

Article

Assessing the Landscape's Ability to Support the Agroecological Transition of Bio-Distretto Delle Lame

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Abstract

Biodiversity and landscape heterogeneity are key components of agroecosystem functioning because they support ecosystem services and strengthen the capacity of agricultural systems to undertake sustainable agroecological transitions. This study assesses the landscape structure of the municipality of Ruvo di Puglia, within the Bio-Distretto delle Lame, to evaluate its potential to support such a transition. Bio-districts are territories in which farmers, local authorities, citizens, and other stakeholders collaborate to manage natural and agricultural resources sustainably, often with a strong connection to organic farming. The research combines freely available Sentinel-2 imagery with UAV-based ground truthing to update land-use/land-cover information and to derive landscape indicators. A systematic sampling scheme was designed in QGIS, and UAV flights over 14 areas were used to generate training and validation vectors. Two classification strategies were tested on 2024 Sentinel-2 data: a supervised pixel-based approach and an unsupervised multi-temporal object-based approach (GEOBIA). The best-performing map was obtained from the supervised classification of July NDVI data, with an overall accuracy of 91.76%. In respect to the 2018 official land-cover dataset indicates a decrease in agricultural land (−490.91 ha), a reduction in arable crops (−1216.43 ha), and an increase in permanent crops (+725.52 ha), suggesting a shift toward specialization. At the same time, natural and semi-natural areas increased, improving the landscape potential for ecological functions. However, the high fragmentation detected by the landscape metrics (average patch size approximately 0.25 ha) may limit habitat continuity and species stability. The results should therefore be interpreted as an assessment of landscape structure and potential biodiversity support, rather than as a direct measurement of biological diversity. Strengthening ecotones, hedgerows and semi-natural linear elements with native species would further improve landscape resilience and support agroecological planning.

Keywords: agroecology; bio-district; landscape diversity; landscape ecology; landscape metrics; remote sensing; Sentinel-2; UAV; land-use; land-cover; classification

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1. Introduction

1.1. Background

Agricultural landscapes currently face the dual challenge of sustaining food production while preserving the ecological foundations on which farming depends. Landscape simplification, biodiversity loss, soil degradation and climate pressures increasingly threaten the long-term resilience of agroecosystems, particularly in Mediterranean areas where climatic variability and land-use intensification interact strongly.

Bio-districts bring together farmers, local authorities, citizens, tourism operators and other local actors to manage natural and agricultural resources in a coordinated and sustainable manner, ensuring the ability to produce food and energy for current and future generations [1]. By fostering short supply chains, supporting organic farming, and maintaining traditional land uses, bio-districts can contribute to the preservation of heterogeneous landscapes composed of mixed crops, terraced fields, hedgerows, woodlots, and semi-natural habitats, such as pastures, rock faces, piles of boulders, caves and chasms, or small headlands that are home to living species useful both for agriculture and for the good state of the environment. Semi-natural habitats (SNHs) are habitats modified and maintained by human activities that still hold naturally occurring species, playing a vital role in delivering key ecosystem services such as crop pollination and biological pest control [2]. These ecosystem functions are further reinforced by organic agriculture, which provides a regulatory and practical framework that prioritizes environmental health by limiting synthetic inputs. Agroecology broadens this perspective by framing agriculture as a socio-ecological system embedded within wider landscapes. From this viewpoint, biodiversity conservation and landscape stewardship must extend beyond individual farms, because ecological processes operate across fields, habitats, and regions and support essential ecosystem services such as soil fertility, pollination, water regulation, and natural pest and disease control [3].

As a result, bio-districts offer a practical context in which biodiversity conservation and landscape management become shared community priorities rather than isolated farm-level decisions. Understanding how biodiversity is shaped and maintained at different spatial scales from plots to farms to entire landscapes is therefore essential for guiding ecological transition processes [4]. The design of a landscape supportive of the agroecological transition is a process entailing the shaping and intentional planning of the landscape according to well-defined goals or outcomes [5].

