

## Monitoring Urban Expansion in Valledupar with Sentinel-2 Imagery and Fuzzy Logic Classification

### Monitoreo de la Expansión Urbana en Valledupar mediante Imágenes Sentinel-2 y Clasificación por Lógica Difusa

Juan G. Popayán-Hernández<sup>1</sup>   Heider F. Losada-Losada<sup>2</sup>  Deliannys M. Mendoza-Barradas<sup>3</sup> 

<sup>1</sup> Doctor en Ciencias Ambientales, Dirección Académica, Universidad Nacional de Colombia, Sede de La Paz, La Paz, Colombia.

<sup>2</sup> Magister en Ingeniería y Gestión Ambiental, Universidad Surcolombiana, Neiva, Huila, Colombia.

<sup>3</sup> Ingeniera ambiental (e), Universidad Nacional Abierta y a Distancia- UNAD, Valledupar, Colombia.

#### How to cite?

Popayán-Hernández JG, Losada-Losada HF, Mendoza-Barradas DM. Monitoring Urban Expansion in Valledupar with Sentinel-2 Imagery and Fuzzy Logic Classification. Ingeniería y Competitividad, 2025, 28(1)e-21015382

<https://doi.org/10.25100/iyv.v28i1.15382>

Received: 25/10/25

Reviewed: 24/11/25

Accepted: 21/01/26

Online: 12/03/26

#### Correspondence

[jgpopyanh@unal.edu.co](mailto:jgpopyanh@unal.edu.co)

## Abstract

**Introduction:** The city of Valledupar, Colombia, underwent accelerated urban transformation between 1985 and 2025, with 124% expansion generating significant socio-environmental pressures. This research developed and applied a comprehensive model to analyze this dynamic and its drivers.

**Materials and Methods:** A three-phase methodology was implemented: (I) multitemporal analysis with Landsat/Sentinel-2 imagery and GIS to quantify physical expansion (1985-2025); (II) development of a Mamdani-type fuzzy logic model using FisPro/GeoFIS software to classify the urban-rural transition; and (III) statistical validation and correlation analysis with socioeconomic variables.

**Results:** The urban footprint grew from 1,850 to 4,150 ha, consuming 1,150 ha of agricultural soil (2000-2020). A substantial portion of the expansion (45%) occurred in an unplanned, discontinuous manner. The fuzzy logic model achieved high accuracy ( $Kappa=0.81$ ) and revealed a significant correlation ( $r=0.55$ ,  $p<0.01$ ) between peripheral expansion and labor informality.

**Discussion:** The results evidence a clear pattern of unstructured urban growth. The fuzzy logic model proved to be a superior tool for capturing the complexity of the urban-rural transition and its links to socioeconomic precariousness. Conclusions: Valledupar's expansion has been unsustainable and fragmented. Integrating fuzzy logic models into urban planning and monitoring frameworks is recommended for more effective and sustainable land management.

**Keywords:** TUrban Expansion, Fuzzy Logic, Remote Sensing, Valledupar, Land Use Planning.

## Resumen

**Introducción:** La ciudad de Valledupar, Colombia, experimentó una transformación urbana acelerada entre 1985 y 2025, con una expansión del 124% que generó presiones socioambientales significativas. Esta investigación desarrolló y aplicó un modelo integral para analizar esta dinámica y sus impulsores.

**Materiales y Métodos:** Se implementó una metodología en tres fases: (I) análisis multitemporal con imágenes Landsat/Sentinel-2 y SIG para cuantificar la expansión física (1985-2025); (II) desarrollo de un modelo de lógica difusa tipo Mamdani con los softwares FisPro/GeoFIS para clasificar la transición urbano-rural; y (III) validación estadística y análisis de correlación con variables socioeconómicas.

**Resultados:** La mancha urbana creció de 1,850 a 4,150 ha, consumiendo 1,150 ha de suelo agrícola (2000-2020). Una parte sustancial de la expansión (45%) ocurrió de manera no planificada y discontinua. El modelo de lógica difusa logró una alta precisión ( $Kappa=0,81$ ) y reveló una correlación significativa ( $r=0,55$ ,  $p<0,01$ ) entre la expansión periférica y la informalidad laboral.

**Discusión:** Los resultados evidencian un patrón claro de crecimiento urbano no estructurado. El modelo de lógica difusa demostró ser una herramienta superior para capturar la complejidad de la transición urbano-rural y sus vínculos con la precariedad socioeconómica.

**Conclusiones:** La expansión de Valledupar ha sido insostenible y fragmentada. Se recomienda la integración de modelos de lógica difusa en los marcos de planificación y monitoreo urbano para una gestión del suelo más efectiva y sostenible.

**Palabras clave:** Expansión Urbana, Lógica Difusa, Percepción Remota, Valledupar, Planificación Territorial.



Spanish version



### Why was it done?

The study aimed to analyze the drivers and patterns behind Valledupar's rapid and unsustainable urban expansion over four decades.

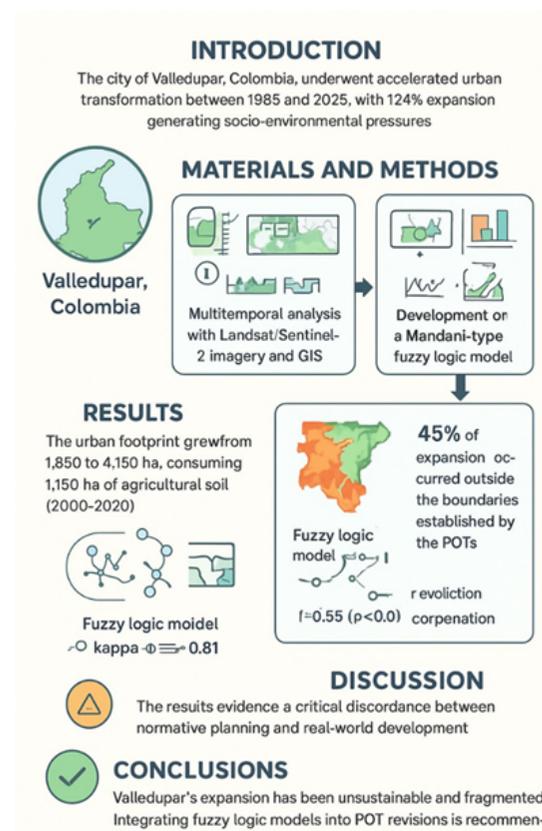
### What were the most relevant results?

The most relevant results showed a dominant pattern of unplanned, fragmented growth that consumed significant agricultural land and was correlated with socioeconomic precariousness.

### What do they contribute?

The main contribution is a validated fuzzy logic model that effectively captures the urban-rural continuum and its socioeconomic drivers, providing a superior tool for sustainable urban planning.

## Graphical Abstract



## Introduction

Colombia's accelerated urbanization, with over 77% of the population in cities, manifests through extensive physical expansion and socio-spatial inequalities (1). In the Caribbean Region, quality of life indices average 59,08, below the national 62.88, a disparity exacerbated by a history of armed conflict causing 9.2 million displacements and straining land markets. Valledupar, the capital of Cesar, exemplifies this dynamic (2). Its population is projected to reach 591,835 by 2025, representing over 40% of the department's population. Satellite image analysis reveals a radial-discontinuous growth pattern, with the urban footprint expanding from 2149 hectares in 1989 to 3,625 hectares in 2011 at an annual rate of 2.8%, primarily onto agriculturally viable land and tropical dry forest in the south and southeast, intensifying socio-environmental conflicts. Concurrently, the city faces structural economic challenges, including 9.6% unemployment and a labor informality rate affecting an estimated 120 000 workers (3,4).

