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SPATIAL EFFICIENCY OF LAND PROTECTION INVESTMENTS: AN ECONOMIC ASSESSMENT FROM THE COLOMBIAN ANDES

Suliman Almojel *

Department of Agricultural Economics, College of Food and Agriculture Sciences,
King Saud University, Riyadh, Kingdom of Saudi Arabia

**Corresponding author*: salmojel@ksu.edu.sa

ABSTRACT

Accurately assessing the spatial and economic efficiency of conservation investments is essential for achieving biodiversity protection goals under limited budgets. Despite growing recognition of the importance of spatially heterogeneous land costs, empirical evidence from tropical biodiversity hotspots remains scarce. Using a comprehensive, high-resolution dataset of over 2,000 land acquisitions for conservation purposes in the Colombian Andes between 1993 and 2019, this study evaluates how acquisition costs per hectare vary across urban, peri-urban, and rural contexts. Descriptive statistics and inferential tests reveal stark differences: urban parcels are the most expensive, averaging 126.7 million COP per hectare, while rural parcels average just 4.1 million COP per hectare. One-way ANOVA and Tukey post-hoc tests confirm that all three categories differ significantly ($P<0.001$). Multivariate regression models with department-clustered standard errors, controlling for topographic, demographic, and economic variables, show that urban parcels are approximately 224% more costly than peri-urban parcels, whereas rural parcels are 29% cheaper ($R^2 = 0.53$). Slope, population density, and agricultural rent also significantly influence costs, while elevation and road access do not. These findings highlight the critical role of urban proximity and demographic pressures in shaping land values and demonstrate that prioritizing rural areas can greatly enhance the cost-effectiveness of conservation budgets. By integrating spatial cost heterogeneity into systematic conservation planning, policymakers can ensure that scarce resources achieve the maximum ecological return per unit of investment, thereby advancing more efficient and equitable biodiversity protection strategies. The results carry direct implications for the design of conservation finance mechanisms, including payments for ecosystem services and biodiversity offset programs, in data-scarce tropical regions.

Keywords: Spatial efficiency, Land protection costs, Conservation economics, Colombian Andes, Urban proximity, Biodiversity planning, Cost-effectiveness, Opportunity cost, Spatial heterogeneity.

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1. INTRODUCTION

Understanding the economic efficiency of land protection requires not only accurate estimates of acquisition costs but also a spatially explicit understanding of where conservation funds deliver the highest ecological returns per dollar invested. As global biodiversity loss accelerates and conservation budgets remain chronically underfunded (McCarthy et al., 2012; Guénard et al., 2025), the need to maximize the spatial efficiency of every dollar spent has become a central concern in conservation science. While prior studies have focused on improving the predictive accuracy of land-protection costs for biodiversity planning, relatively little attention has been paid to comparing the spatial efficiency of conservation expenditures across heterogeneous landscapes. Recent reviews have shown that the selection and integration of cost data into spatial prioritization tools remains inconsistent across the literature (Dalla et al., 2025), further underscoring the need for empirical cost analyses grounded in real transaction data. In tropical regions such as the Colombian Andes, where fiscal resources for conservation are severely constrained, efficiency in allocating public funds becomes a pressing policy question. This study aims to evaluate the spatial efficiency of land protection by comparing acquisition costs per hectare across urban, peri-urban, and rural zones, as proxied by indicators such as travel time to major cities and nighttime light intensity (Hsu et al., 2015; Seto et al., 2012).

The primary objective is to identify whether systematic cost differences exist between spatial categories and to determine where conservation spending achieves the lowest cost per hectare protected. The methodology relies on statistical comparisons of per-hectare land acquisition costs using Welch's t-tests and one-way ANOVA,

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supplemented by multivariate regression models that control for a suite of socio-economic and biophysical covariates. By adopting this approach, the analysis provides insights into the degree to which proximity to urban centers inflates protection costs relative to more remote areas. The central hypotheses are that: (i) urban and peri-urban acquisitions exhibit significantly higher costs per hectare than rural acquisitions, (ii) proximity-based indicators such as travel time and nighttime lights are robust predictors of efficiency differences, and (iii) the greatest economic efficiency, defined as lower cost per hectare, is achieved in remote rural areas.