The structural features of landscapes are fundamental for biodiversity as they provide habitat for species communities, and diversified ecological niches and connected landscapes facilitate species movement and enhance the provision of key ecosystem services. The analysis of landscape biodiversity, measured through indicators such as patch diversity, habitat connectivity, and land-cover composition, is an approach that has repeatedly proven useful and supportive of biodiversity management and conservation strategies that allow the achievement of richer species communities and more stable ecological functions and that is rediscovered as very current. New monitoring tools, including satellite imagery and drone-based surveys, offer unprecedented opportunities to quantify these patterns and assess how agricultural practices and anthropic activities interact with landscape-level biodiversity.

1.2. Problem Statement

Mediterranean agricultural landscapes face growing pressures related to land degradation, the simplification of the agricultural mosaic, and biodiversity loss, conditions that threaten ecological resilience and production stability in a context of increasing climate variability. In response to these challenges, integrated land management approaches, such

as bio-districts, are emerging as key tools for connecting sustainable agricultural practices, landscape planning, and participatory governance. Within the framework of organic farming and inspired by the principles of agroecology, bio-districts promote crop diversification, habitat protection, and coordinated management of natural resources to strengthen ecosystem services related to soil fertility, water regulation, and biodiversity conservation [6]. There are currently about 51 bio-districts in Italy, ranging from completely established to those that are still being formed [7], and each one shows different levels of operational activity.

At present, the Bio-Distretto delle Lame (Figure 1) relies on land-use information that is not sufficiently updated or detailed for operational agroecological planning. The available official cartography provides an important reference baseline, but its spatial resolution and date of production limit its ability to describe current fine-scale landscape patterns, especially small patches, ecotones, and linear semi-natural elements.

This study focuses on the municipality of Ruvo di Puglia within the Bio-Distretto delle Lame, where updated spatial data are needed to support agroecological planning. By developing an updated land-use/land-cover map and calculating landscape ecology indicators, the research proposes a method for assessing the landscape structure that can support biodiversity-related ecosystem services at territorial scale. While acknowledging that landscape metrics are proxies of habitat structure and potential ecological functionality rather than direct measurements of species diversity, the results are intended to inform local planning, community strategies, and future monitoring activities.

1.3. Research Aim

The aim of the research was to assess the landscape endowment and structural conditions of the municipality of Ruvo di Puglia, within the Bio-Distretto delle Lame, in order to evaluate its potential ability to support the agroecological transition. To achieve this aim, remote sensing technologies were used to produce updated land-use/land-cover information, and a set of landscape ecology indicators was calculated to describe composition, fragmentation, and connectivity. The specific objectives were as follows: (i) to evaluate land-cover changes in the municipality of Ruvo di Puglia by updating current data in respect to historical maps and official sources; and (ii) to assess landscape and cropping-system diversity through quantitative indicators relevant to agroecosystem functioning.

2. Materials and Methods

2.1. Study Area

The study was carried out in the municipality of Ruvo di Puglia, which is part of the Metropolitan City of Bari (Apulia, southern Italy) and covers an area of approximately 222.04 km². The municipality borders Bitonto to the east, Corato to the west, Terlizzi to the north-east and Bisceglie to the north (Figure 1). The area is characterized by the karst morphology typical of Apulia, including sinkholes, karst valleys, caves and endorheic depressions (Figures 2 and 3). Agricultural land use, especially olive groves, vineyards, and other permanent crops, is a defining feature of the local economy and landscape (Figures 4–7). A portion of the municipal territory overlaps with the Alta Murgia National Park, a protected area of high biodiversity value (Figure 1) [8].



Figure 1. Map of Bio-Distretto delle Lamae with Ruvo di Puglia and other bordering municipalities (source: generated by authors based on official cartographic data from SIT Puglia—Sistema Informativo Territoriale. <https://pugliacon.regione.puglia.it/>, accessed on 25 June 2025).



Figure 2. Ruvo di Puglia: an example of “lama”, ephemeral water stream with herbaceous crops (source: author Mariano Fracchiolla).



Figure 3. Ruvo di Puglia: endorheic depression and forest (source: author Mariano Fracchiolla).

