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ABSTRACT

In the context of climate policies, land use and land cover monitoring is a key component for assessing the LULUCF sector. In this regard, remote sensing combined with deep learning offers new opportunities for more consistent and spatially detailed mapping. The objective of this study is to evaluate the feasibility of a deep learning architecture based on a Mixture of Experts for the hierarchical identification of LULUCF categories, with a particular focus on forested areas. The proposed methodology relies on a cascaded architecture composed of three specialized U-Net models addressing contextual land-use classification, binary tree detection, and tree-species identification, using high-resolution SIOSE-AR data over an MTN50 sheet in northern Spain. Preliminary results indicate a coherent identification of spatial patterns and major land-use categories, although class imbalance remains a limiting factor. Overall, the approach shows strong potential for LULUCF monitoring using remote sensing data

Keywords: *Remote Sensing, Land Use and Land Cover (LULC), LULUCF Monitoring, Deep Learning, Mixture of Experts*

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Abstract: In the context of climate policies, land use and land cover monitoring is a key component for assessing the LULUCF sector. In this regard, remote sensing combined with deep learning offers new opportunities for more consistent and spatially detailed mapping. The objective of this study is to evaluate the feasibility of a deep learning architecture based on a Mixture of Experts for the hierarchical identification of LULUCF categories, with a particular focus on forested areas. The proposed methodology relies on a cascaded architecture composed of three specialized U-Net models addressing contextual land-use classification, binary tree detection, and tree-species identification, using high-resolution SIOSE-AR data over an MTN50 sheet in northern Spain. Preliminary results indicate a coherent identification of spatial patterns and major land-use categories, although class imbalance remains a limiting factor. Overall, the approach shows strong potential for LULUCF monitoring using remote sensing data.

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Identificación de categorías LULUCF basada en Deep Learning mediante una arquitectura de mezcla de expertos y datos de teledetección

***Resumen**: En el marco de las políticas climáticas, la monitorización del uso y la cobertura del suelo es fundamental para la evaluación del sector LULUCF. En este contexto, la teledetección y el uso de métodos de Deep Learning permiten avanzar hacia cartografías más precisas y detalladas. El objetivo de este trabajo es evaluar la viabilidad de una arquitectura de Deep Learning basada en mezcla de expertos para la identificación jerárquica de categorías LULUCF, con especial atención a áreas forestales. La metodología se basa en una arquitectura en cascada compuesta por tres modelos U-Net especializados en clasificación contextual, detección binaria de arbolado e identificación de especies, utilizando cartografía SIOSE-AR de alta resolución sobre una hoja MTN50 del norte de España. Los resultados preliminares muestran una correcta identificación de patrones espaciales y de las principales categorías, aunque se ve afectada por el desbalanceo entre clases. En conjunto, el enfoque presenta un alto potencial para la monitorización LULUCF basada en datos de teledetección.*

***Palabras clave**: Teledetección, Uso y cobertura del suelo, Monitorización del LULUCF, Aprendizaje Profundo, Mezcla de expertos.*

1. INTRODUCTION

The Paris Agreement's temperature goals make the LULUCF sector crucial, since reaching mid-century targets requires balancing greenhouse gas emissions with removals by carbon sinks (United Nations Framework Convention on Climate Change, 2015). Under IPCC inventory guidelines, LULUCF assessment methods are organized into tiers, and EU member states must apply at least Tier 2 approaches while moving toward Tier 3 methods using spatially explicit models and detailed measurements (Eggleston *et al*., 2006) (Alley *et al*., 2007).

Advances in computing and Earth observation now enable higher-tier monitoring, with machine learning and deep learning offering scalable tools for land-cover classification and change detection (Radeva *et al*., 2023) (Habib & Connolly, 2023). These approaches can support EU regulatory expectations and sustainable land-use planning, including pollution reduction and biodiversity goals (Verburg *et al*., 2008).

