Building an analysis-ready geospatial dataset for Convolutional Neural Networks-based rural property valuation using LiDAR 3D point clouds

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Abstract

In Portugal, fiscal valuation of rural properties is currently based on the agricultural income obtained in the previous year, disregarding both the productive potential of the land and its market value. To address this limitation, we propose a framework in which rural property valuation is based on the productive potential of the land, following the best practices recommended by the Food and Agriculture Organization (FAO) and the agroforestry profitability model proposed by EU Directorate-General for Structural Reform Support (DG REFORM), while incorporating artificial intelligence techniques through convolutional neural networks (CNN). This paper presents the proposed methodology, which comprises four modules: data acquisition (including airborne LiDAR 3D point clouds, land use and land cover (LULC) data, Sentinel-2 imagery, and FAO datasets), geospatial data processing, data integration, and an AI-based rural property valuation model. The first three modules were successfully implemented, resulting in an integrated analysis-ready geospatial dataset composed of 16 normalized bands at a spatial resolution of 10 m in the Portuguese coordinate reference system PT-TM06/ETRS89 (EPSG:3763). In future work, this dataset will be integrated with additional territorial variables influencing rural property valuation, such as accessibility, legal restrictions, easements, environmental risks, and hydrological conditions, serving as the input for the proposed CNN-based valuation model.

1. Introduction

In Portugal, rural properties are currently taxed based on their actual agricultural production, from which the tax asset value (Valor Patrimonial Tributário – VPT) is determined (CIMI, 2003). This approach results in a limited valuation metric that often underestimates the intrinsic productive capacity of rural land, leading to relatively low taxation levels. Under the current Portuguese taxation system, the Municipal Property Tax (Imposto Municipal sobre Imóveis – IMI) applied to rural properties corresponds to 0.8% of the VPT (CIMI, 2003, Art. 112.º), generating limited fiscal revenue while potentially encouraging land abandonment and speculative ownership (Beires et al., 2013).

To address these limitations, recent developments in land administration have emphasized the incorporation of objective geospatial information into valuation processes. In particular, the ISO 19152:2025 (Land Administration Domain Model – Part IV – Valuation Information Model, LADM-VM) establishes a standardized framework for integrating valuation information within land administration systems, supporting both fiscal and non-fiscal applications. Following this perspective, we proposed a conceptual framework in which artificial intelligence (AI) models, including multilayer perceptron (MLP) and convolutional neural network (CNN), are employed to estimate rural property values using geospatial and cadastral information (Moreira et al., 2025).

A key requirement of AI-based valuation models is the availability of standardized and spatially consistent geospatial datasets that integrate environmental, topographic, land cover, and agricultural productivity information. However, despite the increasing availability of Earth Observation products and geospatial databases, these datasets are commonly distributed with different spatial resolutions, coordinate systems, and thematic structures, making their direct integration challenging. To address this issue, this study proposes a modular framework that harmonizes geospatial datasets into an integrated data cube suitable for future AI-based rural property valuation. The framework combines airborne LiDAR 3D point clouds data, Sentinel-2 imagery, land cover information, and agricultural productivity estimates derived from the Global Agro-Ecological Zones (GAEZ) database processed through the GeoCLEWs workflow developed in the CLEWs_GAEZ repository (OSeMOSYS, 2024). The resulting crop yield estimates will be subsequently transformed into Potential Productive Values (PPV) by incorporating synthetic agricultural commodity prices and production costs, providing an economic indicator of agricultural productive capacity.

Unlike conventional studies, which directly apply machine learning algorithms to estimate agricultural productivity, the proposed methodology focuses on constructing a standardized geospatial dataset in which PPV represents one explanatory variable describing the productive potential of rural land. This integrated dataset constitutes an analysis-ready geospatial data cube, designed to support future AI models for rural property valuation by combining productive capacity with environmental, topographic, and territorial characteristics.