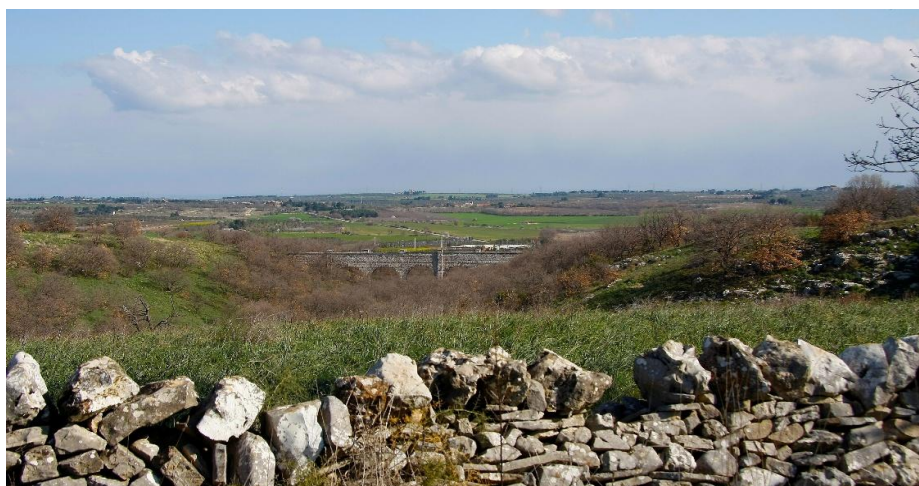


Figure 4. Ruvo di Puglia: artifacts and human constructions in the landscape mosaic (source: author Mariano Fracchiolla).



Figure 5. Ruvo di Puglia: semi-natural habitats and cropland (source: author Mariano Fracchiolla).



Figure 6. Associated crops (olive trees, durum wheat) and diverse soil management practices (source: author Mariano Fracchiolla).



Figure 7. Diverse patterns of permanent crops with olive groves, vineyards, and other permanent crops (source: author Mariano Fracchiolla).

2.2. Data Collection

The methodological framework is built on integrated remote sensing techniques, which make use of electromagnetic radiation to obtain information about the Earth's surface without direct contact, achieving the spatial and spectral data needed for biodiversity evaluation, land use classification, and environmental monitoring. UAV imagery and Multispectral Sentinel-2 satellite data were used as complementary data sources.

2.3. Data Acquisition Procedures

A DJI Mavic 3 Enterprise with a 12 MP RGB camera was used for UAV surveys, enabling extremely high-resolution observations of local land cover features. The Copernicus Program's Sentinel-2 constellation provided systematic, free, and multi-temporal coverage of satellite data [9].

To plan for the drone flights in the municipality, a systematic sampling approach was used (in QGIS 3.34.8-Prizren) to identify the sampling sites, with the identification of sam-

ple areas at regular space intervals. In order to regularly cover the territory and best capture its specific characteristics in detail, a regular mesh matrix of 50×50 m was created. The algorithm “create grid” allowed the generation of a polygonal vector (a grid) covering the extension of the municipality of Ruvo. Once the grid was created, the “regular points” tool was used to create a regular point pattern within the grid, thus providing for each potential sampling point a total area of 2500 m². A new point layer with points arranged in a regular grid with a distance between points of 2500 m from each other was generated, and the point grid was cut according to the boundaries of the Region of Interest (ROI), thus obtaining an adequate number of sample points to determine the characterization of the environmental matrix of the municipality of Ruvo. For each sampling point, a flight plan was created. Further information can be found in the Supplementary Materials, Annex S1: Sampling areas.

The Region of Interest (ROI) covered by the analysis included the entire Municipality of Ruvo di Puglia, but the portion of the Alta Murgia National Park overlapping the municipality was excluded from UAV operations in order to avoid disturbing the inhabiting protected species.

Take-off and landing locations, flight routes with a minimum overlap of 60% frontal and 80% lateral, and the recording of GPS coordinates using Ground Control Points for greater positional accuracy, were all part of UAV mission planning.

