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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

Javier Damián León Ruiz[1]
Diego Andrés Bedoya Peña[1]
Martha Patricia Valbuena Gaona[2]

[1] **Sociedad Latinoamericana en Percepción Remota y Sistemas de Información Espacial (SELPER), Capitulo Estudiantil Colombia, Bogota D.C., Colombia.**

[2] **Procalculo Prosis S.A.S, Gerente de Investigación y Desarrollo, Bogotá D.C, Colombia.**

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Corresponding Author: Javier Damián León Ruiz

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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Outdated cadastral information in Colombia constitutes a structural barrier to the implementation of the Comprehensive Rural Reform (CRR).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.

INTRODUCTION

Legal insecurity in land tenure, aggravated by massive outdated cadastral information, represents a structural barrier to the consolidation of peace and the implementation of development policies such as the Reforma Rural Integral (RRI) in Colombia. Traditional property survey methodologies, although accurate, are logistically unfeasible at the scale and urgency demanded by the country, being time- and resource-intensive and susceptible to human error[1]. In this context, the automation of the extraction of potential property boundaries through remote sensing has become a field of research of vital importance for the modernization of the cadastre.

The use of optical imagery, although effective, is severely constrained by persistent cloud cover in vast regions of the national territory. Therefore, the Radar de Apertura Sintética (SAR) emerges as a strategic technology, thanks to its ability to acquire high-resolution images regardless of atmospheric or illumination conditions[2]. Despite this operational advantage, SAR images present significant technical challenges, mainly 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 the topographic relief[3]. The correction of these phenomena is an indispensable prerequisite for any reliable analysis.

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

To overcome these challenges, this study proposes and validates a comprehensive 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 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 under the 2016 Peace Agreement, represents a microcosm of the country's cadastral challenges. A determining factor in its selection was the availability of a high-quality reference dataset, corresponding to the boundaries surveyed in the field using the Fit-For-Purpose (FFP) methodology in 2018, which was crucial for the quantitative validation of the AI models developed. This article details the complete workflow, from data preprocessing to the comparative analysis of the models, and concludes with a discussion of the practical viability of the solution in the Colombian context.

METHODOLOGY

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

Study Area and Data Inputs

The study area focused on the Costa Rica and Termales villages, 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 territory prioritized for the implementation of the multipurpose cadastre, and (2) the availability of a high-quality validation dataset, corresponding to the boundaries surveyed in the field during the pilot of the Fit-For-Purpose (FFP) methodology in 2018.

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

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

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

Data Preprocessing and Fusion

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, crucial for the subsequent detection of boundaries[9].

Geometric Correction and Orthorectification

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

SAR-Optical Image Fusion

To maximize the extractable information, a fused data product was generated. Fusion was based on the HSI color model (Hue, Saturation, Intensity), a technique that integrates 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 converted back to RGB. This process, based on works such as those by Schmitt & Zhu[11], produces a hybrid image that significantly improves visual interpretability.

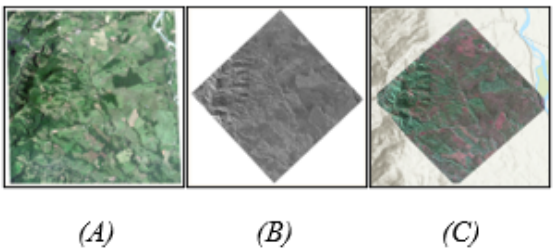


Fig. 1. *Synergistic data fusion. (A) PlanetScope optical image, (B) Capella Space SAR image, and (C) Image resulting from the HSI fusion. Source: Own elaboration.*

Artificial intelligence models

Two main AI paradigms for generating boundary candidates were evaluated and compared:

Machine Learning (ML)

The unsupervised clustering algorithm Segment Mean Shift was implemented through the segmentation tools of ArcGIS Pro. 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 carried out with this approach, the qualitative results showed land-cover segmentation with boundaries that were too thick and imprecise, so it was discarded for in-depth quantitative analysis in favor of DL methods.

Deep Learning (DL)

Two state-of-the-art approaches were explored:

- Land Parcel Extraction (VGG13_bn): The problem was addressed 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 the vectors into a binary mask. This value was selected as a compromise to ensure sufficient representation of the edge 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% test.

The visible boundaries detection model was addressed 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 used as the base architecture for perceptual edge detection, with VGG13 with batch normalization (VGG13_bn) as the backbone. The architecture consists of thirteen convolutional layers organized into five hierarchical blocks, each followed by batch normalization layers and ReLU activation functions.

