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Automation in the detection of potential boundaries: integration of AI algorithms and image fusion

Automatización en la detección de potenciales linderos: integración de algoritmos de IA y fusión de imágenes

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Abstract: Outdated cadastral information in Colombia constitutes a structural barrier to the implementation of the Comprehensive Rural Reform (CRR). This research validates a methodology for the automatic extraction of visible boundaries through the fusion of synthetic aperture radar (SAR) and optical imagery, employing artificial intelligence techniques. Machine learning and deep learning approaches were comparatively evaluated, contrasting the foundational Segment Anything Model (SAM) with a retrained edge detector (VGG13_bn). Quantitative results indicate that, while SAM exhibits a higher level of segmentation, the VGG13_bn model achieved an F1-score of 0.405 and an accuracy of 0.888, emerging as the most balanced and operationally viable alternative. This work provides a reproducible methodological workflow that can support cadastral modernization processes in territorially complex contexts.

Keywords: multipurpose cadastre, edge detection, image fusion, deep learning, arcifinious boundaries.

Resumen: La desactualización catastral en Colombia constituye una barrera estructural para la implementación de la Reforma Rural Integral (RRI). Esta investigación valida una metodología para la extracción automática de linderos visibles mediante la fusión de imágenes de radar de apertura sintética (SAR) y ópticas, empleando técnicas de inteligencia artificial. Se evaluaron comparativamente los enfoques de aprendizaje automático y aprendizaje profundo, contrastando el modelo fundacional Segment Anything Model (SAM) con un detector de bordes reentrenado (VGG13_bn). Los resultados cuantitativos indican que, si bien SAM presenta un mayor nivel de segmentación, el modelo VGG13_bn alcanzó un F1-score de 0.405 y una exactitud de 0.888, configurándose como la alternativa más equilibrada y viable desde el punto de vista operativo. El trabajo aporta un flujo metodológico reproducible que puede apoyar procesos de modernización catastral en contextos de alta complejidad territorial.

Palabras clave: catastro multipropósito, detección de bordes, fusión de imágenes, aprendizaje profundo, límites arcifinios.

1. INTRODUCTION

Legal insecurity in land tenure, aggravated by massive outdated cadastral records, represents a structural barrier for peace consolidation and the implementation of development policies such as the Comprehensive Rural Reform (CRR) in Colombia. Traditional land surveying methodologies, although precise, are logistically unfeasible for the scale and urgency the country demands, being time-intensive, resource-heavy, and susceptible to human error [1]. In this context, the automation of potential property boundary extraction using remote sensing has established itself as a research field of vital importance for cadastral modernization.

The use of optical imagery, while effective, is severely restricted by persistent cloud cover in vast regions of the national territory. Therefore, Synthetic Aperture Radar (SAR) emerges as a strategic technology, thanks to its ability to acquire high-resolution images regardless of atmospheric or lighting conditions [2]. Despite this operational advantage, SAR images present significant technical challenges, primarily speckle noise a granular artifact inherent to the signal that degrades image quality and geometric distortions (e.g., layover, shadow) caused by the interaction of the radar beam with topographic relief [3]. The correction of these phenomena is an indispensable prerequisite for any reliable analysis.

In the recent technical realm, the state of the art presents contrasting advances. On one hand, Fetai et al. [4] validated the superiority of deep convolutional networks for detecting visible boundaries, but their approach depends on Unmanned Aerial Vehicle (UAV) optical imagery, which is unfeasible for massive national coverage. On the other hand, in the radar domain, studies such as Carstairs et al. [5] document that, in short wavelength bands (such as X-Band), canopy penetration is limited and the signal suffers decorrelation in areas of complex topography; while this finding was in the context of forest degradation, it suggests inherent difficulties for defining property boundaries under vegetation. To mitigate these limitations, current literature suggests sensor fusion; Irfan et al. [6] recently demonstrated that multimodal fusion (SAR-Optical) significantly improves land use classification (Land Cover), leveraging radar texture and optical spectrality. In parallel, the emergence of Foundation Models such as the Segment Anything Model (SAM) [7] has opened new possibilities, although there is a technical gap regarding their operational viability compared to lightweight networks retrained for cadastral tasks in a country like Colombia.

