area corresponds to a decrease in the Recreational Amenity Site variable.
- In contrast, a notable positive correlation (0.076) exists between the "Recreational Amenity site" variable and the "Topological formation" variable. This implies that as the Topological Formation variable advances, the Recreational Amenity Site variable tends to rise.
- Most significantly, an exceedingly strong positive correlation (0.941) is evident between the "Recreational Amenity site" variable and the "Visitors Visits" variable. As the Visitors/Visits variable escalates, the Recreational Amenity Site variable witnesses a corresponding upswing.

In a comprehensive perspective, these findings furnish insights into the intricate relationships among various variables within the multiple regression models. The correlation coefficients elucidate the intensity and direction of linear associations across variable pairs, while the significance levels underscore the statistical validity of these relationships. These outcomes serve as a tool to identify the variables most robustly linked to each other and to the dependent variable within the regression model.

5. CONCLUSIONS

This research has illuminated the diverse benefits of various landscape elements, encompassing social, environmental, aesthetic, and economic advantages. The study has focused on highlighting how forest landscape performance can play a pivotal role in enhancing the environmental quality of urban spaces. The multiple regression analysis conducted in this study has unveiled valuable insights into the determinants of landscape performance efficiency at

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recreational amenity sites. The model's high R-squared value underscores the collective explanatory strength of predictors, including poplar coverage area, agricultural coverage area, element ratio within the area, topological arrangement, and visitor metrics. ANOVA results further validate the overall significance of these predictors. The coefficients offer a clear understanding of the direction and magnitude of each predictor's impact. Notably, positive correlations emerged between site performance and factors such as poplar and agricultural coverage areas, as well as topological arrangement. Conversely, a higher element ratio within the area correlated with decreased performance. The study also emphasizes the positive influence of visitor volume on site performance.

These findings emphasize the importance for landscape managers and planners to consider these variables when striving to optimize the design and management of recreational amenity sites. By strategically harnessing landscape elements and enhancing visitors' experiences, the overall allure and effectiveness of these sites can be elevated. This research significantly contributes to a deeper comprehension of the intricate interplay between landscape attributes and site performance. As a result, it empowers more informed decision-making within landscape management and planning endeavors.

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