The hyperparameters used were:

- Loss function: Binary Cross-Entropy Loss (BDCE)
- Optimizer: Adam
- Learning rate: 1 x 10^{-4}
- Batch size: 8

It was run on a laptop 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 the ArcGIS Pro Deep Learning Framework)
- Software: ArcGIS Pro 3.4.0 / Arcpy 3.6
- Segment Anything Model (SAM): The Meta AI foundational model was applied in its automatic mode. Thanks to its Transformer-based architecture and its massive pre-training, this model performs zero-shot segmentation of all identifiable objects in the image, without requiring training specific to this project[7].

Evaluation of Results

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

RESULTS AND DISCUSSION

Evaluation Metrics

To quantify model performance from a comprehensive perspective, two complementary metrics were used. First, accuracy was calculated, which measures the overall proportion of correct model predictions relative to the total number of image pixels, indicating its general stability:

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

Where:

TP: True Positives.

TN: True Negatives.

FP: False Positives.

FN: False Negatives.

Additionally, the F1-score was incorporated. Since boundary detection involves class imbalance (where potential boundaries occupy a minimal portion of the image relative to the background), this metric allows evaluating the specific balance between precision (P) and recall (R) in the delineation of linear vectors:

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

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

Interpreting both values together makes it possible to validate both the model's ability to generalize the environment and its performance in the specific task of extracting potential boundaries.

Comparison of AI Models

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

Performance and Discarding of the Machine Learning Approach

Unsupervised ML algorithms, with Segment Mean Shift as their most robust representative, were evaluated on the synergy. As shown in Fig. 2, the result is a land cover segmentation in the form of a mosaic of irregular polygons. Although the large land use masses are differentiated, the generated boundaries are thick, geometrically imprecise, and show numerous discontinuities, which makes them unsuitable for extracting boundary vectors at a cadastral scale. The low quality of this

output, together with the considerable computational effort that its post-processing would require, justified discarding this paradigm and concentrating efforts on DL methods (42% contained within the accuracy buffer)

The DL models produced qualitatively superior and conceptually distinct results.

- Land Parcel Extraction Approach (VGG13_bn) - Synergy: The VGG13_bn model (Land Parcel Extraction), trained specifically for edge detection, reached its optimal performance after 10 training epochs, with an F1-score of 0.405, an accuracy of 0.888, and a validation loss (valid_loss) of 4.941e9. Although the F1-score may seem modest, it is a significant result given the complexity of edge detection in SAR images. The qualitative evaluation (Fig. 3) is more revealing: the model produces thin linear vectors that align correctly with roads and parcel divisions, a direct output that is far more useful for the cadastral purpose than the one generated by ML methods (84% contained within the accuracy buffer)



Fig. 2. *Potential Boundaries Segment Mean Shift.*
Source: Own elaboration.



Fig. 3. *Potential Boundaries Land Parcel Extraction.*
Source: Own elaboration.

- Segment Anything Model (SAM) Approach: SAM produced the most detailed and precise segmentation of all the models

tested. It not only delineated the main boundaries but also identified land cover variations within the same parcels, showing good contextual sensitivity (67% contained within the accuracy buffer)

Its evaluation was carried out against the reference information collected in the field. For this purpose, a tolerance buffer of 1.04 m was generated around the boundaries obtained through the FFP methodology, in accordance with the positional accuracy established for the cartographic input in IGAC Resolution 471 of 2020 [15], considering as true positives those boundaries extracted within the buffer and as false positives those located outside it.



Fig. 4. *Potential Boundaries SAM.*
Source: Own elaboration.

The Dilemma between Theoretical Precision and Practical Viability

Previous studies have shown that cadastral boundary extraction is 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, stands 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 but operationally unviable tool for mass production.

In contrast, the VGG13_bn model, although it has a lower F1-score, emerges as the pragmatic and scalable solution. Its ability to run on conventional hardware in reasonable times and the possibility of tailoring its training to specific regional needs make it the most balanced and recommendable approach for immediate implementation within the framework of the multipurpose cadastre. This finding underscores that, in applied engineering, the “best” solution is not always the most accurate, but the most efficient and sustainable.

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

For their part, Fetai et al.[16]evaluated a convolutional model for the review of visible cadastral boundaries, reporting F1-score values between 0.55 and 0.60 and precision values of up to 0.71, depending on the geometric complexity and fragmentation of the parcels analyzed. 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 precision of 0.75, recall of 0.65 and F1-score of 0.70 using fully convolutional networks for the detection of visible boundaries. Although these metrics exceed those achieved by the VGG13_bn model in the present case study, it should be considered that UAV images have 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 SAR images and fused SAR–optical

products are used. These results reinforce the idea that, in operational cadastral applications, intermediate metrics can be considered acceptable when the objective is to generate candidate physical boundaries that support field validation processes, rather than to produce definitive legal delimitations.