To overcome these challenges, this study proposes and validates an integral methodology that applies Artificial Intelligence (AI), specifically Deep Learning (DL) approaches [8], to automate the extraction of potential visible boundaries. The core of the methodology lies in the fusion of high-resolution SAR imagery and optical data, combining the structural information of the radar with the spectral information of the optical image to create a fused product of greater visual interpretability. This approach not only addresses the technical problems of SAR but also lays a robust methodological foundation for future cadastral applications.

For the development and validation of this proposal, the municipality of Vistahermosa (Meta) was selected as the study area. This territory, prioritized within the framework of the 2016 Peace Agreement, represents a microcosm of the country's cadastral challenges. A determining factor for its selection was the availability of a high-quality reference dataset corresponding to boundaries surveyed in the field using the Fit-For-Purpose (FFP) methodology in 2018, which was crucial for the quantitative validation of the developed AI models. This article details the complete workflow, from data preprocessing to the comparative analysis of the models, and concludes with a discussion on the practical viability of the solution in the Colombian context.

2. METHODOLOGY

The research followed a quantitative-experimental design; the workflow comprises data acquisition, preprocessing, image fusion, deep learning model training, and quantitative evaluation.

2.1. Study Area and Data Inputs

The study area focused on the Costa Rica and Termales rural districts (veredas) in the municipality of Vistahermosa (Meta), Colombia. This zone was strategically selected for two main reasons: (1) its relevance in the post-conflict context, being a prioritized territory for the implementation of the multipurpose cadastre, and (2) the availability of a high-quality validation dataset corresponding to boundaries surveyed in the field during the Fit-For-Purpose (FFP) methodology pilot in 2018.

The primary data used consisted of two types of satellite images acquired on close dates to ensure temporal consistency:

- SAR Image: An image from the Capella Space constellation (X-band, 50 cm spatial resolution), acquired on September 24, 2023. Its very high resolution was key for discerning fine structural details.
- Optical Image: A multispectral PlanetScope image (3 m spatial resolution), from September 30, 2023, essential for land cover analysis and the creation of a fused product.

2.2. Data Preprocessing and Fusion

The methodological workflow began with rigorous preprocessing to mitigate artifacts inherent to SAR images and standardize the data for analysis.

2.2.1 Speckle Noise Reduction

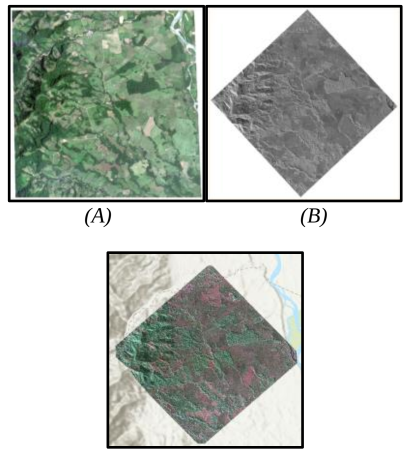
To address the granular noise characteristic of SAR images, eight spatial filters were evaluated. The IDAN (Intensity-Driven Adaptive-Neighborhood) filter, implemented in the SNAP software, was selected because its adaptive neighborhood algorithm demonstrated the best balance between noise suppression and the preservation of edges and fine linear features, which are crucial for subsequent boundary detection [9].

2.2.2 Geometric Correction and Orthorectification

Geometric distortions inherent to SAR, caused by relief, were corrected through the generation of a Digital Elevation Model (DEM). The radargrammetry technique was employed on the stereo pair of SAR images in the ENVI SARscape software to derive a high-resolution DEM. This DEM was subsequently used for the precise orthorectification of the SAR image, ensuring its correct geometric correspondence with the terrain and other coordinate systems [10].