The proposed framework therefore represents a preparatory step towards implementing the valuation methodology envisioned by the LADM-VM standard and the conceptual model of Moreira et al. (2025). Although the complete land valuation model requires additional cadastral, socioeconomic, and market-related information, the present study addresses one of its fundamental challenges: the generation of a harmonized geospatial dataset capable of supporting robust and reproducible AI-based valuation models.

Therefore, the objective of this study is to develop and validate a modular geospatial framework for integrating remote sensing, topographic, land cover, and agro-ecological information into an analysis-ready geospatial dataset representing the productive potential of rural land. The proposed methodology is demonstrated through a case study conducted in the municipality of Condeixa-a-Nova, Central Portugal.

2. Literature review

The literature review is organized into four sections: first, the study area is introduced; second, the valuation framework proposed by DG Reform for the Portuguese context is presented, aimed at establishing a new reference value for rural properties; third, GAEZ framework is described and discussed on how it can be employed to estimate the productive potential of rural land; finally, CNN are reviewed, highlighting their relevance and potentialities when applied to rural property valuation.

2.1 Study area

The proposed framework was applied to the municipality of Condeixa-a-Nova, located in Coimbra Region, central Portugal (Figure 1). The municipality covers a diversified agricultural landscape composed of croplands, forests, pastures, and scrubland (DGT, 2025a). This area was selected as the case study due to the significant extent of land classified as scrubland. These underutilized areas provide an opportunity to assess their potential agricultural productivity through the proposed geospatial framework.

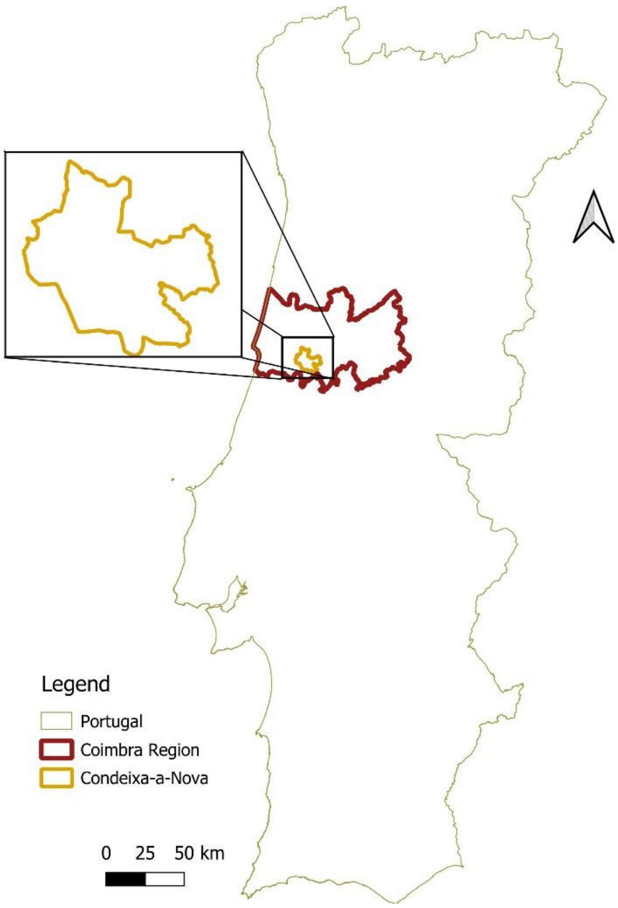

Figure 1: Map of Condeixa-a-Nova municipality in central Portugal's mainland.

2.2 DG Reform proposal

The European Commission's Directorate-General for Structural Reform Support (DG Reform) launched with the Portuguese Tax and Customs Authority the *Designing a New Valuation Model for Rural Properties in Portugal* project (DG-Reform, 2024), with the objective of developing a technically robust methodology for determining the reference value of rural properties, thereby supporting a future reform of the Portuguese rural property valuation system (DG-Reform, 2024).