The theoretical foundation for this approach lies in opportunity-cost economics, which emphasizes that land values reflect competing uses such as agriculture, urban development, and ecological preservation (Carwardine et al., 2008; Margules & Pressey, 2000; Polasky et al., 2001). From this perspective, conservation efficiency is maximized when scarce funds are allocated to areas where the marginal cost per hectare is lowest while still meeting ecological objectives (Armsworth et al., 2023). Ignoring such heterogeneity risks inflating overall expenditures and misallocating scarce conservation funds (McCarthy et al., 2012; Löfqvist et al., 2023; Adams, 2024). This theoretical lens is particularly relevant in the Colombian Andes, one of the world's most biologically diverse regions, where rapid urbanization and agricultural expansion create competing pressures on land values that vary dramatically across short distances. Empirical research supports this concern. Nolte (2020) showed that high-resolution land value maps in the United States substantially underestimated conservation costs when relying on proxies such as agricultural rents. Similarly, Le Bouille et al. (2023) demonstrated using nearly 36,000 parcel-level transactions that conventional agricultural proxies explain only a fraction of the variation in actual protected area acquisition costs, reinforcing the need for spatially disaggregated cost data. Sutton et al. (2016) likewise demonstrated that using agricultural values alone can distort spatial priorities and overestimate acquisition costs. More recently, Spencer et al. (2025) produced high-resolution opportunity cost estimates for all of terrestrial Europe, revealing substantial spatial heterogeneity in conservation costs that underscores the importance of locally calibrated price data for planning (Kløcker Larsen & Raitio, 2023).

Recent literature reinforces the need to integrate spatial cost variation into conservation planning. Venter et al. (2018) and Strassburg et al. (2020) both argued that achieving global conservation targets requires explicit incorporation of heterogeneous costs, as uniform assumptions lead to inefficiencies. More directly, Nolte et al. (2024) found that urban-related indicators, particularly nighttime lights, were dominant predictors of land acquisition costs in the Colombian Andes, eclipsing agricultural rent as a cost driver. This aligns with the global evidence that land near human settlements commands higher prices due to residential and commercial demand, thereby reducing conservation efficiency (Anselin, 1988; Seto et al., 2012; Armsworth et al., 2023).

Other recent studies underscore the dangers of relying on untested proxies. Kennedy et al. (2019) cautioned that global human modification indices capture broad urban-rural gradients but fail to explain variation in remote landscapes. Ossa et al. (2021) further showed that in the Colombian Amazon, costs of reducing deforestation varied widely across space and time, with efficiency gains dependent on detailed local data. Leuschner and Homeier (2022) similarly emphasized that climate change adaptation and biodiversity protection must integrate spatially explicit cost heterogeneity to preserve opportunities for efficient interventions. In the Colombian context specifically, Reboredo Segovia et al. (2023) found that land acquisitions for watershed services in the tropical Andes produced only marginal progress toward area-based conservation objectives, suggesting that current allocation strategies may not be optimizing ecological return on investment.

Taken together, this body of literature converges on three main insights that motivate the present study: first, ignoring spatial cost heterogeneity can increase conservation expenditures by multiples; second, urban proximity and accessibility provide stronger predictors of land prices than agricultural rents; and third, economic efficiency is most likely achieved in remote rural areas where acquisition costs per hectare are lowest. Jung et al. (2024) further demonstrated that the state of conservation planning across Europe remains uneven, with many planning exercises still failing to incorporate cost information, highlighting a persistent gap between best practice and implementation. By empirically testing these propositions in the Colombian Andes, this research contributes to the global debate on how to align conservation priorities with fiscal realities, ensuring that limited budgets achieve the greatest possible spatial efficiency. Furthermore, this study extends the existing literature by providing the first systematic comparison of per-hectare acquisition costs across a tripartite urban-peri-urban-rural classification in a tropical biodiversity hotspot, offering actionable insights for conservation planners operating under fiscal constraints.