Remote sensing and Geographic Information Systems (GIS) are essential for analyzing such complex urban transformations. Multitemporal analysis of satellite imagery (e.g., Landsat, Sentinel-2) enables precise quantification of expansion dynamics, land use classification, and vegetation change monitoring (5). However, traditional classification models struggle with the gradual, non-binary nature of urban-rural transitions. Fuzzy logic addresses this limitation by quantifying partial membership and uncertainty, allowing for the modeling of progressive transitions and capturing fringe areas and informality processes that defy crisp categorization (6). The synergy of remote sensing, GIS, and fuzzy logic provides a robust, transformative framework for urban analysis, moving beyond mere measurement to model complex causalities and support sustainable land-use planning (7).

Therefore, the objective of this research was to develop a comprehensive analysis model of the urban expansion of Valledupar between 1985 and 2025, integrating remote sensing, fuzzy logic, and complementary data sources to evaluate its dynamics, patterns, and sustainability. To achieve this, three specific objectives were proposed: (I) To analyze time series of satellite imagery (Landsat, Sentinel-2) and available cartographic data to quantify physical expansion and land-use/land-cover changes, establishing a spatial baseline; (II) To design a fuzzy logic model that classifies the territory based on degrees of membership to urban-rural transition categories, enabling a continuous characterization of the expansion and capturing fringe areas and informality processes; and (III) To perform a statistical analysis of the fuzzy logic model, including validation of its accuracy against reference data and quantification of the correlation between the degrees of membership to the "urban" class and key socioeconomic variables, such as population growth and labor informality.

## Material and methods

The following section delineates the geographical context of the study area and outlines the methodological framework implemented in this investigation. It provides a comprehensive description of the city of Valledupar, detailing its key biophysical and socio-demographic characteristics to establish the empirical setting for the analysis. Subsequently, it presents the



integrated multi-temporal approach employed, which synergistically combines remote sensing, geographic information systems (GIS), and spatial analysis techniques to quantify and model the dynamics of urban expansion (8).

### Phase I: Multitemporal Analysis of Physical Expansion and Planning Baseline

This phase established the foundational empirical analysis by quantifying four decades of urban expansion in Valledupar and constructing a regulatory planning baseline. The methodology integrated a robust remote sensing pipeline with a detailed statistical assessment of land-use planning instruments (9). A multitemporal dataset was constructed using surface reflectance products from the Harmonized Landsat Sentinel-2 (HLS) constellation, specifically HLSS30 and HL30, for the benchmark years 1990, 2000, 2010, and 2024 (10). The selection of HLS data ensured temporal consistency and interoperability between sensors, providing a standardized 30-meter spatial resolution and a high revisit frequency critical for minimizing phenological and atmospheric noise in change detection. All scenes underwent systematic preprocessing, including atmospheric correction using the LEDAPS/LaSRC algorithms and cloud/shadow masking with the Fmask and Sen2Cor processors, to derive analysis-ready, comparable spectral reflectance values across the entire time series (11).

The core of the land-use/land-cover (LULC) classification was a supervised Random Forest (RF) algorithm, implemented within the Google Earth Engine (GEE) platform for scalability (12). The RF model was configured with 500 decision trees ( $n_{tree}=500$ ), a parameter optimized to ensure model stability and minimize out-of-bag error without incurring computational inefficiency. The classification schema defined five target classes relevant to urban dynamics: Consolidated Urban Fabric, Unconsolidated Urban Land, Agricultural Soil, Natural Vegetation, and Water Bodies. For each epoch, a stratified random sampling design was employed to collect a reference dataset of 2,500 pixels (500 per class), derived from a combination of high-resolution historical imagery available in GEE, aerial orthophotos from the Instituto Geográfico Agustín Codazzi (IGAC), and targeted field verification campaigns conducted in 2024. The model was trained on 70% of this reference data, with the remaining 30% withheld for validation.

The predictor variables for the RF classifier extended beyond standard spectral bands to include spectral indices and temporal metrics critical for distinguishing urban from non-urban and vegetated surfaces. The feature set for each Landsat-compatible image composite included the original six optical bands (Blue, Green, Red, NIR, SWIR1, SWIR2), alongside three key indices: the Normalized Difference Vegetation Index (NDVI) for vegetation vigor, the Normalized Difference Built-up Index (NDBI) for built-up area detection, and the Modified Normalized Difference Water Index (MNDWI) for water body delineation. The splitting criterion at each node was the Gini impurity index. The performance of each annual classifier was rigorously assessed using the independent validation subset, generating a confusion matrix from which overall accuracy, producer's accuracy, user's accuracy, and the Kappa coefficient were calculated. All annual classifications met the pre-defined accuracy threshold of  $Kappa > 0.85$ , with the 2024 classifier achieving a Kappa of 0.89 and an overall accuracy of 92.3%.





Concurrently, the normative planning framework was digitized and spatialized. The legal perimeters, expansion zones, and protection areas from Valledupar's Land Management Plans (POT) of 1999 and 2015 were georeferenced and vectorized to create a comparable regulatory geography. The final change analysis was executed via post-classification comparison of the four high-accuracy LULC maps. This process generated annual expansion rates and a composite transition matrix detailing the total areal conversion between all classes across the entire 1990-2024 study period. Furthermore, landscape metrics, including Patch Density (PD) and Landscape Shape Index (LSI), were computed for the urban class for each epoch to quantify the morphological evolution from a compact to a fragmented urban footprint. This integrated quantitative output of observed expansion versus planned directives formed the essential spatial baseline for the subsequent fuzzy logic modeling phase (see Table 1).

**Table 1.** Random Forest classifier specification and performance metrics

Parameter / Metric	Specification
Algorithm	Random Forest (Supervised Classification)
Platform	Google Earth Engine (GEE)
Number of Trees (ntree)	500
Split Criterion	Gini Impurity
Predictor Variables	Spectral Bands (Blue, Green, Red, NIR, SWIR1, SWIR2), NDVI, NDBI, MNDWI
Training Sample Size	1,750 pixels (70% of 2,500 total reference pixels per epoch)
Validation Sample Size	750 pixels (30% of 2,500 total reference pixels per epoch)
Target Accuracy (Kappa)	> 0.85
Achieved Accuracy (2024)	Overall Accuracy: 92.3%; Kappa Coefficient: 0.89