The methodology proposed by DG Reform is based on the integration of multiple territorial, agricultural, and forestry data sources, combining variables related to agricultural suitability, land use and land cover (LULC), farming and forestry production systems, productivity, and economic returns. The conceptual framework aims to identify homogeneous land use systems, estimate reference values associated with these systems, and subsequently model the spatial distribution of property values through the relationships between biophysical, environmental, and territorial variables. To achieve this, the methodology incorporates spatial analysis techniques and statistical models, particularly Geographically Weighted Regression (GWR), allowing local spatial variations in productivity, land use, and economic returns to be explicitly captured (DG-Reform, 2024).

Although this approach represents a significant advancement over traditional land valuation methods, it remains strongly dependent on static variables, such as official LULC maps and conventional agricultural suitability maps. These variables primarily describe the current condition of the territory and do not necessarily reflect its actual productive potential. Consequently, parcels currently classified as shrubland, abandoned land, or low-intensity land use may still possess high productive potential, yet remain undervalued when assessed solely based on their observed land use.

To overcome the limitation above, the present study introduces a methodological procedure based on the integration of the GAEZ framework, jointly developed by the Food and Agriculture Organization of the United Nations (FAO) and the International Institute for Applied Systems Analysis (IIASA), (Fischer et al., 2021). In addition, the proposed framework investigates the use of CNN as an alternative to the GWR model adopted by DG Reform (2024), with the objective of evaluating whether deep learning techniques can provide more accurate rural property valuation estimates.

2.3 Global Agro-Ecological Zones (GAEZ)

GAEZ is a recognized framework for assessing agricultural productive potential at the global scale. It integrates climatic, soil, topographic, and agronomic information to estimate potential crop productivity under different land use and management scenarios.

Unlike approaches based solely on current LULC, GAEZ provides estimates of key indicators, such as potential yield, attainable yield, agro-ecological suitability, water constraints, climatic constraints, and biomass production potential. Consequently, each land parcel can be characterized not only by its current production but also by its potential productivity under suitable environmental conditions and appropriate management practices.

The present study proposes the use of the GeoCLEWs workflow (OSeMOSYS, 2024), to automate the processing of GAEZ data, enabling the generation of continuous spatial surfaces representing agricultural productive potential across the Portuguese territory.

2.4 Convolution Neural Network

Recent studies have demonstrated the potential of CNN in real estate valuation, particularly in urban contexts. Research conducted by Jain and Srihari (2023), showed that CNN-based models, when integrating both visual and non-visual attributes, such as architectural quality, design, and neighbourhood characteristics, outperform traditional machine learning (ML) methods, including linear regression, gradient boosting, and random forest. These models are more effective in capturing the complex relationships between visual attractiveness and property value (Jain and Srihari, 2023). Furthermore, studies such as Poursaeed et al., 2018, and Jafary et al., 2024 have highlighted the relevance of deep learning (DL), particularly CNN, for extracting meaningful features from visual data, thereby improving the accuracy of valuation models.

However, most of the studies above focus on urban environments, leaving a significant gap in the application of such approaches to rural territories. Thus, while the applicability of CNN to real estate valuation is well established in the urban context (Jain and Srihari, 2023; Poursaeed et al., 2018), their use for rural property valuation remains largely unexplored.

3. Methodology

The proposed methodological framework is structured into four sequential modules (Figure 2). However, the present study implements and validates the first three modules, while the fourth module is presented as the conceptual extension required to support the rural property valuation framework.