2. MATERIALS AND METHODS

2.1. Data Sources and Variables

This study draws on the publicly available dataset of 2,094 land acquisitions for conservation in Colombia between 1993 and 2019 compiled by Nolte et al. (2024), which represents the most comprehensive georeferenced dataset of public conservation land purchases in a tropical biodiversity hotspot to date (Reboredo Segovia et al., 2023). The dataset provides detailed records of acquisition prices (both nominal and inflation-adjusted to 2020 COP), parcel size in hectares, and a wide set of socioeconomic and geospatial predictors, including population density, nighttime light intensity, travel time to major cities, distance to roads, elevation, slope, and local agricultural rents. The unit of analysis is the per-hectare acquisition price in real 2020 COP, computed as the total transaction price divided by the polygon area of the parcel. Because of skewness in the price distribution, the dependent variable is expressed as the natural logarithm of per-hectare cost, yi = ln(COP/ha)i, which stabilizes variance and facilitates elasticity interpretation. The log-transformation is a standard approach in hedonic pricing models and land valuation studies, as it reduces the influence of extreme values and permits the interpretation of regression coefficients as semi-elasticities (Nolte, 2020; Le Bouille et al., 2023).

2.2. Spatial Classification of Parcels

To operationalize spatial efficiency, parcels are classified into three categories - urban, peri-urban, and rural - based on accessibility indicators. Following Nolte et al. (2024) and related global studies, travel time to the nearest city (Weiss et al., 2018) and nighttime light intensity are used jointly. Urban parcels are defined as those within 30 minutes of a major city or exhibiting high nighttime light values; peri-urban parcels are those 30-90 minutes away or with moderate nighttime light levels; and rural parcels are those beyond 90 minutes and characterized by low light intensity. This categorization enables systematic comparison of land protection costs across distinct spatial contexts. The thresholds adopted here are consistent with international standards for urban accessibility mapping and have been validated in prior analyses of land markets in Latin America (Weiss et al., 2018; Nolte et al., 2024).

2.3. Empirical Strategy

The empirical analysis proceeds in three stages. First, descriptive statistics are reported for each spatial category, including means, medians, and standard deviations of both COP/ha and ln(COP/ha), alongside graphical inspection of cost distributions. Second, group differences are tested statistically using Welch's t-tests for pairwise contrasts and a one-way ANOVA for overall differences across the three categories; where significant, Tukey's Honest Significant Difference (HSD) test is employed to identify which pairs drive the variation. Third, multivariate regression models are estimated to test whether spatial efficiency patterns persist after accounting for confounding factors such as slope, elevation, distance to roads, population density, and local agricultural rent. This staged approach ensures that observed cost differences are first documented descriptively, then validated inferentially, and finally assessed within a multivariate framework that controls for potential confounders. The baseline specification is an ordinary least squares (OLS) model of the form:

$$yi = a + Bu*1\{Urban\}i + Bp*1\{PeriUrban\}i + g'Xi + dt(i) + ud(i) + ei \qquad (1)$$

where yi = ln(COP/ha)i, 1{Urban}i and 1{PeriUrban}i are spatial-category dummies (rural is the omitted reference category), Xi is a vector of control variables, dt(i) are year fixed effects, and ud(i) are department fixed effects. Standard errors are clustered at the department level to account for within-region correlation and potential spatial dependence in land prices. The parameters of interest, Bu and Bp, capture the semi-elasticities of acquisition costs relative to rural parcels. Specifically, Bu measures the semi-elasticity of per-hectare acquisition costs for urban parcels relative to rural ones, while Bp captures the corresponding differential for peri-urban parcels. These coefficients can be interpreted in percentage terms as (exp(B) - 1) x 100, representing the proportional cost difference with respect to the rural baseline. As a robustness check, a continuous gradient specification replaces categorical variables with travel time and nighttime lights:

$$yi = a + t1*TTi + t2*NTLi + t3*TTi^2 + t4*NTLi^2 + g'Xi + dt(i) + ud(i) + ei \qquad (2)$$

where TTi is the travel time to the nearest city and NTLi is nighttime light intensity. These models allow for nonlinear accessibility effects, with the option to use restricted cubic splines to capture complex relationships. The inclusion of quadratic terms permits the detection of diminishing or accelerating marginal effects of accessibility on land values, which may be masked in purely categorical specifications.