2.2.3 SAR-Optical Synergism

In order to maximize the extractable information, a fused data product was generated. A fusion based on the HSI color model (Hue, Saturation, Intensity) was applied, a technique that allows integrating the structural detail of a high-resolution image (SAR) with the chromatic information of a lower-resolution multispectral image (optical). The Intensity (I) component of the optical image (transformed to HSI) was replaced by the SAR image, and the result was reconverted to RGB. This process, grounded in works such as those by Schmitt & Zhu [11], produces a hybrid image that significantly improves visual interpretability.



(A) *(B)*

(C)

Fig. 1. *Synergistic data fusion. (A) PlanetScope optical image, (B) Capella Space SAR image, and (C) Resulting HSI fusion image.*
Source: *Author's elaboration.*

2.3. Artificial Intelligence Models

Two main AI paradigms were evaluated and compared for the generation of boundary candidates:

2.3.1 Machine Learning (ML)

The unsupervised clustering algorithm Segment Mean Shift was implemented using ArcGIS Pro segmentation tools. This method was chosen for its theoretical robustness in delineating irregular shapes without the need to predefine the number of clusters [12]. Although tests were conducted with this approach, the qualitative results showed land cover segmentation with overly thick and imprecise edges; thus, it was discarded for deep quantitative analysis in favor of DL methods.

2.3.2 Deep Learning (DL):

Two avant-garde approaches were explored:

- Land Parcel Extraction (VGG13_bn): The problem was approached as a supervised edge detection task. A pre-trained BDCN (Bi-Directional Cascade Network) model [13] with a VGG13_bn backbone [14] was retrained. The training data were generated by creating a 0.5-meter buffer around the reference boundaries, converting he vectors into a binary mask. This value was selected as a compromise to ensure sufficient boundary representation at the pixel level without introducing noise from adjacent land covers; the total set (1573 labels) was partitioned as follows: 70% training, 15% validation, and 15% testing. The visible boundary detection model was approached as an edge detection problem by retraining a pre-trained deep convolutional network, following the Deep Learning Edge Detection workflow implemented by ESRI.

  A Bi-Directional Cascade Network (BDCN) was employed as the base architecture for perceptual edge detection, using VGG13 with batch normalization (VGG13_bn) as the backbone. The architecture is composed of thirteen convolutional layers organized into five hierarchical blocks, each followed by batch normalization layers and ReLU activation functions.

  The hyperparameters employed were:

  - Loss Function: Binary Cross-Entropy Loss (BDCE)
  - Optimizer: Adam
  - Learning Rate: 1 x 10^{-4}
  - Batch Size: 8

  The process was executed on a portable computer with the following specifications:

  - CPU: Core i7 13620H 2.4 GHz
  - GPU: NVIDIA GeForce RTX 4060 8 GB (VRAM)
  - Memory: 24 GB (RAM)
  - Framework: PyTorch (Integrated into ArcGIS Pro Deep Learning Framework)
  - Software: ArcGIS Pro 3.4.0 / Arcpy 3.6

- Segment Anything Model (SAM): Meta AI's foundation model was applied in its automatic mode. This model, thanks to its Transformer-based architecture and massive pre-training, performs zero-shot segmentation of all identifiable objects in the image, without requiring specific training for this project [7].

2.4. Results Evaluation

The quality of the extracted potential boundaries was evaluated through a quantitative analysis of positional accuracy, commission, and omission. To do this, a tolerance buffer of 1.04 meters was generated around the reference boundaries (FFP), a threshold defined based on IGAC normative standards for cadastral cartography at the working scale [17]. The length of the extracted boundary candidates that fell within this buffer (True Positives) was quantified, as well as those that fell outside (False Positives or commission errors) and the reference boundaries that were not detected (False Negatives or omission errors).

3. RESULTS AND DISCUSSION

3.2. Evaluation Metrics

To quantify model performance from a comprehensive perspective, two complementary metrics were employed. First, Accuracy was calculated, which measures the global proportion of model hits with respect to the total image pixels, indicating its general stability:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

Where:
TP: True Positives.
TN: True Negatives.
FP: False Positives.
FN: False Negatives.