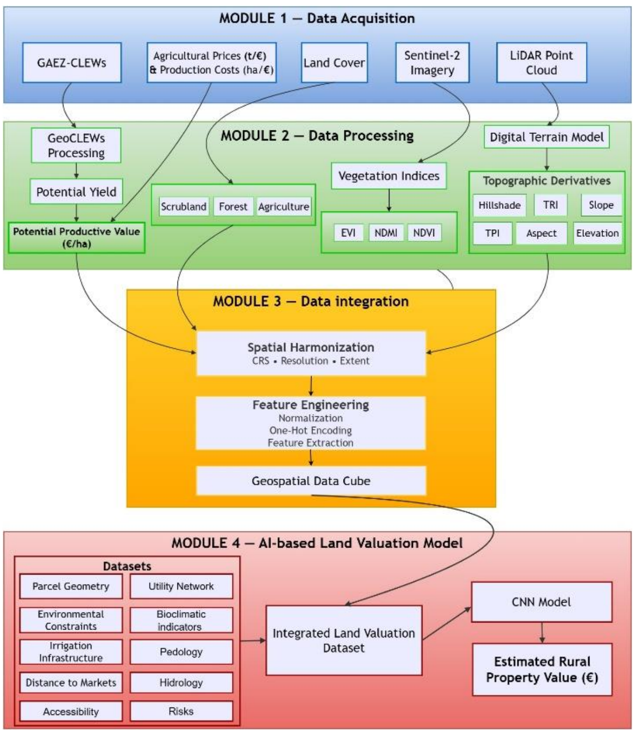

Figure 2: Flowchart representing all proposed modules.

The first module consists of acquiring and organizing the datasets required for the proposed framework. These include airborne LiDAR 3D point clouds data provided by the Portuguese national mapping and cadastral agency (DGT-Direção-Geral do Território), Sentinel-2 multispectral imagery, the Portuguese Land Cover Map (COS), administrative boundaries (CAOP), and the GAEZ database processed through the GeoCLEWs workflow (OSeMOSYS, 2024). Agricultural commodity prices and production cost information were synthetically generated for the purposes of this study.

Each dataset provides complementary information describing the physical, environmental, and economic characteristics of rural landscapes. LiDAR supplies high-resolution topographic information, Sentinel-2 imagery characterizes vegetation dynamics, COS represents current LULC, while the GeoCLEWs framework estimates the agricultural potential of representative crop types under the environmental conditions of the study area. The CAOP provides the boundaries of the municipality of Condeixa-a-Nova (DGT, 2025b).

The second module consists of generating the geospatial variables required for the integrated dataset. LiDAR 3D point clouds are processed to generate a Digital Terrain Model (DTM), from which several topographic derivatives are computed, including elevation, slope, aspect, Terrain Ruggedness Index (TRI), Topographic Position Index (TPI) and hillshade.

Sentinel-2 imagery is processed to derive vegetation indices, namely: Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI), and Enhanced Vegetation Index (EVI), which provide information regarding vegetation vigor, moisture conditions and photosynthetic activity. The COS database is converted into raster format and transformed using one-hot encoding, allowing land cover classes (e.g., agriculture, forest, pasture, and scrubland) to be incorporated as categorical explanatory variables. In parallel, the GeoCLEWs framework is executed using GAEZ data to estimate the potential yield of representative crops for the study area. These potential yields were subsequently converted into Potential Productive Values (PPV, €/ha) by combining crop yield potential with synthetic agricultural commodity prices (AP, €/t) and production costs (PC, €/ha), according to Eq. 1. Since detailed crop-specific production cost data were unavailable, production costs were synthetically estimated as a proportion of the corresponding crop revenue, representing low-input rain-fed production systems. This approach ensured economically consistent PPV estimates while preserving the relative economic differences among crop types.

$$PPV = (Yield * AP) - PC. \qquad (1)$$

where PPV = potential productive values (€/ha)
Yield = crop yield potential
AP = agricultural commodity prices (€/t)
PC = production costs (€/ha)

Unlike conventional approaches, where the PPV is directly used as the target variable for a predictive model, in the proposed framework the resulting PPV constitutes one of the explanatory variables describing the productive capacity of the territory. Consequently, the PPV complements the environmental information derived from remote sensing and terrain analysis, representing the potential economic productivity associated with each GeoCLEWs cluster.

The third module consists of integrating all geospatial variables into a unified analysis-ready dataset. Initially, all raster layers are harmonized to a common coordinate reference system, spatial extent, grid alignment, and spatial resolution (10m). Continuous variables are normalized using Min-Max scaling, while categorical land cover information is represented through one-hot encoding.