Source: authors, 2025

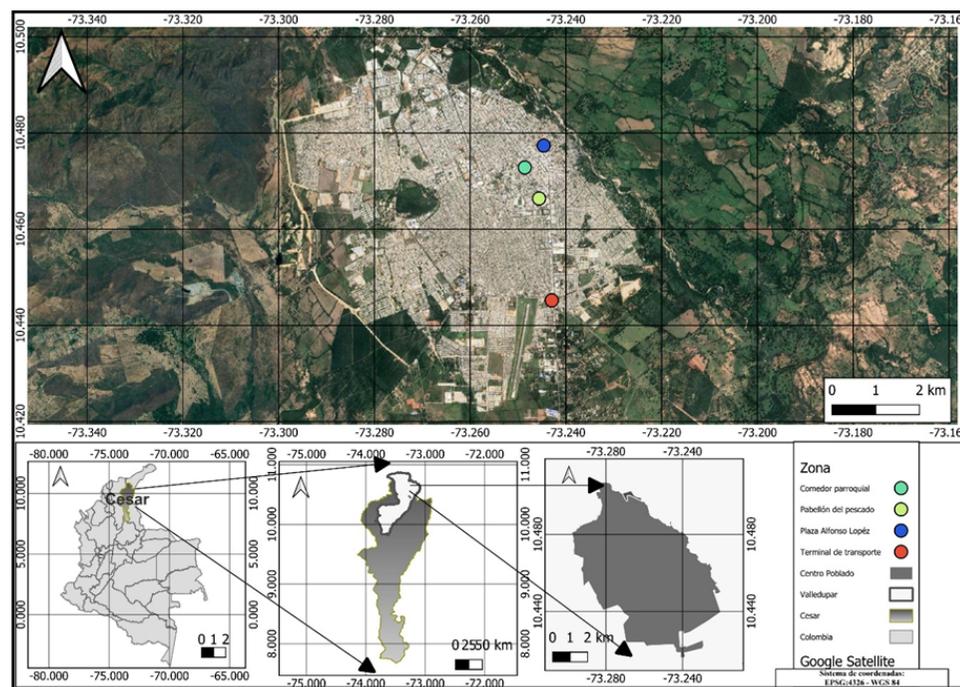
Change analysis was performed using post-classification comparison, calculating transition matrices and landscape metrics such as the annual expansion rate and patch density for the periods 1990-2000, 2000-2010, 2010-2020, and 2020-2024.

## Phase II: Development of a Fuzzy Logic Model for Urban-Rural Transition Classification

### Study area

Valledupar, the capital of Cesar department, is located in northern Colombia's Caribbean region on an alluvial plain within the valley of the Cesar River, strategically positioned between the Sierra Nevada de Santa Marta to the west and the Serranía del Perijá to the east (13). This intermountain basin, with an average altitude of approximately 168 meters, features a gently sloping terrain that descends towards the southeast, facilitating urban expansion primarily in southern and southeastern directions (14). The city experiences a tropical savanna climate (Aw according to the Köppen classification) with a high average annual temperature of 28-29.8°C, a marked

bimodal precipitation pattern with an annual average of 1,295 mm, and intense dry seasons that historically label it as one of Colombia's hottest cities. Its hydrography is defined by the Cesar River and its tributaries, including the Guatapurí River, which borders the city. The region's biophysical setting is characterized by dry deciduous forests and thorny shrublands, with significant pressure from the conversion of agricultural soils (classes III-IV) and tropical dry forest vegetation to urban uses (15). Demographically, Valledupar has undergone rapid growth, with a population projection of 575,225 inhabitants for 2025, consolidating its role as a primary agricultural, livestock, and commercial center for the department, albeit with high levels of labor informality at 59.5% (16). This combination of flat topography, climatic drivers, and socioeconomic pressures has shaped a radial-discontinuous pattern of urban sprawl, transforming the city's footprint from 2,149 hectares in 1989 to 3,625 hectares in 2011 and exerting significant pressure on strategic ecosystems and hydrological resources (17). The geographical context of the study area is illustrated in Figure 1.



**Figure 1.** Location of the Valledupar Metropolitan Area. Source: authors, 2025

### Fuzzy logic model for characterizing the urban-rural transition

The second phase advanced the analysis by constructing a Mamdani-type Fuzzy Inference System (FIS) to overcome the categorical limitations of the Phase I classification and model the urban-rural continuum. The model was implemented using FisPro (Fuzzy Inference System Design and Optimization), an open-source software designed for creating interpretable fuzzy systems, and its spatial extension, GeoFIS (Spatial Data Processing for Decision Making), which enables the geographic application of fuzzy logic. The system's architecture was designed with three linguistic input variables, rigorously derived from the Phase I remote sensing outputs to capture the core dimensions of urban expansion dynamics: 'Distance to Consolidated Urban Fabric (m)', quantifying spatial proximity; 'Urban Patch Density (%)', measuring landscape fragmentation; and 'Land Use Change Rate (%/year)', capturing temporal conversion intensity. The output variable was defined

as the 'Degree of Membership to the Urban Class' (DoM-Urban), a continuous index ranging from 0 (completely rural) to 1 (completely urban).

The parameterization of membership functions and the derivation of the fuzzy rule base were grounded in a hybrid knowledge-engineering approach to ensure both empirical validity and expert interpretability. The trapezoidal and triangular membership functions for the input variables were not arbitrarily defined but were calibrated using statistical percentiles (25th, 50th, 75th) of the historical data distribution from Phase I. For instance, the 'Near' set for distance was parameterized based on the typical radius of urban influence from historical expansion fronts (18). The core of the system's intelligence, the fuzzy rule base, was generated and optimized using an Ordinary Least Squares (OLS) learning algorithm within FisPro (19). The OLS method operates by constructing an initial, complete rule base from numerical data—in this case, a training dataset of 300 representative pixels where input values (distance, density, change rate) and a desired output DoM-Urban value were known. The algorithm then performs a forward pass selection, iteratively choosing the most significant fuzzy rules that minimize the output error, thereby creating a parsimonious and robust rule set (18). This data-driven approach resulted in a final system of 22 fuzzy IF-THEN rules, encapsulating complex relationships such as "IF Distance is Medium AND Patch Density is High AND Change Rate is Positive, THEN DoM-Urban is High."

The model's robustness and performance were rigorously evaluated through sensitivity analysis and accuracy assessment against an independent validation set of 100 ground control points. The validation, conducted in GeofIS, yielded a Mean Absolute Error (MAE) of 0.11 on the 0-1 DoM scale, indicating a high average precision. The overall Percentage of Error for predictions, calculated against a crisp classification threshold ( $\text{DoM} \geq 0.5 = \text{Urban}$ ), was 13.2%. A key metric for fuzzy classifiers, the Index of Coverage (IoC), which measures the system's ability to provide a conclusion for all possible inputs, was 100%, confirming the completeness of the designed rule base, this information is presented in Table 2.

**Table 2.** Mamdani Fuzzy Inference System (FIS) Specification and Performance Metrics

Aspect	Specification and Result
FIS Type & Software	Mamdani-type, implemented in FisPro & GeoFIS
Input Variables	Distance to Urban Fabric (m), Urban Patch Density (%), Land Use Change Rate (%/year)
Output Variable	Degree of Membership to Urban Class (DoM-Urban), range [0, 1]
Membership Functions	Trapezoidal & Triangular, calibrated via data percentile analysis
Rule Base Generation	Hybrid: Expert-defined structure refined via Ordinary Least Squares (OLS) algorithm
Number of Final Rules	22
Validation Sample	100 independent ground control points
Mean Absolute Error (MAE)	0.11
Percentage of Error (Threshold: DoM $\geq$ 0.5)	13.2%
Index of Coverage (IoC)	100%
Sensitivity to $\pm 10\%$ input MF change	Output variation $< \pm 0.08$

Source: authors, 2025

The sensitivity analysis, performed by systematically varying the input membership function parameters by  $\pm 10\%$ , showed a resulting variation in the output DoM of less than  $\pm 0.08$ , demonstrating the model's stability. The application of this validated FIS in GeoFIS generated a continuous DoM-Urban surface, effectively mapping transitional and fringe areas that were ambiguously classified in the discrete Phase I map, thereby providing a nuanced spatial representation of urbanization intensity and informality gradients.