Additionally, the F1-Score was incorporated. Given that boundary detection implies a class imbalance (where potential boundaries occupy a minimal portion of the image compared to the background), this metric allows evaluating the specific balance between Precision (P) and Sensitivity (Recall - R) in delineating linear vectors:

$$F1 = 2 \cdot \frac{(P \cdot R)}{P + R} \qquad (2)$$

Where P is the predictive precision and R is the true positive rate (Recall).

The joint interpretation of both values allows validating both the model's capacity to generalize the environment and its performance in the specific task of extracting potential boundaries.

3.2. Comparison of AI Models

The experimental phase was designed to systematically contrast Machine Learning (ML) and Deep Learning (DL) approaches.

3.2.1 Performance and Discarding of the Machine Learning Approach

Unsupervised ML algorithms, with Segment Mean Shift as their most robust representative, were evaluated on the synergistic product. As observed in Fig. 2, the result is a land cover segmentation in the form of a mosaic of irregular polygons. Although a differentiation of large land use masses is achieved, the generated edges are thick, geometrically imprecise, and present numerous discontinuities, making them unsuitable for extracting boundary vectors at a cadastral scale. The low quality of this output, added to the considerable computational effort required for its post-processing, justified discarding this paradigm and concentrating efforts on DL methods (42% contained within the Accuracy Buffer).

Fig. 2. *Potential Boundaries - Segment Mean Shift.*
Source: *Author's elaboration.*

DL models produced qualitatively superior and conceptually distinct results.

- **Land Parcel Extraction (VGG13_bn) Approach - Synergism:** The VGG13_bn model (Land Parcel Extraction), trained for specific edge detection, reached its optimal performance after 10 training epochs, achieving an F1-Score of 0.405, an Accuracy of 0.888, and a validation loss (valid_loss) of 4.941e9. Although the F1-Score value may seem modest, it is a significant result in the context of the complex task of edge detection in SAR imagery. The qualitative evaluation (Fig. 3) is more revealing: the model produces thin linear vectors that correctly align with roads and parcel divisions, representing a direct output that is much more useful for cadastral purposes than that generated by ML methods (84% contained within the Accuracy Buffer).

Fig. 3. *Potential Boundaries - Land Parcel Extraction.*
Source: *Author's elaboration.*

- **Segment Anything Model (SAM) Approach:** SAM produced more detailed and precise segmentation than all tested models; it not only delineated the main boundaries but also identified land cover variations within the same properties, demonstrating good contextual sensitivity (67% contained within the Accuracy Buffer).

Fig. 4. *Potential Boundaries - SAM..*
Source: *Author's elaboration.*

Its evaluation was conducted with respect to the reference information surveyed in the field; for this, a tolerance buffer of 1.04 m was generated around the boundaries obtained using the FFP methodology, in accordance with the positional accuracy established for cartographic inputs in IGAC Resolution 471 of 2020 [15], considering as true positives those extracted boundaries within the buffer and false positives those found outside.

3.3. Discussion of Results and Implications

3.3.1 The Dilemma between Theoretical Precision and Practical Viability

Previous studies have demonstrated that the extraction of cadastral boundaries constitutes a highly challenging problem due to the linear and thin nature of the objects of interest, as well as the strong class imbalance Fetai et al. [16]; the comparison between SAM and VGG13_bn exposes a central dilemma for the application of AI in institutional contexts. SAM, with its superior precision, establishes itself as the technical benchmark. However, its computational cost (more than 7 hours of processing on specialized hardware for the study area) makes it an academically valuable tool but operationally unfeasible for mass production.

In contrast, the VGG13_bn model, although with a lower F1-Score, emerges as the pragmatic and scalable solution. Its capacity to run on conventional hardware in reasonable times and the possibility of adjusting its training to specific regional needs make it the most balanced and recommended approach for immediate implementation within the framework of the multipurpose cadastre. This finding highlights that, in applied engineering, the "best" solution is not always the most precise one, but the most efficient and sustainable one.