After preprocessing, all variables are combined into a multi-band geospatial data cube. This integrated dataset includes the PPV derived from GeoCLEWs together with vegetation indices extracted from Sentinel-2, topographic variables derived from LiDAR data, and land cover information obtained from LULC dataset. The resulting geospatial data cube represents a spatially consistent repository of environmental and economic variables that characterizes the agricultural and territorial conditions of the study area.

The integrated dataset constitutes the primary output of the proposed framework and provides a standardized set of explanatory variables for subsequent AI applications. Although no predictive model is implemented in the present study, the resulting data cube was specifically designed to support future ML and DL models aimed at rural property valuation.

The fourth module corresponds to the conceptual rural property valuation model based on the framework proposed by DG Reform (2024), replacing the Geographically Weighted Regression approach with a CNN. In this future stage, the integrated geospatial dataset generated in Module 3 will be combined with additional territorial variables influencing rural property value, including parcel geometry, irrigation infrastructure, accessibility, utility networks, environmental constraints, hydrology, pedology, bioclimatic indicators, risk factors, and proximity to markets.

Those variables above will serve as explanatory factors in an AI model designed to estimate rural property values for fiscal purposes. In this context, the PPV will act as one explanatory variable among several biophysical, environmental, and socioeconomic predictors, allowing agricultural productivity to be integrated into a comprehensive land valuation framework.

This modular architecture separates agro-ecological productivity assessment from economic land valuation, improving methodological transparency, data interoperability, and model interpretability. Furthermore, the integrated geospatial dataset generated in the first three modules could potentially be adapted for use in land management, agricultural planning, and other spatial decision-support applications beyond rural property valuation.

Although the proposed framework comprises four modules, the present study focuses on the implementation and validation of the first three modules, namely data acquisition, geospatial processing, and the construction of the integrated geospatial dataset. The fourth module, corresponding to the AI-based rural property valuation model, is presented as a conceptual extension of the framework and constitutes future work, as its implementation requires additional cadastral, socioeconomic, and market-related datasets that are beyond the scope of the present paper.

All geospatial analyses were performed using QGIS (Version 3.44.8-Solothurn; QGIS Development Team, 2026) running on a Windows 11 operating system, with support from the GDAL library (Version 3.12.2) and the PROJ library (Version 9.8.0). In addition, several processing tasks were automated using Python scripts executed within the Windows Subsystem for Linux (WSL2) running Ubuntu 24.04 LTS, and geospatial libraries, including Rasterio, GeoPandas, SciPy, and NumPy, to support raster processing, vector data manipulation, and numerical computations throughout the workflow.

4. Results and discussion

This section presents the results obtained from the geospatial data processing workflow. The analysis begins with the potential crop maps generated through the GeoCLEWs framework, followed by the reclassification of the LULC dataset. Subsequently, the vegetation indices derived from Sentinel-2 imagery are presented, and finally, the topographic variables generated from the airborne LiDAR data through DTM processing are described.

We first present the results obtained from the GeoCLEWs workflow, which identified five potential crops for the study area. Among the available production scenarios, the rain-fed, low-input condition was selected, representing the absence of irrigation and low precipitation. This scenario was adopted to evaluate the most conservative agricultural production conditions.

Under the selected scenario, wheat and barley exhibited moderate yield potential, whereas grain maize showed the highest productive potential. The estimated crop yields were subsequently converted into PPV by combining synthetic agricultural commodity prices and production costs. Under these assumptions, maize remained the crop with the highest economic potential, while oats presented the lowest PPV. Although synthetic economic parameters were adopted, the proposed methodology preserved the relative economic differences among crop types, providing a consistent representation of agricultural productive potential for the integrated geospatial dataset.

The second process involved identifying and extracting the following classes from the LULC dataset: agriculture, scrubland, pasture, and forest. The result was converted to a raster format, then categorized and integrated into a geospatial dataset using one-hot encoding. Figure 3 highlights a considerable area classified as scrubland (2034.12ha), indicating its potential for future conversion to agricultural or forest land. Forest is the dominant land cover class in the study area, occupying 6289.04 ha, followed by agriculture with 3880.03ha.