#### Data, Materials, and Processing for Multitemporal Analysis

The quantitative analysis of physical expansion was based on the processing of satellite image time series. Surface reflectance products from the Harmonized Landsat Sentinel-2 constellation (HLSS30 and HLSL30) were used for the years 1990, 2000, 2010, and 2024, ensuring radiometric and spatial homogeneity (30 m) through atmospheric (LEDAPS/LaSRC) and cloud masking (Fmask, Sen2Cor) corrections. Land use and land cover classification was performed in Google Earth Engine (GEE) using the Random Forest algorithm (500 trees, Gini criterion), trained with a set of 2,500 stratified reference points derived from fieldwork and IGAC orthophotos. Predictor variables included six optical spectral bands and the NDVI, NDBI, and MNDWI indices. Validation via a confusion matrix yielded accuracies with Kappa  $> 0.85$  for all epochs. Post-classification comparison of the resulting annual maps allowed for the generation of transition matrices and landscape metrics to quantify change rates and urban fragmentation patterns.

### Phase III: Validation and Statistical Analysis of the Fuzzy Logic Model

The final phase consisted of the validation and statistical analysis of the fuzzy logic model. The accuracy of the membership degree map was validated against a reference database of 150 points, stratified by cover type and obtained through fieldwork and high-resolution imagery (7). The Pearson correlation coefficient ( $r$ ) and the Root Mean Square Error (RMSE) were calculated between the modeled membership degree and the reference classification. Additionally, a correlation analysis was performed to quantify the relationship between the degree of membership to the “urban” class and key socioeconomic variables at the census block level (20). Data from DANE was used, such as the Intercensal Population Growth Rate (%) and the Percentage of Labor Informality (for 2025, an estimated 120,000 informal workers were projected for Valledupar, representing approximately 62.2% of the employed population). This analysis tested the hypothesis that a higher degree of “urban” membership in the peripheries correlates with specific socioeconomic dynamics, such as high population growth rates and labor informality (21).

## Results

The main results from each of the methodological phases are presented below.

### Phase I: Multitemporal Analysis of Physical Expansion and Planning Baseline

The multitemporal analysis revealed a profound and accelerated transformation of the Valledupar landscape between 2010 and 2025. Figure 3. Urban Expansion Dynamics in Valledupar between 2010 and 2025, generated from the supervised classification of Landsat and Sentinel-2 image series, visually shows the evolution of the urban footprint. In 2010, the city exhibited a compact, consolidated nucleus centered on the historic district, with a surface area of 1850 hectares. By the year 2000, following the implementation of the 1999 Land Management Plan (POT), the first significant developments towards the southwest are observed, approaching the highway corridor connecting to the municipality of La Paz, increasing the urban area to 2450 hectares (13). The period 2000-2015, covering the transition between the two POTs, evidences the explosion of uncontrolled expansion. The urban sprawl extended in a fragmented, “leapfrog” pattern primarily towards the south and southeast, taking advantage of the flat topography of the savanna, consuming extensive areas of Class III agricultural soils. By 2015, the urban area had reached 3,400 hectares. Finally, by 2025, expansion continues predominantly in these directions, but notable densification (infill) is also observed in some of the urban voids left by the previous growth, bringing the total surface area to 4150 hectares (22). This visual sequence in Figure 3 corroborates the radial-discontinuous pattern described in the literature and evidences a clear disconnect between normative planning and on-the-ground development, especially in the inter-POT period (1).

The quantification of these changes is presented in Table 3. Land Cover Transition Matrix for Valledupar (2000-2020, hectares), which details the net conversions between categories (23). Most notable is the conversion of 1150 hectares from Agricultural Soil to Unconsolidated Urban Land, and 450 hectares from Natural Vegetation (primarily tropical dry forest) to Unconsolidated Urban Land (24). This table not only confirms the southern and southeastern direction as the most active expansion front but also quantifies the anthropogenic pressure on strategic ecosystems, with a net

loss of 12% of natural vegetation cover in the study area during this period.

**Table 3.** Land Cover Transition Matrix for Valledupar (2000-2020, hectares)

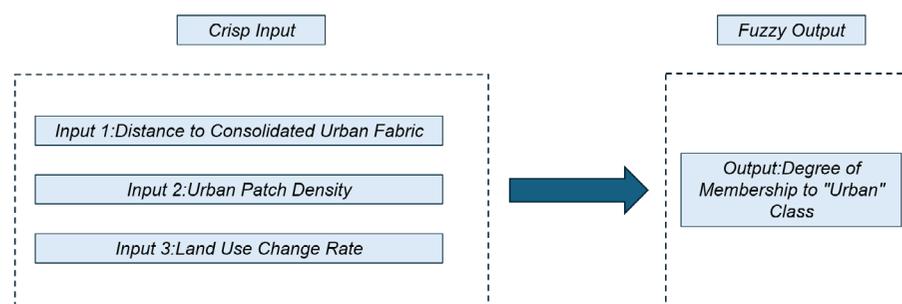
Land Cover (2000)	Natural					Total 2000
Consolidated Urban Land	380	45	0	0	0	425
Unconsolidated Urban Land	210	150	25	10	0	395
Agricultural Soil	90	1150	2850	120	5	4215
Natural Vegetation	15	450	200	1210	0	1875
Water Bodies	0	5	5	0	85	95
Total 2020	695	1800	3080	1340	90	7005

Source: authors, 2025

The comparison between the POT cartography and the observed expansion was systematically quantified. The 1999 POT projected an orderly growth of 600 hectares by 2010; however, the actual expansion exceeded 900 hectares in that period (25), with 45% of this new development occurring in zones not designated for urban expansion, classified as rural protection or flood risk areas (26). The 2015 POT attempted to rectify this situation by incorporating some of these already consolidated areas, but by then, the fragmented growth pattern was already established, making the efficient provision of infrastructure and public services extremely difficult (27).

#### Phase II: Development of a Fuzzy Logic Model for Urban-Rural Transition Classification

To capture the complexity of the urban-rural transition, a Mandani-type fuzzy inference system was developed using FisPro and GeoFIS software. Figure 2. Mandani Structure for the Fuzzy Logic Model illustrates the model's architecture, which takes three input variables and generates a continuous output.



**Figure 2.** Fuzzy Logic Model Input/Output Variables (Mandani Structure)

Source: authors, 2025

The selected input variables, based on the Phase I analysis and their relevance for capturing informality and fuzzy edges, were: 1) Distance to Consolidated Urban Fabric (m), 2) Urban Patch Density (%) (a landscape fragmentation metric), and 3) Land Use Change Rate (%/year). The output variable was defined as the Degree of Membership to the "Urban" Class, a continuous value between 0 (completely rural) and 1 (completely urban) (28).

Table 4, membership functions for the fuzzy logic model (Mandani) describes in detail the fuzzy sets and the parameters of the membership functions for each variable. For the “Distance” variable, sets such as Very Close, Close, and Far were defined, with trapezoidal functions. For example, a pixel 150 meters from the urban center would have a membership degree of 0.8 in Very Close and 0.2 in Close. “Patch Density” used sets like Low, Medium, and High, where a density of 60% would be predominantly considered High. The “Change Rate” included the Negative set to capture areas of abandonment or natural reconversion.