Other studies on the subject, such as Zhang et al. [17], report precision results of 88%, recall of 75%, and an F1-score of 81% employing U-Net with a ResNet34 backbone for property boundary detection from satellite images; while these values are superior to those obtained in the present study, it is important to point out that said approach is based on a dense semantic segmentation scheme and on datasets with more homogeneous spectral conditions, which tends to favor higher global metrics.

On the other hand, Fetai et al. [16] evaluated a convolutional model for reviewing visible cadastral boundaries, reporting F1-score values between 0.55 and 0.60 and precisions of up to 0.71, depending on the geometric complexity and fragmentation of the analyzed parcels. These authors highlight that spatial variability and textural similarity between boundaries and adjacent land covers significantly influence model performance, which is consistent with the error patterns observed in this work.

Similarly, in a study focused on UAV images, Fetai et al. [16] obtained a precision of 0.75, recall of 0.65, and F1-score of 0.70 using fully convolutional networks for visible boundary detection. Although these metrics surpass those achieved by the VGG13_bn model in the present case study, it must be considered that UAV images present significantly higher spatial resolutions and less radar noise interference, which facilitates the detection of continuous edges.

In this context, the F1-score of 0.405 and the accuracy of 0.888 obtained in the present study fall within the range reported in the literature for boundary detection tasks in complex scenarios, especially when employing SAR imagery and SAR–Optical fused products. These results reinforce the idea that, in operational cadastral applications, intermediate metrics can be considered acceptable when the objective is to generate candidates for physical boundaries to support field validation processes, rather than producing definitive legal delimitations.

3.3.3 Limitations of the Methodology

T A critical analysis of the VGG13_bn model results reveals systematic error patterns. Omission errors (false negatives) are concentrated in radar shadow areas and on boundaries defined by low vegetation whose texture is very similar to that of surrounding pastures. Commission errors (false positives) tend to appear in high-texture zones, such as dry riverbeds or drainage patterns, which the model confuses with linear structures. These findings suggest that future improvements should focus on incorporating additional information, such as polarimetric data or DEMs, to help the model disambiguate these complex situations.

4. CONCLUSIONS

This study developed and validated an integral methodology for the automatic extraction of visible boundaries through the fusion of SAR and optical imagery. The experimental results allow establishing three fundamental technical conclusions:

First, the superiority of Deep Learning (DL) over traditional Machine Learning methods for this specific task was demonstrated. While algorithms such as Segment Mean Shift generated discontinuous segmentations, neural networks managed to abstract the linear geometry of the boundaries. Specifically, the VGG13_bn model consolidated itself as the most balanced solution, reaching an Accuracy of 0.888, which makes it operationally viable compared to foundation models like SAM, whose computational cost limits its scalability in resource-constrained environments.

Second, the image fusion strategy proved decisive. It was verified that integrating the structural information of radar with the spectral richness of optics mitigates the individual deficiencies of each sensor. This complementarity allowed the model to identify boundaries in conditions where passive optical sensors usually fail due to cloud cover, validating the use of SAR data as a critical input for the cadastre in tropical zones.

The study identified important limitations and technical restrictions. It was observed that the radar X-Band presents limited penetration in areas of dense arboreal vegetation, generating interruptions in the continuity of detected edges. Likewise, commission errors (false positives) associated with dry drainage patterns that the model confuses with physical boundaries were reported. These limitations suggest that, for a productive implementation, the future integration of longer wavelength bands (such as L-Band) or LiDAR data is required.

Finally, this work provides a replicable workflow that transitions from theory to a functional proof of concept. Although it does not replace legal field validation, the tool constitutes a technical input capable of optimizing land sweeping times, contributing technologically to the objectives of cadastral updating and formalization of rural property in Colombia.