Methodology Limitations:

A critical analysis of the results of the VGG13_bn model 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 the surrounding pastures. Commission errors (false positives) tend to appear in high-texture areas, 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 or DEM data, to help the model disambiguate these complex situations.

CONCLUSIONS

This study developed and validated a comprehensive methodology for the automatic extraction of visible boundaries through the fusion of SAR and optical images. The experimental results allow establishing three fundamental technical conclusions: Primero, se demostró la superioridad del Aprendizaje Profundo (DL) sobre los métodos de Machine traditional learning for this specific task. While algorithms such as Segment Mean Shift generated discontinuous segmentations, neural networks succeeded in abstracting the linear geometry of the boundaries. Specifically, the VGG13_bn model was consolidated as the most balanced solution, reaching an accuracy of 0.888, which makes it operationally viable compared with foundation models such as 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 from radar with the optical spectral richness mitigates the individual deficiencies of each sensor. This complementarity allowed the model to identify boundaries under conditions where passive optical sensors usually fail due to cloud cover, validating the use of SAR data as a critical input for cadastre in tropical areas.

The study identified important limitations and technical constraints. It was observed that the X band of the radar presents limited penetration in areas of dense tree vegetation, which generates interruptions in the continuity of the 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 the L band) or LiDAR data is required.

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

RECOMMENDATIONS

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

- Conduct 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 penetration of the tree canopy, to improve precision in areas of dense vegetation.
- Integration with Legal Data: Develop hybrid workflows that use existing cadastral cartography as an input to guide or adjust the AI models, seeking to close the gap between the physical and the legal boundary.

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CONFLICT OF INTEREST

None

AUTHORSHIP CONTRIBUTIONS

Drafting – original draft: Javier Damián León Ruiz, Diego Andrés Bedoya Peña, Martha Patricia Valbuena Gaona.

Writing–review and editing: Javier Damián León Ruiz, Diego Andrés Bedoya Peña, Martha Patricia Valbuena Gaona.

ANNEXES

Appendix A: detailed maps of the extraction of potential boundaries

The maps generated for each of the methodologies evaluated are presented below.

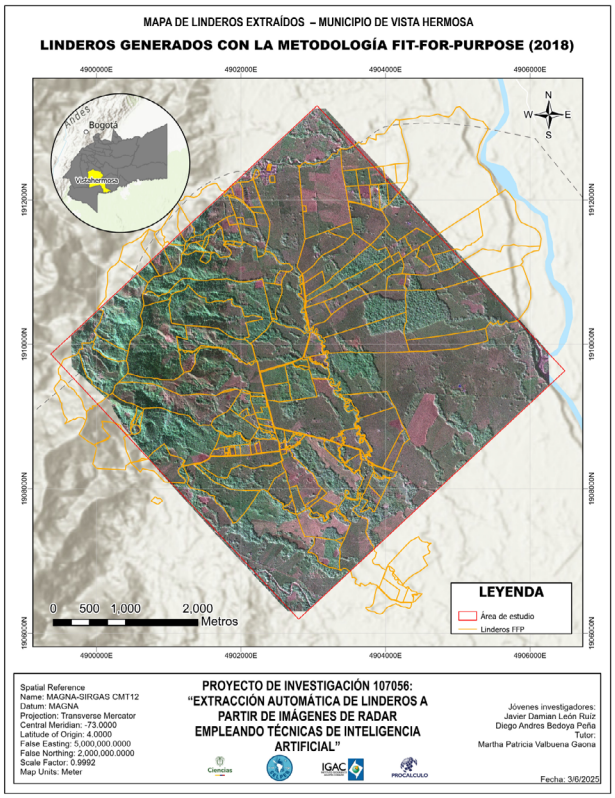


Fig. A.1. Map of the reference boundaries surveyed in the field using the Fit-For-Purpose (FFP) methodology in 2018. Source: Own elaboration.