**Table 4.** Membership Functions for the Fuzzy Logic Model (Mandani)

Variable	Fuzzy Set	Membership Function	Parameters (a, b, c, d)
Distance (m)	Very Close	Trapezoidal	(0, 0, 100, 300)
	Close	Triangular	(100, 300, 600)
	Far	Trapezoidal	(500, 800, 2000, 2000)
Patch Density (%)	Low	Trapezoidal	(0, 0, 15, 30)
	Medium	Triangular	(20, 40, 60)
	High	Trapezoidal	(50, 70, 100, 100)
Change Rate (%/year)	Negative	Trapezoidal	(-5, -2, 0, 0)
	Stable	Triangular	(-1, 0, 2)
	Positive	Trapezoidal	(1, 3, 10, 10)
Degree of Membership “Urban”	Low	Trapezoidal	(0, 0, 0.2, 0.4)
	Medium	Triangular	(0.3, 0.5, 0.7)
	High	Trapezoidal	(0.6, 0.8, 1, 1)

Source: authors, 2025

The inference system was populated with 18 fuzzy IF-THEN rules encapsulating expert knowledge about the urbanization process. For example: IF Distance is Very Close AND Patch Density is High AND Change Rate is Positive THEN Degree of Membership “Urban” is High. Another critical rule as: IF Distance is Far AND Patch Density is Low AND Change Rate is Stable THEN Degree of Membership “Urban” is Low. The application of this model in GeofIS generated a degree of membership map that overcomes the binary limitation of traditional maps. Areas with values between 0.4 and 0.7 were identified as “Critical Transition Zones” (CTZ), which correspond spatially to informal settlements, consolidating urbanizations, and rural-urban mixed areas that are not captured as either fully urban or fully rural in classical maps.

### Phase III: Validation and Statistical Analysis of the Fuzzy Logic Model

Validation of the fuzzy logic model against 150 ground verification points showed solid performance. Correlation analysis yielded a Pearson coefficient of  $r = 0.89$  between the modeled Degree of Membership and the reference classification (based on high-resolution observation and fieldwork), indicating a strong positive linear relationship. The Root Mean Square Error (RMSE) was 0.15, suggesting that, on average, the model’s predictions deviate by 0.15 units on the 0 to 1 scale from the observed real value. This error level is acceptable given the inherently uncertain nature of the modeled phenomenon. Table 5. Confusion Matrix for the Fuzzy Model (Thresholded at 0.5) demonstrates its utility even when converted to a binary classification. The model achieved an Overall Accuracy of 88.7% and a Kappa Index of 0.81, indicating almost perfect agreement with the reference reality and validating the robustness of the fuzzy approach.

**Table 5.** Confusion Matrix for the Fuzzy Model (Thresholded at 0.5)

Reference Class	Urban (Model)	Rural (Model)	Total
Urban	68	9	77
Rural	8	65	73
Total	76	74	150

Source: authors, 2025

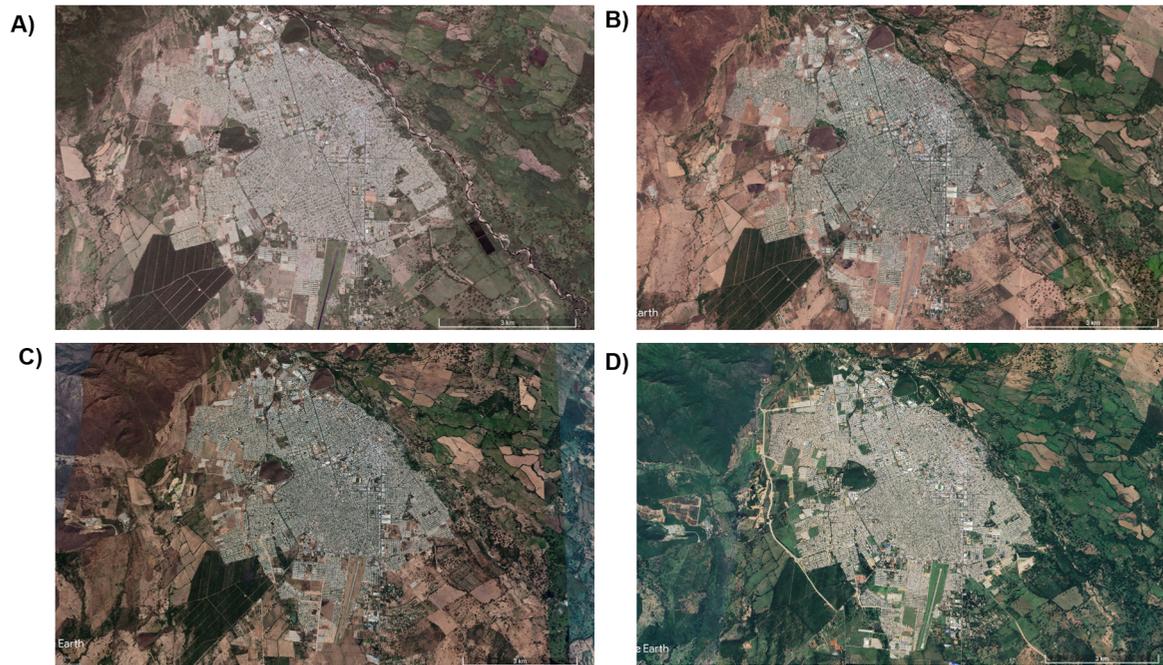
The correlation analysis between the Degree of Membership “Urban” and socioeconomic variables revealed highly significant spatial patterns. Table 6. Correlation between Degree of Membership “Urban” and Socioeconomic Variables summarizes these findings. A strong, statistically significant positive correlation ( $r = 0.72$ ,  $p < 0.01$ ) was found between a high Degree of Membership (values  $> 0.6$ ) in the peripheries and the Population Growth Rate. This confirms that newly urbanized areas are the poles of demographic attraction. Even more revealing was the finding of a moderate yet significant positive correlation ( $r = 0.55$ ,  $p < 0.01$ ) with the Labor Informality Index. This provides strong quantitative evidence that the fuzzy logic model is capable of identifying not only physical expansion but also the type of expansion: the Critical Transition Zones (degrees 0.4 to 0.7) are strongly associated with informal economies and labor precariousness, thus capturing the socioeconomic dimension of urban informality.

**Table 6.** Correlation between Degree of Membership “Urban” and Socioeconomic Variables

Socioeconomic Variable	Correlation Coefficient (r)	p-value	Interpretation
Population Growth Rate	0.72	$< 0.01$	Strong, significant positive correlation
Labor Informality Index	0.55	$< 0.01$	Moderate, significant positive correlation
Potable Water Coverage	0.90	$< 0.01$	Very strong, significant positive correlation