However, maintaining high-resolution land-use cartography like SIOSE is highly labor-intensive, which contributes to datasets becoming outdated (Maniatis *et al*., 2021). The proposed deep learning approach could reduce the effort and time needed for land-use cataloguing and map updates and could later be adapted to tasks such as forest species recognition using imagery.

This study specifically evaluates a deep learning Mixture of Experts (MoE) architecture based on U-Net models to predict forest areas across Spain using SIOSE-derived LULUCF categories. By applying cascade inference with specialized experts, it aims to improve accuracy and computational efficiency, and to strengthen land-use assessment methods that support climate mitigation and adaptation planning.

2. MATERIAL AND METHODS

2.1. Study area

This study was conducted in northern Spain, within the Cantabrian mountain range. The imagery derived from Spanish National Plan for Aerial Orthophotography (PNOA) and the area corresponds to the region of *Cangas del Narcea,* sheet 0050 of the *Mapa Topográfico Nacional* at 1:50,000 scale (MTN50) with spatial resolution of 0.25m. These images consist of three spectral bands in the visible domain (Red, Green, and Blue), which are commonly used for visual interpretation and high-resolution land-cover mapping. This sheet was used as a case study to develop the complete project workflow.

The high-resolution (HR) product of the *Sistema de Información de Ocupación del Suelo de España* (SIOSE), known as SIOSE-HR, represents the most up-to-date polygon-based HR land-occupation cartography available for Spain (SIOSE, E.T.N., n.d.). The dataset used in this study corresponds to the 2017 release, which was also adopted as the reference year for the analysis. Using SIOSE-HR, only polygons within the boundaries of MTN50 sheet were retained by clipping the dataset to the sheet extent. In this product, the minimum mapping unit is 1 hectare (1 ha).

The remote sensing data were used as the primary input for all three expert models within the Mixture-of-Experts architecture. Image patches of fixed size (e.g., 512 × 512 pixels) were extracted and paired with corresponding rasterized labels derived from SIOSE-HR polygons.

2.2. Land use and categories

To categorize polygons based on canopy cover, we first applied a filter within the first expert to select classes corresponding to tree-related areas. This expert included the following categories: water, artificial surfaces, forested areas, crops, pasture and bare land. Polygons classified as forest were then transferred to the next expert, specializing in binary selection of tree presence.

Therefore, categorization has been conducted at three distinct levels: one in which the classes align with those designated by LULUCF, another design for refining using binary approach for presence of tree canopy and the other aiming to achieve separation down to the individual species.

2.3. Photointerpretation

Image datasets corresponding to each expert were manually evaluated to enhance the overall quality of the training data. Images were assigned to three quality categories: high-quality images, used for model training; medium-quality images, used for model tuning and validation; and low-quality images, reserved for global system testing.

In this context, quality is defined as the degree to which polygon labels accurately represent real-world conditions. The classification criteria comprised (i) label assignment accuracy and (ii) the delineation quality of polygon boundaries. To support this process, a dedicated methodology was developed based on visual verification through the superimposition of polygons onto the corresponding imagery (Maniatis *et al*., 2021) (Figure 1a).

2.4. Model inputs and predictors

The input data for the deep learning models consist of image patches extracted from RGB orthophotos, along with their corresponding segmentation masks derived from SIOSE-HR data. In addition to raw spectral information, the models implicitly learn spatial and contextual features such as texture, shape, and spatial relationships between land-cover elements through convolutional operations. These features are particularly relevant for distinguishing between land-use categories and for identifying tree canopy structures.

Unlike traditional machine learning approaches, where predictors are explicitly defined, convolutional neural networks automatically extract hierarchical feature representations from the input imagery. Consequently, the importance of individual predictors cannot be directly obtained from model coefficients.