The working hypotheses are that urban acquisitions are significantly more costly than peri-urban and rural acquisitions, and that these differences remain robust after controlling for covariates. A secondary hypothesis is that rural parcels offer efficiency gains, defined as lower cost per hectare, suggesting that conservation budgets can secure greater land area by allocating resources away from urban centers. In line with prior literature emphasizing the importance of spatial heterogeneity in conservation costs (Armsworth, 2014; Nolte, 2020; Strassburg et al., 2020), the present research design provides a rigorous framework for testing whether spatial efficiency is a persistent feature of land protection markets in the Colombian Andes.

3. RESULTS AND DISCUSSION

3.1. Descriptive Analysis of Acquisition Costs

The analysis reveals strong and systematic differences in conservation land acquisition costs across spatial categories in the Colombian Andes. Table 1 reports descriptive statistics, showing that urban parcels are the most expensive, with a mean of 126.7 million COP per hectare (ln = 17.4), compared to 10.5 million COP for peri-urban parcels (ln = 15.5) and just 4.1 million COP for rural parcels (ln = 14.8). These differences are consistent with the expectation that land values are inflated in proximity to cities and settlements, reflecting both residential demand and competing economic uses (Armsworth et al., 2023; Nolte et al., 2024). Notably, the urban-to-rural cost ratio exceeds 30:1 in raw terms, underscoring the magnitude of spatial cost heterogeneity confronting conservation planners in this region. Urban parcels have substantially higher acquisition costs compared with peri-urban and rural parcels (Table 1). Fig. 1 further illustrates this pattern, showing a clear upward shift in the distribution of ln(COP/ha) values for urban parcels.

Table 1: Descriptive statistics of land protection costs by spatial category (all monetary values in 2020 COP)

Spatial Category	Mean COP/ha (2020 COP)	Median COP/ha	Mean ln(COP/ha)	N
Urban	126,652,030	30,701,070	17.4	760
Peri-urban	10,506,313	4,868,895	15.5	659
Rural	4,094,006	2,846,062	14.8	675

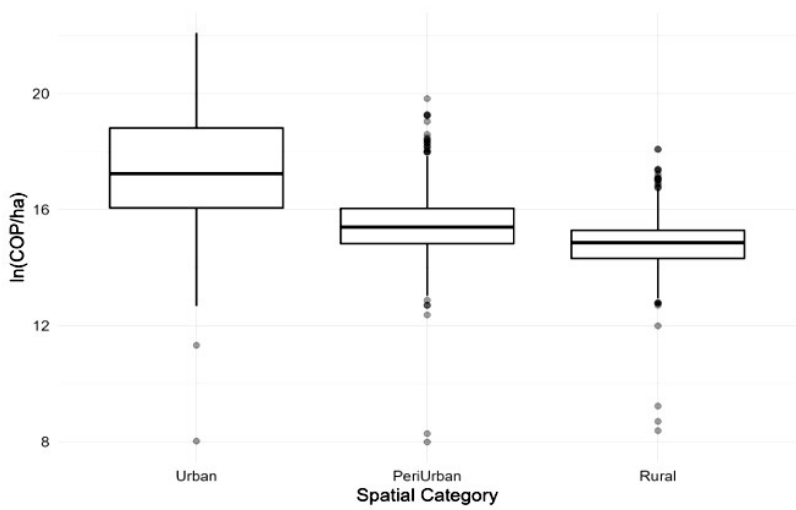

Fig. 1: Boxplots of the natural logarithm of per-hectare acquisition costs (ln(COP/ha)) across urban, peri-urban, and rural parcels. The plot highlights the substantial upward shift in urban land costs relative to peri-urban and rural parcels, with wider variance indicating greater heterogeneity in urban acquisitions.