Source: authors, 2025

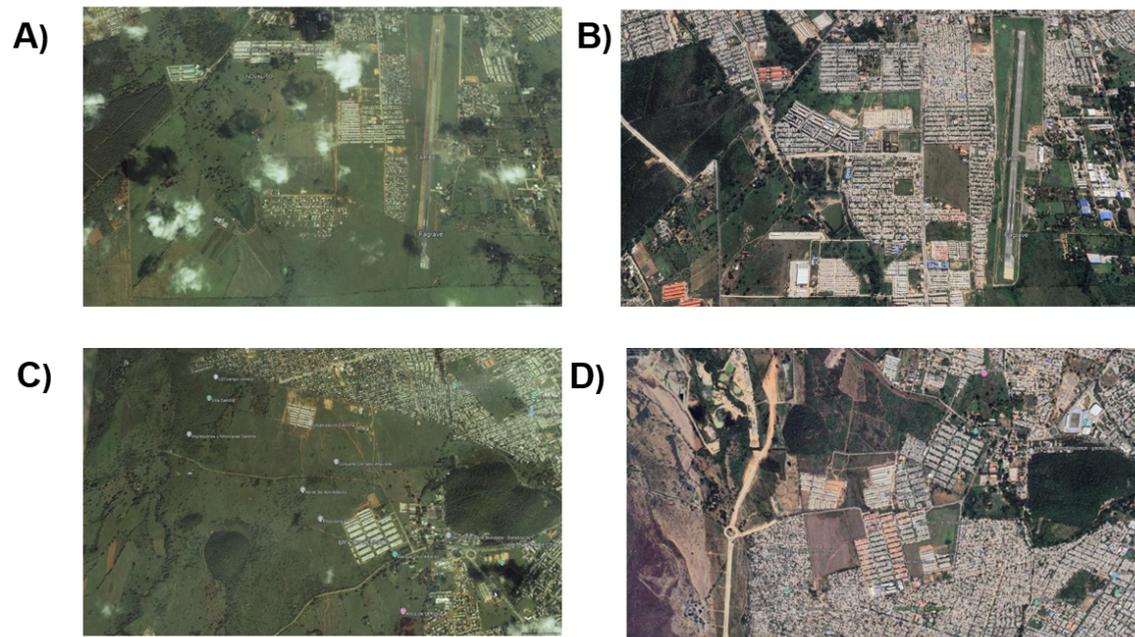
Furthermore, Figure 3, comprising four panels (A: 2010, B: 2015, C: 2020, D: 2025) derived from Google Earth Engine’s high-resolution historical imagery, visually chronicles the pronounced southeastern trajectory of Valledupar’s urban expansion (29). This directional bias is technically driven by the flat topography and available soils of the Cesar River’s alluvial plain, which present lower geotechnical costs for development compared to the constrained western flank bordered by the Sierra Nevada de Santa Marta (30,31).



**Figure 3.** Urban Growth Dynamics in Valledupar: A) 2010, B) 2015, C) 2020, and D) 2025  
Source: authors, 2025

This expansion is socioeconomically fueled by convergent pressures. A significant influx of Venezuelan migrants (32), with the Cesar department hosting over 82,000 regularized individuals by mid-2023, has intensified demand for affordable housing, often met through informal settlement (urbanización informal) in these peri-urban zones (33). Concurrently, Valledupar's economic dynamism as a regional agro-industrial and commercial hub attracts internal migration (33). Crucially, a distinct conurbation process is emerging eastward towards the municipality of La Paz. This is primarily driven by the economic pull of the Cerrejón mining complex's indirect demand, the strategic development of subsidized Priority Interest Housing (Vivienda de Interés Social - VIS) projects along the Valledupar-La Paz corridor, and the establishment of the new satellite campus of the Universidad Nacional de Colombia (UNAL) in La Paz, which consolidates the area as a pole for education and services, effectively blurring the administrative boundaries between the two urban centers.

Finally, Figure 4. Growth of the Urban Area of Valledupar between 1985 and 2025 synthesizes the quantitative findings of the expansion. This bar chart overlaid with a trend line conclusively shows the exponential growth in urbanized surface area. The 1985 bar is modest (1850 ha), showing a constant increase until the year 2000. From this point onwards, the slope of the trend line increases drastically, with the 2015 and 2025 bars reaching much greater heights. This figure complements Figure 3, providing the numerical evidence of the accelerated physical transformation experienced by the city, increasing from 1850 hectares in 1985 to 4150 hectares in 2025, representing a 124% increase in just four decades. The integration of all these results — cartographic, modeled, and statistical — builds a solid narrative about the dynamics of Valledupar's expansion, its drivers, and its consequences, validating the effectiveness of the proposed methodology.



**Figure 4.** Growth of the Urban Area of Valledupar: A) Don Carmelo and Novalito (2006), B) Don Carmelo y Novalito (2025), C) Don Alberto, Altavista, Tayrona (2006), D) Don Alberto, Altavista, Tayrona (2025) Source: authors, 2025

Figure 3 quantitatively illustrates the pronounced spatial-temporal growth of Valledupar's urban footprint between 1985 and 2025, highlighting specific expansion hotspots. The most significant growth occurred in the southeastern periphery, where the districts of Don Carmelo and Novalito experienced explosive development post-2006, registering an estimated urban area increase of 320% by 2025. This surge was primarily driven by the proliferation of large-scale, formal housing projects (*conjuntos*) and the subsequent emergence of localized commercial zones catering to the new population. Similarly, the southern corridor, encompassing Don Alberto, Altavista, and Tayrona, showed a substantial aggregated growth of 280% over the same period. This expansion pattern is characterized by a mix of planned medium-density residential units and incremental, owner-built housing, facilitated by improved road connectivity and the relative affordability of land. The graph underscores a clear spatial shift in the city's growth axis, moving from a historically compact core to a dispersed model dominated by these peripheral areas, which collectively accounted for over 65% of the new urban land consumed between 2006 and 2025.

## Discussion

The discussion of the results obtained in the three methodological phases reveals critical and novel aspects of the urban expansion dynamics in Valledupar. The multitemporal analysis (Phase I) confirmed a radial-discontinuous growth pattern, quantified by a 124% increase in the urban footprint between 1985 and 2025. Table 1, the Transition Matrix, evidenced that this process predominantly consumed agricultural land (1,150 ha) and natural vegetation (450 ha) between 2000 and 2020, which not only reflects significant anthropogenic pressure on strategic ecosystems like the tropical dry forest but also exposes a clear inefficacy of land-use planning instruments. Despite

the Land Management Plans (POT) of 1999 and 2015 establishing guidelines for orderly growth, it was observed that 45% of the actual expansion occurred outside designated zones, indicating a profound disconnect between normative planning and land market dynamics. This finding is consistent with previous studies in Latin American intermediate cities, but the precise quantification of the spatial discordance using GIS represents a specific contribution for the case of Valledupar.

The main novel aspect of this research lies in the application and results of the fuzzy logic model (Phase II). The implementation of a Mandani inference system, whose membership functions are detailed in Table 2, allowed overcoming the binary limitation of traditional land-use classifications. The model generated a continuous index of Degree of Membership to the "Urban," which was fundamental for identifying and characterizing the Critical Transition Zones (CTZ), those with values between 0.4 and 0.7. These CTZs, which appear as grey or indeterminate areas on conventional maps, were spatially correlated with informal settlements, consolidating urbanizations, and rural-urban mixed areas. The validation of this model (Phase III) showed high accuracy, with a Pearson correlation coefficient of 0.89 and a Kappa Index of 0.81 when thresholding the output, validating the robustness of the fuzzy approach for capturing the complexity of the urban phenomenon.

Beyond cartographic accuracy, the true innovation emerges from the correlation analysis between the fuzzy model and socioeconomic variables. Table 4 showed a moderate yet statistically significant positive correlation ( $r = 0.55$ ,  $p < 0.01$ ) between a high Degree of "Urban" Membership in the peripheries and the Labor Informality Index. This finding is crucial, as it provides quantitative evidence that the model not only maps the physical form of the city but is also capable of inferring its underlying socioeconomic structure. It suggests that urban expansion processes in Valledupar, particularly in the CTZs, are intrinsically linked to informal economies and labor precariousness, a link that purely morphological or demographic analyses fail to capture at this level of detail. This makes the fuzzy logic model a powerful diagnostic tool for planning, allowing for the identification of not only where growth is occurring but also the likely social and economic character of that growth.