Sentinel-2 Level-2A images were downloaded from the Copernicus Open Access Hub, selecting cloud-free scenes.

2.4. Data Processing and Classification

UAV imagery was processed through Agisoft Metashape Professional (Version 2.1.0 build 17526) using a typical photogrammetric methodology that includes picture alignment, dense point cloud generation, and the creation of Digital Terrain Models (DTMs) and Digital Elevation Models (DEMs). These steps were used to build orthorectified mosaics that, after being exported as georeferenced TIFF files, were then imported into QGIS. Based on UAV orthomosaics, representative land-cover samples were manually digitized to produce training datasets for satellite image classification. Two independent datasets were prepared: a primary training vector used to calibrate the classifier (training vector) and an independent validation vector used for accuracy assessment (validation vector) [9].

Training data consisted of 1185 manually digitized polygons extracted from orthomosaics generated from 14 UAV surveys. An independent validation dataset (validation vector) comprising 357 additional polygons (approximately 30% of the training sample size) was created using different polygons digitized from the same UAV orthomosaics and was reserved exclusively for accuracy assessment. Sampling locations were selected using a systematic sampling scheme implemented in QGIS based on a regular grid with points spaced 2500 m apart across the municipality, excluding the protected area of Alta Murgia National Park. The UAV surveys provided the field reference (ground-truth) information used to generate both the training and validation datasets. Additional ground-truth validation was provided by involved local actors and by one of the authors.

2.4.1. Pre-Processing of Satellite Images

The Sentinel-2 satellite images time series for 2024 were prepared following two different approaches, A and B, aiming to explore possibilities for maximizing the potential and limitations offered by data, i.e., the available spatial resolution, the wealth of spectral information, and the advantage of observing the same piece of land and the corresponding land cover categories at different moments of the year.

Approach A consisted of supervised classification of monthly Sentinel-2 multispectral images and monthly NDVI layers. Random Forest and Support Vector Machine classifiers were tested using UAV-derived training data (training vector). The Random Forest model was configured with 500 trees and cross-validation enabled; the official regional Digital Terrain Model was included as an additional input variable to account for topographic effects. Classification performance was evaluated through confusion matrices and standard accuracy metrics.

Approach B consisted of an unsupervised multi-temporal Geographic Object-Based Image Analysis (GEOBIA) workflow designed to explore whether land-cover patterns could be derived with reduced dependence on a priori labeled training data [10]. Twenty-four Sentinel-2 images from 2024 (tile 33TXF), corresponding to two cloud-free scenes per month, were used to produce monthly multispectral and NDVI composites.

Image segmentation was performed using the GRASS GIS *i.segment* module within a semi-automated processing chain developed at the CIHEAM [11] Bari, Geometrics Laboratory. Objects were described using spectral, geometric, textural and contextual features. K-means and ISODATA clustering were then applied to the multi-temporal NDVI series, and Dynamic Time Warping was used to aggregate phenologically similar groups.

2.4.2. Obtaining Land Cover Classes

Both the multispectral and NDVI time series products generated through Approaches A and B were subsequently processed to derive harmonized macro land-cover classes and refine vegetation typologies. The final classification was performed using the Random Forest (RF) algorithm implemented in the Orfeo Tool Box (OTB) within the QGIS environment. The RF model was configured with 500 trees and a minimum split size of 3, while the cross-validation option was enabled to assess model robustness. The official regional Digital Terrain Model was also included as an ancillary input variable to account for topographic effects on spectral response. The outputs obtained from the supervised pixel-based workflow and the unsupervised/object-based workflow were then harmonized into a common set of macro land-cover classes and evaluated using the same accuracy assessment procedure. This step was essential to compare the two methodological approaches under a consistent validation framework and to identify the most reliable cartographic product for the subsequent calculation of landscape metrics. The resulting datasets were therefore subjected to the final accuracy analysis.

2.4.3. Accuracy Assessment

In order to assess classification reliability and to compare supervised pixel-based and unsupervised object-based approaches, independent validation datasets (validation vector) from UAV orthomosaics were used to assess accuracy.