2.5. Model architecture

In this study, we investigate the use of deep learning, specifically, U-Net–based modelling, combined with a

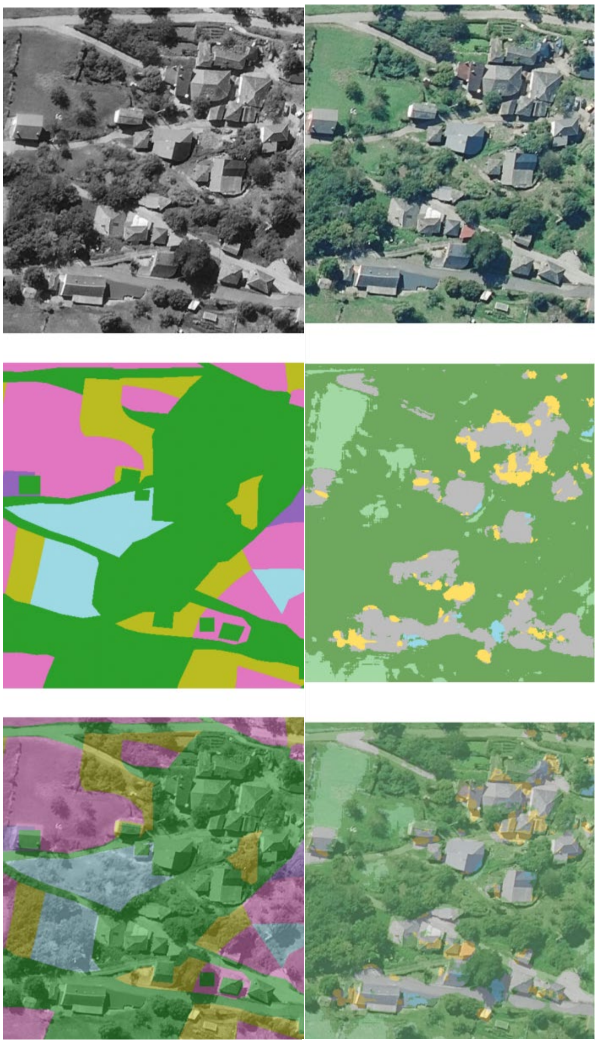

Figure 1a. Verification images to assess quality. Top superposition of mask and image, middle image, bottom mask. Green: artificial, Pink: crops, Yellow: pasture, Blue: forest, Purple: bare land.

Figure 1b. Predicted masks generated by the model. Top superposition of mask and image, middle image, bottom mask. Dark green: forest, Light green: crops, Yellow: bare land, Grey: artificial, Blue: water.

Mixture-of-Experts (MoE) architecture that integrates three independent expert models, each addressing a distinct task. The workflow establishes a cascade in which information is progressively filtered and refined from one expert to the next, providing increasingly informative inputs for subsequent inference (Figure 2).

Each expert serves a specific purpose. The first model, the context expert, identifies structural patterns and land-use classes, including forest cover. The second model, the binary expert, takes as input the forest-related information produced by the context expert and refines it, yielding a substantially more precise delineation. This design markedly reduces computational cost and runtime, as the species expert is applied exclusively to areas where tree presence is confidently detected.

Although architecture comprises three distinct models, the system is designed to produce results jointly. Accordingly, evaluation metrics are primarily reported at the system level; however, intermediate assessments

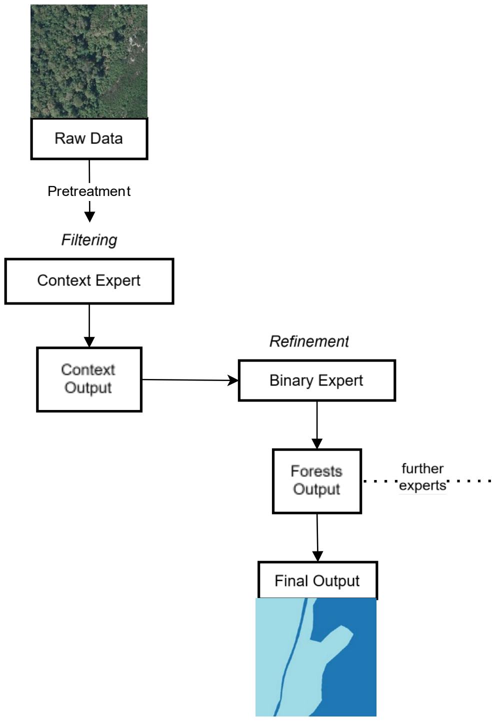

Figure 2: Cascade inference using mixture of experts architecture.

were also conducted to quantify the performance of individual experts and to ensure the robustness of each component.