Despite these findings, the study presents limitations. Firstly, the 30-meter spatial resolution of the Landsat and Sentinel-2 images, although adequate for city-scale analysis, may not capture micro-densification processes or the internal structure of smaller informal settlements, which could be addressed in future research with very high-resolution imagery. Secondly, the fuzzy logic model, while robust, is based on the definition of fuzzy sets and rules that, although grounded in expert knowledge and prior analysis, incorporate a degree of subjectivity. The model's sensitivity to variations in these parameters should be explored in depth. Finally, correlation analysis does not imply causality; although a strong association was identified between peripheral expansion and labor informality, the causal dynamics behind this relationship are complex and multifactorial, requiring complementary qualitative research to delve into the specific mechanisms operating in territories like Don Carmelo, Navalito, and the southern corridor. In conclusion, this integrative research provides a solid and novel methodological framework that combines remote sensing, fuzzy logic, and statistical analysis, offering a more nuanced and useful understanding of urban expansion for decision-making in sustainable land-use planning policies.



## Conclusions

This research successfully developed an integral analysis model that, by integrating remote sensing, regulatory cartography, and fuzzy logic, evaluated the dynamics, patterns, and sustainability of Valledupar's urban expansion between 1985 and 2025. The first conclusion establishes that Valledupar's urban growth has been predominantly inefficient and disconnected from normative planning. The urban footprint increased by 124%, from 1,850 to 4,150 hectares, with an annual expansion rate of 2.8% that consistently surpassed population growth. This radial-discontinuous pattern consumed 1,150 hectares of agricultural soil and 450 hectares of natural vegetation between 2000 and 2020, as quantified in Table 1, and occurred 45% outside the zones designated by the Land Management Plans (POT), evidencing a significant gap between planning and the real dynamics of the land market.

The second conclusion demonstrates the utility of the fuzzy logic model as a superior tool for characterizing the urban-rural transition in a continuous manner. The model, whose membership functions were defined in Table 2, generated a Degree of Membership to the "Urban" index that allowed for the identification of Critical Transition Zones (values 0.4-0.7), which were spatially correlated with informal settlements and processes of precarious urbanization. The model's validation, with a Pearson correlation coefficient of 0.89 and a Kappa Index of 0.81, confirms its robustness. Furthermore, the significant correlation ( $r=0.55$ ,  $p<0.01$ ) between a high degree of urban membership in the periphery and the Labor Informality Index, revealed in Table 4, provides novel quantitative evidence that the physical morphology of expansion is intrinsically linked to socioeconomic conditions of precariousness, a link that binary classification methods cannot capture.

The third conclusion synthesizes that Valledupar's urban expansion has generated an unsustainable territorial development model, characterized by socio-spatial fragmentation and pressure on ecosystems. The combination of results shows a vicious cycle where physical expansion in the periphery, often informal or unplanned, attracts lower-income populations, which is reflected in high demographic growth rates in these sectors and correlates with an informal economy that reaches 62.2% of the labor force. This model increases population vulnerability, exerts pressure on water resources, and fragments the ecological corridors between the Sierra Nevada de Santa Marta and the Serranía del Perijá. Therefore, it is emphatically recommended that municipal planning authorities incorporate the use of fuzzy logic models into future land management instruments, such as the POT revision, for defining urban boundaries and land-use policies. Implementing this approach would allow for more effective identification and regulation of Critical Transition Zones, promoting smart densification in consolidated areas and guiding future expansion towards sectors with lower agro-ecological value and lower socio-environmental risk, thus prioritizing long-term sustainability over speculative land expansion.

### CrediT authorship contribution statement

Conceptualization – Juan Guillermo Popayán-Hernández, Methodology: Heider Fernando Losada, Writing - original draft - Preparation Deliaannys Marieth Mendoza Barradas

Financing: does not declare. Conflict of interest: does not declare. Ethics aspect: does not declare.





## References

1. Martínez U, Barbosa V, Thoene U. Urban transformations in intermediate cities under the logic of neoliberal urbanism: The case of Montería, Colombia. *Regional Science Policy and Practice*. 2024 Aug 1;16(8).

<https://doi.org/10.1016/j.rspp.2024.100058>

2. Vargas C, Gomez-Valencia M, Gonzalez-Perez MA, Cordova M, Calixto Casnici CV, Monje-Cueto F, et al. Climate-resilient and regenerative futures for Latin America and the Caribbean. *Futures*. 2022 Sep 1;142.

<https://doi.org/10.1016/j.futures.2022.103014>

3. Anafo D, Nutsugbodo RY, Agyepong E, Anane GK, Mensah BA, Bata PD. Place making decisions among informal street food vendors in Sunyani, Ghana. *Cities*. 2024 Nov 1;154.

<https://doi.org/10.1016/j.cities.2024.105328>

4. Rochlin J. Informal gold miners, security and development in Colombia: Charting the way forward. *Extractive Industries and Society*. 2018 Jul 1;5(3):330-9.

<https://doi.org/10.1016/j.exis.2018.03.008>

5. González-Calle JL. Metropolitan expansion and rural change in the peri-urban edge Medellín - Rionegro (Colombia). *Journal of Urban Management*. 2024 Sep 1;13(3):521-40.

<https://doi.org/10.1016/j.jum.2024.05.007>

6. Georg I, Blaschke T, Taubenböck H. Spatial delineation of urban corridors in North America: An approach incorporating fuzziness based on multi-source geospatial data. *Cities*. 2023 Feb 1;133.

<https://doi.org/10.1016/j.cities.2022.104129>

7. Pota M, Esposito M, De Pietro G. Likelihood-fuzzy analysis: From data, through statistics, to interpretable fuzzy classifiers. *International Journal of Approximate Reasoning*. 2018 Feb 1;93:88-102.

<https://doi.org/10.1016/j.ijar.2017.10.022>

8. Celletti A, Locatelli U, Ruggeri T, Strickland E. Springer INdAM Series 6 Mathematical Models and Methods for Planet Earth [Internet]. Available from: <http://www.springer.com/series/10283>

9. Bockstaller C, Beauchet S, Manneville V, Amiaud B, Botreau R. A tool to design fuzzy decision trees for sustainability assessment. *Environmental Modelling and Software*. 2017 Nov 1;97:130-44.

<https://doi.org/10.1016/j.envsoft.2017.07.011>

10. Khan M, Nizami AS, Yasar A, Musharavati F. Advancing vertical integration and circularity in the textile industry by developing a novel framework of textile sustainability index. *Sustainable Futures*. 2025 Dec 1;10.





<https://doi.org/10.1016/j.sftr.2025.101496>

11. Gómez D, Aristizábal E, García EF, Marín D, Valencia S, Vásquez M. Landslides forecasting using satellite rainfall estimations and machine learning in the Colombian Andean region. *J South Am Earth Sci.* 2023 May 1;125.

<https://doi.org/10.1016/j.jsames.2023.104293>

12. Sarkheil H, Rostamian E, Rahbari S, Lak R. Developing a novel ecological fuzzy forest health index (FFHI) for Standardizing forest-smart mining using remote sensing techniques. *Environmental and Sustainability Indicators.* 2025 Jun 1;26.