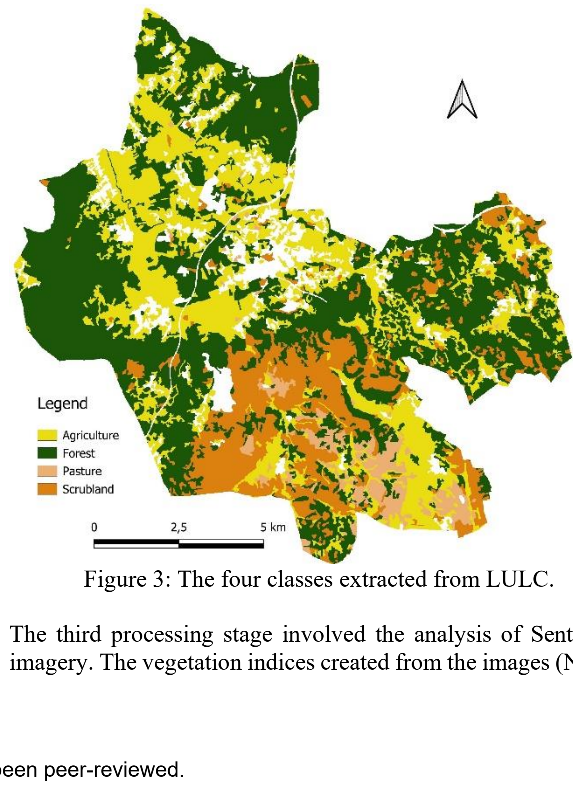

Figure 3: The four classes extracted from LULC.

The third processing stage involved the analysis of Sentinel-2 imagery. The vegetation indices created from the images (NDVI, NDMI, and EVI) were normalized to the range [0,1] using Min-Max scaling before being incorporated into the integrated geospatial dataset.

The fourth processing stage consisted of deriving terrain variables from airborne LiDAR 3D point clouds. The LiDAR point clouds data were acquired using open-access Python scripts provided by DGT (DGT, 2024). These data were subsequently processed to generate a DTM (Figure 4) with a 0.5m spatial resolution, then resampled to a 10m, from which six topographic variables were extracted: elevation, slope, aspect, hillshade, TRI, and TPI. These variables characterize the terrain morphology and are expected to contribute significantly to the representation of local environmental conditions.

To ensure numerical consistency among all explanatory variables, different normalization procedures were applied according to the characteristics of each dataset (Table 1). Elevation, TRI, and TPI were normalized using Min-Max scaling. Hillshade and slope were normalized by dividing each pixel value by its corresponding maximum value. Aspect was transformed into two continuous variables, northness and eastness, through sine and cosine transformations, thereby eliminating the discontinuity associated to circular angular measurements and providing a more suitable representation for subsequent spatial analyses.

Variable	Unit	Normalization
Elevation	m	Min-Max
TRI	—	Min-Max
TPI	—	Min-Max
NDVI	—	Min-Max
NDMI	—	Min-Max
EVI	—	Min-Max
Hillshade	0–255	Value / Maximum
Slope	degrees	Value / Maximum
Northness	[-1,1]	sin(Aspect)
Eastness	[-1,1]	cos(Aspect)

Table 1: Methods applied for normalizing the variables.

Finally, the integrated geospatial dataset was generated, comprising seven topographic bands, one LULC layer, three environmental variables derived from Sentinel-2 (NDVI, NDMI, and EVI), and five crop-specific PPV bands. All layers were normalized to values ranging from 0 to 1 to standardize the input variables for future CNN models. This normalization was applied only to ensure that variables with different units and value ranges could be integrated into the same dataset, without changing the relative information represented by each layer. The final integrated dataset has a spatial resolution of 10m and is referenced in the PT-TM06/ETRS89 coordinate reference system (EPSG:3763).