Confusion matrices were used to compute overall accuracy, Kappa coefficient, producer's accuracy and user's accuracy, allowing the reliability of each cartographic output to be compared.

2.5. Biodiversity Analysis

Based on the best-performing map identified through the accuracy assessment, landscape diversity was evaluated through a set of quantitative indicators describing spatial heterogeneity, fragmentation and connectivity. These indicators were used as proxies for the landscape potential to support biodiversity-related ecological functions.

According to existing principles of landscape ecology, the landscape is understood as a mosaic of spatially different patches (ecotopes or habitats) and transition zones (ecotones) [12]. Input for the GIS-based methods used in the analysis was provided by the elaboration of both Sentinel-2 satellite imagery and UAV-derived orthomosaics. Sentinel-

2 repeatedly underwent supervised classification; the findings were verified by focused field surveys.

Ruvo di Puglia's whole municipal area was the reference analytical unit (ecoregion). Using QGIS 3.34.8 (Prizren), a structured workflow comprising GIS-based interpretation, integration of official cartographic data, field verification, data validation, map modification, database construction, and indicator computation was used to characterize the landscape. Urban areas, water bodies and channels, wetlands, herbaceous and permanent crops, and ecological infrastructures such as hedgerows, spontaneous vegetation patches, tree lines, forests, and woodlands were among the identified land cover categories. In order to facilitate landscape-level analysis, these classes were then combined into macrocategories (Table 1).

Table 1. Macrocategories of land use and cover classes.

Macrocategories	Cover Classes
MA	artifacts (urban fabric and other man-made categories)
EN	natural herbaceous vegetation
AN	natural arboreous vegetation
ASN	natural herbaceous and arboreous
W	wetlands
CP	permanents crops
CE	herbaceous crops
CA	associated crops

Fourteen landscape indicators were selected from the scientific literature according to their relevance for ecological and agroecological functions (Table 2). The indicators were selected to capture the three key dimensions of diversity of the agroecosystem: composition, fragmentation, and connectivity. The Relative Richness Number (RR) measures the diversity of ecotone types present and reflects landscape heterogeneity and potential habitat diversity. Relative Richness Area (RA) quantifies the importance of each land-cover class. Land Use Sustainability (LUS) evaluates the ratio and the balance between natural/semi-natural areas and managed agricultural land, providing a proxy for ecological stability and resilience. Patch Average Area (PAA) is about patch size (both in general and for each land cover class) that strongly influences habitat quality, species persistence, and ecological stability. Patch Density (PD) is a measure of landscape fragmentation and, when calculated for individual classes, reveals whether specific crops or habitats are concentrated or widely distributed across the territory. Sustainability of the Ecotone System (SES) was included because ecotones, as transition zones, increase ecological interactions, habitat availability, and ecosystem services. Agricultural Ecotone Composition (CEtopeC) reports the balance among different agricultural ecotopes and the structural diversity of cropping systems. Connectivity indicators (Road Density, Water Body Density, ecotone length, and ecotone intensity) express potential ecological flows, species movement, and landscape resilience. All selected indicators aim to translate the concept that biodiversity at the landscape level depends not only on the number of land-cover types, but also on their size, spatial arrangement, degree of fragmentation, and ecological connectivity, all of which influence the provision of ecosystem services and then agroecosystem sustainability. Together, these metrics describe the spatial arrangement of land-cover classes, the degree of fragmentation of the landscape mosaic, and the potential continuity of ecological interfaces.

Table 2. List and classification of the chosen indicators of landscape diversity.

Indicators of composition	1	Relative Richness Number (RR) [13]
	2	Relative Richness Area (RA) [13]
	3	Land Use Sustainability (LUS)
Indicators of fragmentations	4	Patch Average Area (PAA) [14]
	5	Patch Average Area (for individual classes) [14]
	6	Patch Density (PD) [15]
	7	Patch Density (for individual classes) [15]
	8	Sustainability of the Ecotone System (SES)
	9	Agricultural Ecotope Composition (CEtotopeC)
	10	Road Density (RD)
Indicators of connection	11	Crop Ecotope Composition (CEtotopeC)
	12	Water Body Density (WBD) [16]
	13	Ecotone Length (EL)
	14	Ecotone Intensity (EI)

Further information can be found in Supplementary Materials Annex S2: Biodiversity indicators.