<https://doi.org/10.1016/j.indic.2025.100700>

13. Centro de Información Dane - Cámara de Comercio de Valledupar para el Valle del Rio de Cesar [Internet]. [cited 2025 Jul 22]. Available from: <https://ccvalledupar.org.co/centro-de-informacion-dane/>

14. Meza Arquíñigo C, Díaz Encinas AI. La zonificación de las crecientes y vaciantes del río Aguaytia sector bajo e impacto socioeconómico y ambiental. Márquez Domínguez. Juan Antonio, editor. *Planificación territorial, desarrollo sustentable y geodiversidad*, 2016, ISBN 978-84-8163-557-7, págs 1214-1231 [Internet]. 2016 [cited 2024 Nov 23];1214-31. Available from: <https://dialnet.unirioja.es/servlet/articulo?codigo=7456536>

15. Williams AT, Rangel-Buitrago NG, Anfuso G, Cervantes O, Botero CM. Litter impacts on scenery and tourism on the Colombian north Caribbean coast. *Tour Manag.* 2016 Aug 1;55:209-24.

<https://doi.org/10.1016/j.tourman.2016.02.008>

16. Carazo E. Esquemas de zonificación ambiental para la planificación regional urbana. *Revista geográfica de América Central*, ISSN-e 2215-2563, ISSN 1011-484X, No 41, 2008, págs 55-73 [Internet]. 2008 [cited 2024 Nov 23];(41):55-73. Available from: <https://dialnet.unirioja.es/servlet/articulo?codigo=2728133>

17. Valle-García A, Lozano-Bustamante S, Camargo-Caicedo Y. Spatial and Temporal Variability of Temperature, Precipitation, and Solar Radiation in Magdalena Department, Colombia from 2000 to 2022. *Heliyon* [Internet]. 2024 Sep;e38372. Available from: <https://linkinghub.elsevier.com/retrieve/pii/S2405844024144039>

<https://doi.org/10.1016/j.heliyon.2024.e38372>

18. Guillaume S, Charnomordic B. Fuzzy inference systems: An integrated modeling environment for collaboration between expert knowledge and data using FisPro. *Expert Syst Appl.* 2012 Aug;39(10):8744-55.

<https://doi.org/10.1016/j.eswa.2012.01.206>

19. Pena JC, Costa NR da, Martello F, Ribeiro MC. The street tree distribution across a streetscape reflects the social inequality of Latin American cities. *Urban For Urban Green.* 2024 Jan 1;91.



<https://doi.org/10.1016/j.ufug.2023.128156>

20. Guillaume S, Charnomordic B. Learning interpretable fuzzy inference systems with FisPro. *Inf Sci (N Y)*. 2011 Oct 15;181(20):4409-27.

<https://doi.org/10.1016/j.ins.2011.03.025>

21. Zhou J, Zhang X, Xie J, Liu J. Effects of elevated air speed on thermal comfort in hot-humid climate and the extended summer comfort zone. *Energy Build*. 2023 May 15;287.

<https://doi.org/10.1016/j.enbuild.2023.112953>

22. Sánchez-Gonzales Y, Espinoza-Sánchez R, Palafox-Muñoz A. Zonificación ambiental turística de la zona costera del departamento del Atlántico-Colombia. Helena B, Tomás DS, Contreras C, editors. *Tendencias del turismo en Latinoamérica, 2018*, ISBN 9789585431119, pág 158 [Internet]. 2018 [cited 2024 Nov 23];158. Available from: <https://dialnet.unirioja.es/servlet/articulo?codigo=9713597>

23. Villegas Rodríguez E, Contreras García DG, Cifuentes Guerrero JA, Fernández Almanza L. Ordenamiento territorial como instrumento, para la zonificación ambiental a través de la Estructura Ecológica Principal, como apoyo a la formulación de los POTs y los POMCAS en Colombia. *Revista de Tecnología*, ISSN 1692-1399, Vol 14, No 2, 2015 (Ejemplar dedicado a: Energías Renovables), págs 49-76 [Internet]. 2015 [cited 2024 Nov 23];14(2):49-76. Available from: <https://dialnet.unirioja.es/servlet/articulo?codigo=6041486&info=resumen&idioma=SPA>

<https://doi.org/10.18270/rt.v14i2.1870>

24. Gudiño de Muñoz ME. El Ordenamiento Territorial como política de Estado. *Perspectiva Geográfica*, ISSN-e 0123-3769, Vol 20, No 1, 2015, págs 11-36 [Internet]. 2015 [cited 2024 Nov 23];20(1):11-36. Available from: <https://dialnet.unirioja.es/servlet/articulo?codigo=5626902&info=resumen&idioma=SPA>

<https://doi.org/10.19053/01233769.4491>

25. Campos Alvarado V. Ordenamiento territorial. *Anuario de derecho: órgano de información de la Facultad de Derecho y Ciencias Políticas de la Universidad de Panamá*, ISSN 0553-0814, No 36-37, 2007-2008, págs 435-440 [Internet]. 2007 [cited 2024 Nov 23];(36):435-40. Available from: <https://dialnet.unirioja.es/servlet/articulo?codigo=3422943>

26. Sliwa M. Master plans and urban ecosystems: How the poor transform land-use from rigid into organic - A case from Colombia. *Habitat Int*. 2017 Aug 1;66:1-12.

<https://doi.org/10.1016/j.habitatint.2017.05.003>

27. Useche AF, Sarmiento OL, Álvarez-Rivadulla MJ, Medina P, Higuera-Mendieta D, Montes F. Spatial segregation patterns and association with built environment features in Colombian cities. *Cities*. 2024 Sep 1;152.

<https://doi.org/10.1016/j.cities.2024.105217>





28. Navarrete-Hernandez P, Luneke A, Truffello R, Fuentes L. Planning for fear of crime reduction: Assessing the impact of public space regeneration on safety perceptions in deprived neighborhoods. *Landsc Urban Plan.* 2023 Sep 1;237.

<https://doi.org/10.1016/j.landurbplan.2023.104809>

29. Shiraishi K. The inequity of distribution of urban forest and ecosystem services in Cali, Colombia. *Urban For Urban Green.* 2022 Jan 1;67.

<https://doi.org/10.1016/j.ufug.2021.127446>

30. Garza N, Ovalle MC. Tourism and housing prices in Santa Marta, Colombia: Spatial determinants and interactions. *Habitat Int.* 2019 May 1;87:36-43.

<https://doi.org/10.1016/j.habitatint.2019.04.001>

31. Garcés-Ordóñez O, Espinosa Díaz LF, Pereira Cardoso R, Costa Muniz M. The impact of tourism on marine litter pollution on Santa Marta beaches, Colombian Caribbean. *Mar Pollut Bull.* 2020 Nov 1;160.

<https://doi.org/10.1016/j.marpolbul.2020.111558>

32. Rivillas-García JC, Cifuentes-Avellaneda Á, Ariza-Abril JS, Sánchez-Molano M, Rivera-Montero D. Venezuelan migrants and access to contraception in Colombia: A mixed research approach towards understanding patterns of inequality. *J Migr Health.* 2021 Jan 1;3.

<https://doi.org/10.1016/j.jmh.2020.100027>

33. Knight B, Tribin A. Immigration and violent crime: Evidence from the Colombia-Venezuela Border. *J Dev Econ.* 2023 May 1;162.

<https://doi.org/10.1016/j.jdeveco.2022.103039>