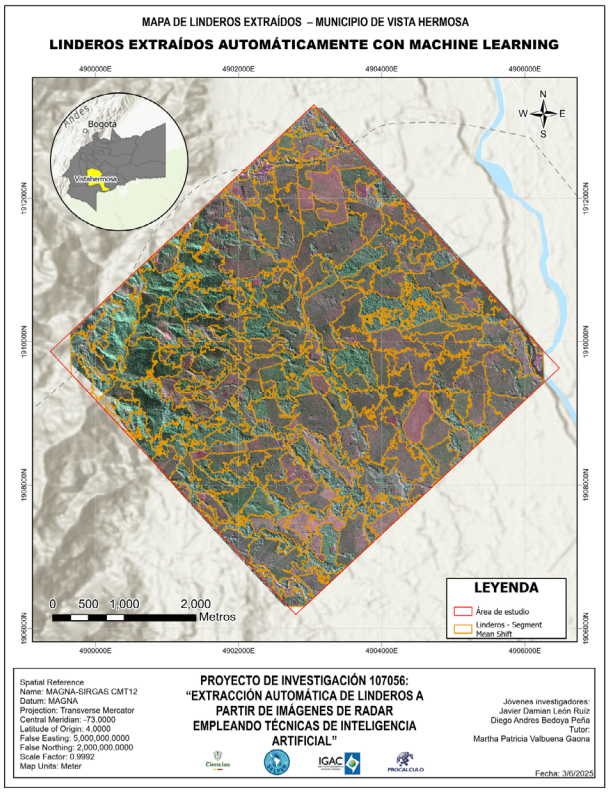


Fig. A.2. Map of the potential linear boundaries extracted with the Segment Mean Shift machine learning algorithm. Source: Own elaboration.

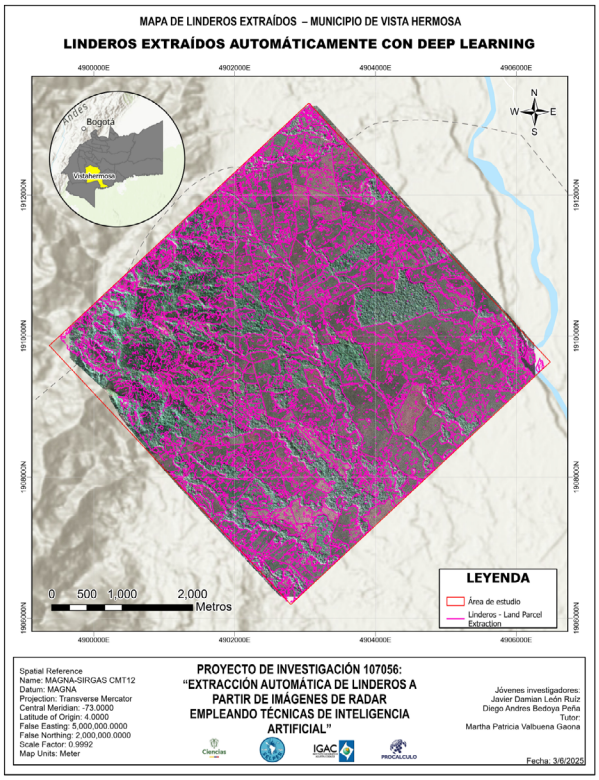


Fig. A.3. Map of the potential linear boundaries extracted with the Land Parcel Extraction deep learning model (VGG13_bn). Source: Own elaboration.

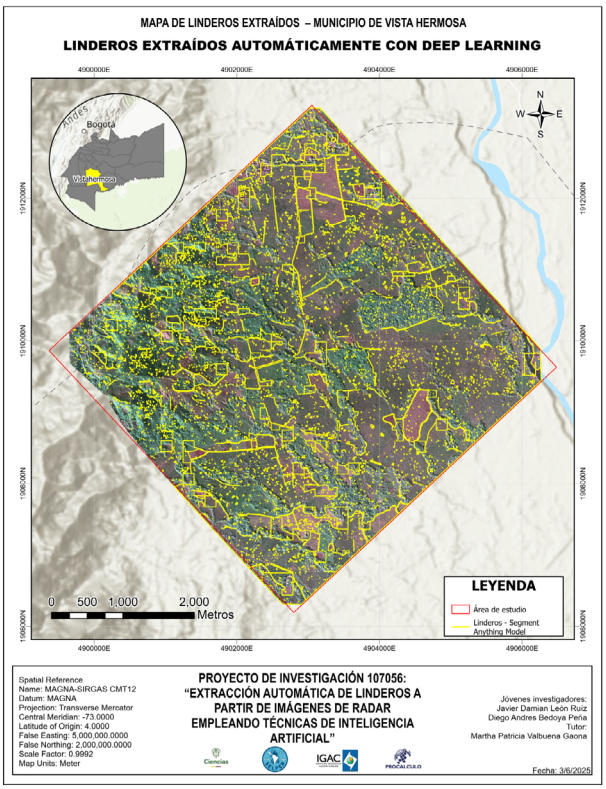


Fig. A.4. Map of the potential linear boundaries extracted with the Segment Anything Model (SAM) deep learning model. Source: Own elaboration.