5. RECOMMENDATIONS

Based on the findings, the following lines of work are proposed:

- Perform a rigorous field validation in diverse Colombian ecosystems to quantify the positional accuracy of the VGG13_bn model and evaluate its generalization capacity.
- Investigate the use of SAR data in longer wavelength bands (e.g., L-band), which offer better canopy penetration, to improve precision in areas of dense vegetation.
- Integration with Legal Data: Develop hybrid workflows that utilize existing cadastral cartography as an input to guide or adjust AI models, seeking to close the gap between the physical and legal boundary.

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ANEXOS

Appendix A: detailed maps of potential boundary extraction

Below are the maps generated for each of the evaluated methodologies.

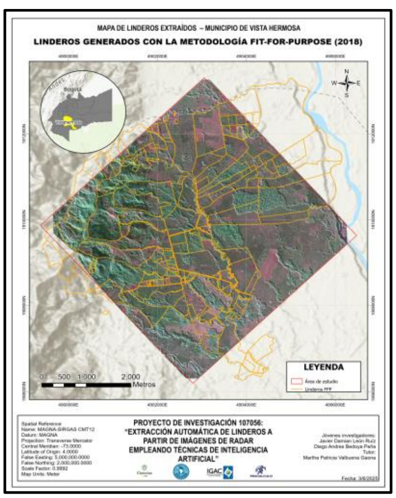

Fig. A.1. *Map of reference boundaries surveyed in the field using the Fit-For-Purpose (FFP) methodology in 2018..*
Source: *Author's elaboration.*

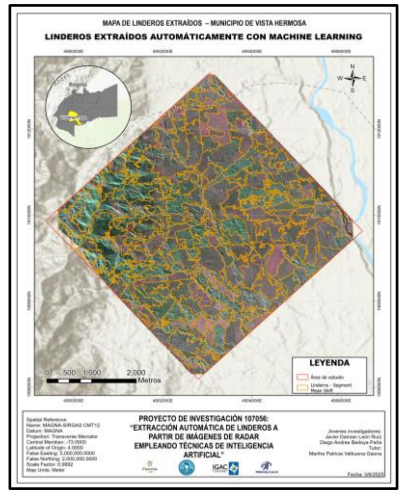

Fig. A.2. *Map of linear potential boundaries extracted with the Segment Mean Shift Machine Learning algorithm.*
Source: *Author's elaboration.*

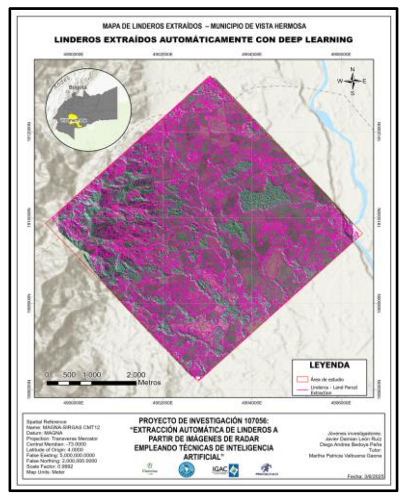

Fig. A.3. *Map of linear potential boundaries extracted with the Land Parcel Extraction (VGG13_bn) Deep Learning model.*
Source: *Author's elaboration.*

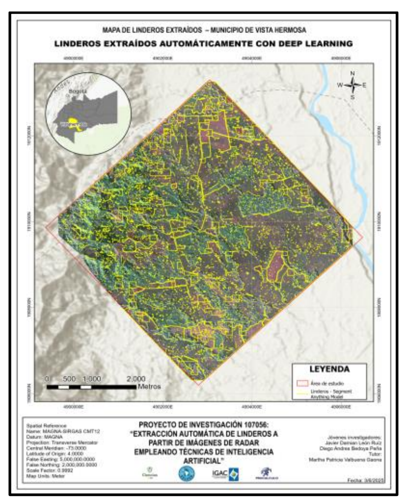

Fig. A.4. *Map of linear potential boundaries extracted with the Segment Anything Model (SAM) Deep Learning model.*
Source: *Author's elaboration.*