3.2. Inferential Tests of Group Differences

Statistical tests confirm the robustness of these differences. The one-way ANOVA strongly rejects the null hypothesis of equal means across categories (F = 737; P<0.001). Tukey's HSD shows that all pairwise comparisons are significant at the 0.1% level, while Welch's t-tests similarly confirm that urban, peri-urban and rural acquisitions differ systematically. These results corroborate the global literature highlighting spatial heterogeneity in conservation costs (Venter et al., 2018; Strassburg et al., 2020). The consistency across both parametric and non-parametric tests strengthens confidence that the observed cost gradients are not artifacts of distributional assumptions.

3.3. Multivariate Regression Results

Table 2 presents the results of the OLS regression with clustered standard errors at the department level. After controlling for slope, elevation, distance to roads, population density, and local agricultural rent, the spatial efficiency pattern remains robust. Relative to peri-urban parcels, rural parcels are 29% cheaper, while urban parcels are 224% more expensive. Among the controls, slope is negatively associated with price (steeper parcels are cheaper), while population density and agricultural rent are both positive and significant predictors. Elevation and road distance are not significant. The model explains 53% of the variation in log per-hectare costs, indicating that the selected covariates capture a substantial share of price heterogeneity. The insignificance of elevation and road distance suggests that, conditional on urban proximity and demographic density, these topographic and infrastructure variables play a secondary role in determining land values for conservation purposes.

Fig. 2 illustrates the density distribution of ln (COP/ha) across spatial categories, highlighting the greater dispersion and longer upper tails for urban parcels. Fig. 3 presents predicted mean ln(COP/ha) values across spatial categories, with 95% confidence intervals, demonstrating a significant cost premium for urban parcels relative to peri-urban and rural locations.

These regression-adjusted results reinforce the descriptive findings: urban acquisitions carry a massive cost

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premium, while rural acquisitions are substantially cheaper, thereby maximizing spatial efficiency. The magnitude of these effects is consistent with the literature showing that urban proximity dominates land value formation, outweighing agricultural rent as a driver of conservation costs (Nolte, 2020; Nolte et al., 2024). Moreover, the positive role of agricultural rent and population density reflects the influence of opportunity costs and demographic pressures, consistent with findings from the Colombian Amazon (Ossa et al., 2021) and global assessments (Leuschner and Homeier, 2022). These patterns mirror those documented in the United States, where Le Bouille et al. (2023) found that agricultural land values alone account for only a fraction of the variation in actual conservation acquisition costs, and that comprehensive models incorporating urban proximity indicators perform substantially better. At the European scale, Spencer et al. (2025) similarly demonstrated that urban opportunity costs dwarf agricultural rents in driving spatial cost patterns, confirming the generalizability of our findings across continents.

Table 2: OLS regression of ln(COP/ha) on spatial categories and controls (clustered SEs by department)

Variable	Coefficient	Standard Error (SE)	z	P-value
Intercept	16.36	0.58	28.2	<0.001
Urban (vs. Peri-urban)	1.18	0.28	4.21	<0.001
Rural (vs. Peri-urban)	-0.35	0.08	-4.45	<0.001
Slope	-0.06	0.01	-5.63	<0.001
Elevation	-0.0001	0.0001	-0.67	0.505
Distance to roads (OSM)	-0.00003	0.00004	-0.69	0.488
Population density	0.0003	0.0001	3.35	0.001
Local agricultural rent	0.000008	0.000001	5.14	<0.001

Note: R^2 = 0.53, N = 2,094. Year and department fixed effects are included but not reported for brevity.