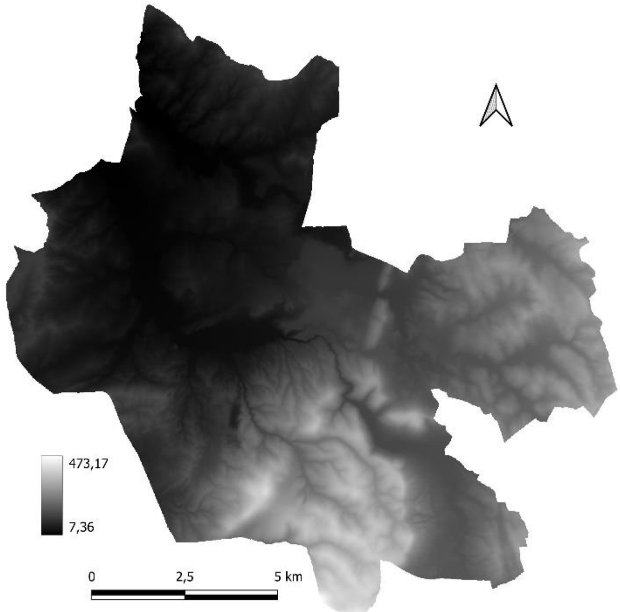

Figure 4: The Digital Terrain Model of study area.

Figure 5 presents an RGB visualization of the integrated geospatial dataset. The displayed colours do not represent individual variables but rather the combined spectral response of the stacked layers. In this representation, we selected the following bands: NDVI, northness, and slope.

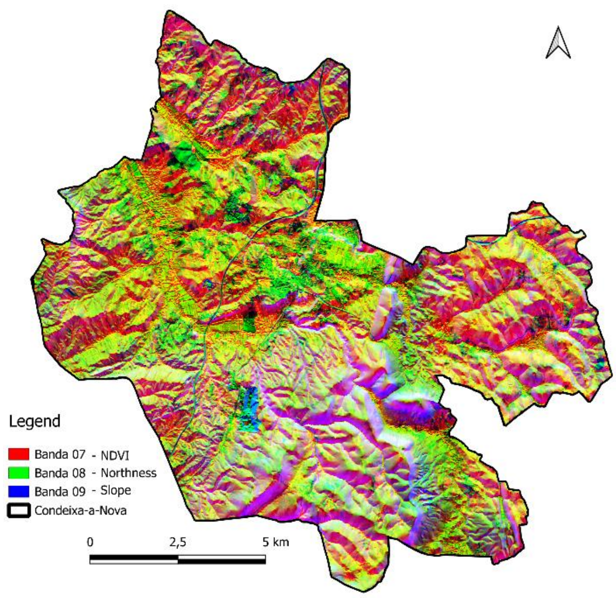

Figure 5: RGB visualization of the integrated geospatial dataset (R = NDVI, G = Northness, B = Slope).

5. Conclusion and future work

The study described in this paper proposes a modular geospatial framework for integrating environmental, topographic, land cover, and agro-ecological datasets into an analysis-ready geospatial dataset representing the productive potential of rural land. The proposed methodology establishes a standardized workflow for preparing spatial data to support future AI applications in rural property valuation.

The resulting integrated dataset represents an important intermediate product that bridges agro-ecological assessment and land administration. In particular, the incorporation of PPV provides an economic representation of agricultural productive capacity while preserving the spatial variability captured by Earth Observation and topographic data.

Future research will focus on implementing and validating the proposed CNN-based rural property valuation model. While this component was originally envisioned as part of the proposed framework, its implementation is beyond the scope of this paper and was therefore left for future work.

Thereby, the integrated geospatial dataset developed in this study was used as the primary source of explanatory variables. Additional cadastral, socioeconomic, infrastructure, accessibility, and market-related datasets will be incorporated to estimate rural property values through advanced ML and DL techniques. Furthermore, alternative DL architectures, including PointNet (Qi et al., 2017), will be investigated to directly process LiDAR 3D point clouds, enabling a comparative assessment between raster-based and point cloud-based approaches for rural property valuation.

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