3. RESULTS AND DISCUSSION

At the current stage of the study, preliminary results obtained from the proposed modelling framework (Figure 1b) are encouraging. Despite de exploratory nature of the current implementation and with further refinements, the model is already able to recognize structural patterns and delineate terrain boundaries between major land-use classes.

However, an important limitation at this stage concerns class imbalance with the available datasets. At this stage, only a single MTN50 sheet has been used to assess the feasibility of the proposed approach and to validate the correct operation of the processing pipeline. This limitation expected to be addressed in subsequent phases by incorporating additional MNT50 sheets, thereby increasing the representation of under-represented classes and reducing the relative dominance of more frequent categories such as pasture or cropland.

Given the preliminary nature of the study and the limited spatial extent currently analyzed, this work focuses primarily on qualitative and visual assessment of model outputs. A comprehensive quantitative evaluation including class-specific performance metrics is planned once the dataset is expanded and class imbalance is mitigated (Table 1).

Table 1. Preliminary metrics for individual models and cascade. PixAcc: % of pixels correctly clasified, mIoU: IoU mean for all classes, F1macro: F1 mean for all classes.

Metric	Context	Binary	Cascade
pixAcc	0.6599	0.6183	0.6009
mIoU	0.3156	0.3569	0.3418
F1macro	0.4565	0.4779	0.4600

The adoption of this methodology within remote sensing and cartographic production could represent a substantial shift in how high-resolution mapping and LULUCF categorization are implemented (Radeva *et al*., 2023) (Verburg *et al*., 2008). Specifically, the proposed approach aims to reduce the time required to construct and update maps while improving the consistency and reliability of polygon-level classification. Moreover, the underlying architecture is readily transferable and could be adapted to a broad range of related tasks, including land-use characterization and the detection of structural patterns in the landscape.

Nevertheless, several challenges remain. A major limitation, common to many deep learning pipelines, concerns data storage and management. Remote sensing datasets typically comprise large volumes of high-resolution imagery and associated products, making them difficult to store, curate, and process at scale (Müller *et al*., 2019). Without adequate infrastructure, assembling representative datasets can be a bottleneck for model development and evaluation. Despite these constraints, it is feasible to establish streamlined pipelines based on smaller, well-curated datasets, which can be easier to assess, validate, and replicate while still providing meaningful experimental evidence.

4. CONCLUSIONS

This work presents a methodology that integrates deep learning and data science with traditional labeling to address key limitations of manual LULUCF assessment. Although still under development, the current results and processing pipeline demonstrate its feasibility while highlighting challenges that warrant further refinement.

The proposed framework seeks to reduce temporal obsolescence and improve spatial detail in cartographic products by streamlining the production and revision of thematic maps, enabling more frequent updates as new observations become available. This is particularly relevant in dynamic landscapes, where land cover and land use are subject to rapid changes driven by urban expansion, agricultural practices, natural disturbances, or seasonal variability.

Furthermore, the methodology has the potential to enhance spatial precision and consistency at finer scales, mitigating common issues in traditional workflows such as operator subjectivity, heterogeneous interpretation criteria, and polygon generalization due to production constraints. Overall, it provides a pathway toward more accurate and up-to-date cartographies, strengthening monitoring capabilities and supporting improved decision-making in environmental management, land-use planning, and LULUCF reporting.

Finally, the framework could be extended to additional land-surface structures and processes (e.g., forest restoration, vegetation damage, or cropland and pasture abandonment), with the broader aim of establishing a standardized modeling approach applicable to multiple land-cover–related tasks.

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