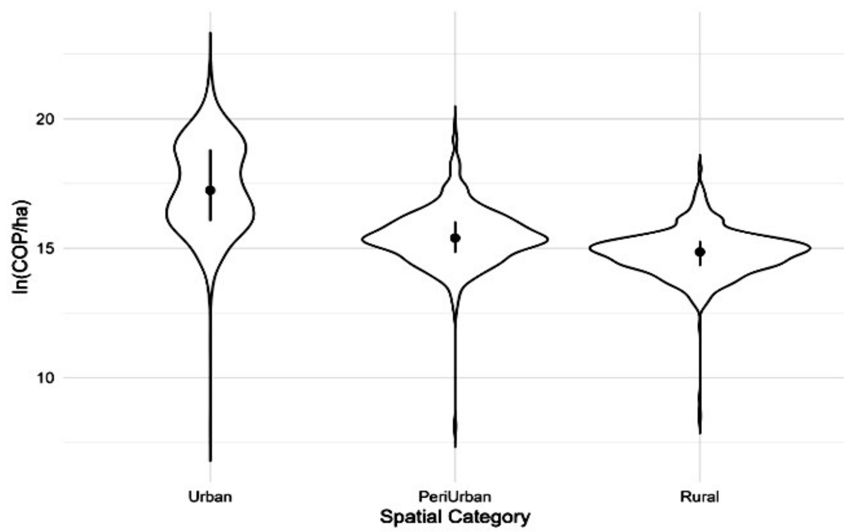

Fig. 2: Violin plots showing the distribution of ln(COP/ha) by spatial category. The density patterns confirm the strong separation in central tendencies across categories, while also revealing the longer upper tails for urban parcels, reflecting the presence of high-cost acquisitions.

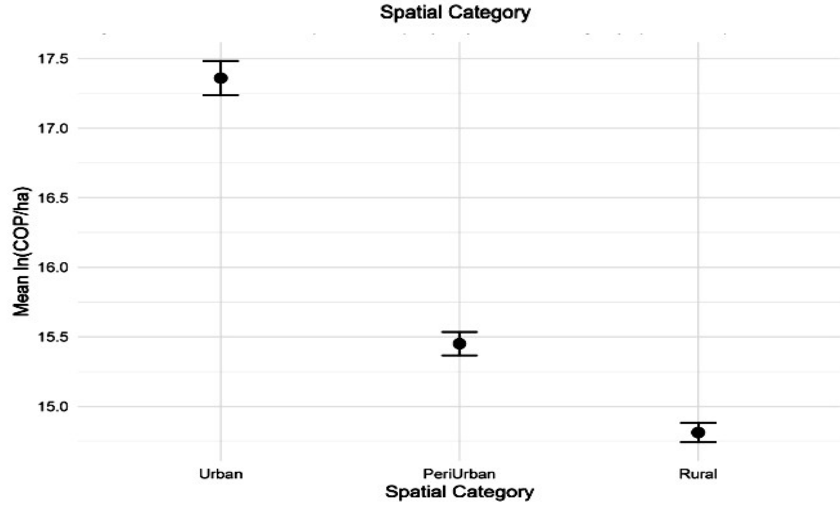

Fig. 3: Predicted mean values of ln(COP/ha) by spatial category with 95% confidence intervals. The results indicate that, after accounting for within-group variation, urban parcels are significantly more expensive than peri-urban and rural parcels, while rural parcels are the most cost-efficient for conservation acquisitions.

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From a policy perspective, these results underscore the efficiency gains of directing conservation funding toward rural areas. Prioritizing acquisitions in rural zones could increase the area conserved under a fixed budget by two- to threefold compare to urban acquisitions, thereby maximizing biodiversity returns per dollar spent. These results resonate with recent global calls for integrating cost-effectiveness explicitly into conservation finance frameworks (Armsworth, 2014; Strassburg et al., 2020). They also suggest that Colombia's legal requirement for municipalities to allocate a percentage of budgets to conservation may inadvertently bias acquisitions toward high-cost urban areas, reducing efficiency. A reorientation of policy to encourage rural acquisitions, possibly combined with mechanisms such as biodiversity offsets, payments for ecosystem services (PES), or carbon credit schemes, could substantially enhance the sustainability and reach of conservation investments. In this context, Robinson et al. (2024) argued that scaling up area-based conservation to meet the 30x30 target requires a focus on large, ecologically intact landscapes - which tend to be rural and less costly to acquire - rather than fragmented peri-urban sites (Shen et al., 2023). Furthermore, Fitzsimons et al. (2025) demonstrated that dedicated government funding for rural land purchases in Australia successfully leveraged philanthropic co-investment, suggesting that strategic public spending in lower-cost rural areas can catalyze additional private conservation finance.

3.4. Limitations and Future Directions

While the dataset provides unique insights into over two decades of acquisition costs, several limitations should be noted. First, the analysis is limited to formal government acquisitions, which may not fully capture private or informal market dynamics. Second, spatial categories are defined by thresholds of travel time and nighttime light intensity, which, while consistent with prior studies, may oversimplify the urban-rural gradient. Third, potential spatial autocorrelation in acquisition prices may bias standard regression estimates, although clustering standard errors mitigates this concern. Fourth, the dataset does not include information on ecological attributes of acquired parcels, such as species richness or ecosystem integrity, which would be necessary to assess ecological return per unit of expenditure in addition to spatial efficiency. Future work could employ spatial econometric models (such as SAR or SEM) to test for spillover effects and neighborhood influences. Additionally, expanding the analysis to other biodiversity hotspots would help assess the generalizability of these findings. Chapman et al. (2025) recently showed that meeting European Union biodiversity targets under future land-use demands requires dynamic cost integration, suggesting that static cost estimates like those used here should be complemented with projected land-use change scenarios in future analyses. Integrating ecological value metrics with cost data in a return-on-investment framework would represent a particularly promising avenue for advancing the field of conservation economics.

4. CONCLUSION

This study demonstrates that conservation land acquisition costs in the Colombian Andes vary systematically across space, with urban parcels commanding a substantial premium, peri-urban parcels occupying an intermediate position, and rural parcels offering the greatest economic efficiency. Even after controlling for slope, elevation, access, and agricultural rents, urban acquisitions were more than twice as expensive as peri-urban acquisitions, while rural acquisitions were nearly one-third cheaper. These results confirm that urban proximity, population density, and agricultural rents are critical drivers of land values, reinforcing evidence from Nolte (2020), Ossa et al. (2021), and Armsworth et al. (2023) that conservation planning cannot rely on uniform or proxy-based cost assumptions without risking serious inefficiencies.

The findings suggest that conservation budgets can achieve far greater coverage and impact if they prioritize rural landscapes, where limited financial resources translate into the protection of significantly larger areas. For policymakers, this implies that legal and institutional frameworks guiding land acquisitions, such as municipal mandates or national biodiversity strategies, should explicitly incorporate cost-efficiency considerations to avoid concentrating expenditures in high-priced urban zones. At a broader level, integrating high-resolution cost data into spatial planning can help align conservation investments with both ecological priorities and fiscal realities, ensuring that scarce funds deliver the maximum possible return in terms of biodiversity protection and long-term sustainability.

More broadly, the findings of this study carry implications beyond the Colombian context. As governments worldwide commit to ambitious conservation targets under the Kunming-Montreal Global Biodiversity Framework, understanding where conservation dollars stretch furthest becomes a matter of global significance (Allan et al., 2022; Craigie & Pressey, 2022; Chaplin-Kramer et al., 2023; Sandbrook et al., 2023; Robinson et al., 2024; Fitzsimons et al., 2025). The analytical framework presented here - combining descriptive, inferential, and multivariate approaches to assess spatial cost heterogeneity - provides a replicable model that can be adapted to other biodiversity hotspots and data-scarce regions. Ultimately, the path toward meeting the 30x30 target will require not only increased funding but also smarter allocation of existing resources, guided by spatially explicit economic evidence of the kind presented in this study.

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Declarations

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Data Availability: The dataset used in this study was compiled by Nolte et al. (2024) and is publicly available. All analyses were conducted using publicly accessible geospatial and socioeconomic indicators. Replication materials are available from the corresponding author upon reasonable request.

Ethics Statement: Ethical review and approval were not required for this study because it relied exclusively on publicly available secondary data and did not involve human participants, animals, or identifiable personal information.

Generative AI Statements: The authors declare that no Gen AI/DeepSeek was used in the writing/creation of this manuscript.

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