2.6. Validation Phase

To guarantee the reliability of intermediate and final results, validation was incorporated throughout the research workflow. The generated land-use/land-cover maps were checked against official reference datasets, including the Corine Land Cover 2018 inventory [15] provided through regional and national geographic information systems, and against UAV and field-derived evidence. Because CLC 2018 has a coarser spatial resolution and a larger minimum mapping unit than the Sentinel-2/UAV-based products, comparisons between 2018 and 2024 were interpreted cautiously as observed differences may reflect both real land-cover change and differences in mapping scale and thematic detail.

A participatory review with Bio-Distretto delle Lame stakeholders, including local authorities, farmers' associations and research institutes, was also planned to verify the practical usefulness of the generated maps and to support their integration into future agricultural and territorial decision-making.

3. Results

3.1. Results from Classification of Satellite Images

For all outputs of the classification processes, an accuracy assessment was performed using the validation vector. The seven best-performing maps are reported in Table 3 with details of single-class accuracy. This table shows that the highest classification accuracy was achieved using the supervised classification method applied to imagery from the month of July (map A2) (Table 4).

Table 3. Accuracy assessment results of raster classification maps.

Map ID	Overall Accuracy (%)	Kappa	Lowest PA Class	PA (%)	Lowest UA Class	UA (%)
A1	90.20	0.78	natural vegetation	3	arable land	21
A2	91.76	0.81	artificial surfaces	1	natural vegetation	3
A3	88.21	0.71	artificial surfaces	1	arable land	21
B1	63.17	0.26	natural vegetation	3	arable land	21
B2	60.43	0.25	arable land	21	arable land	21
B3	60.60	0.21	artificial surfaces	1	arable land	21
B4	56.83	0.17	arable land	21	arable land	21

PA = producer's accuracy; UA = user's accuracy.

The classification process produced seven cartographic outputs derived from two methodological approaches: Approach A, based on supervised pixel-based classification, and Approach B, based on unsupervised multi-temporal object-based analysis followed by supervised labeling. The main characteristics of each cartographic output are reported in Table 3, and the corresponding maps are shown in Figures 8–15.

Table 4. Characteristics of Approach A (S-pb) and Approach B (Us/Mt-ob).

Approach	Map ID	Method	Features	Spatial Resolution
A	A1	Supervised SCP	Sentinel-2 (May)	10 × 10 m
A	A2	Supervised OTB	NDVI (July)	10 × 10 m
A	A3	Supervised OTB	NDVI (November)	10 × 10 m
B	B1	Unsupervised GEOBIA + Supervised OTB	60 clusters	10 × 10 m
B	B2	Unsupervised GEOBIA + Supervised OTB	20 clusters	10 × 10 m
B	B3	Unsupervised GEOBIA + Supervised OTB	14 clusters	10 × 10 m
B	B4	Unsupervised GEOBIA + Supervised OTB	10 clusters	10 × 10 m

Note: SCP = Semi-Automatic Classification Plugin; OTB = Orfeo ToolBox; GEOBIA = Geographic Object-Based Image Analysis.

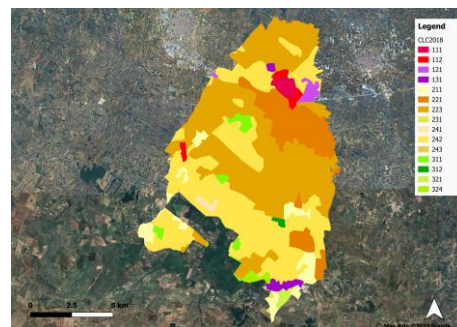


Figure 8. CLC 2018 map of the study area (source: generated by authors based on ISPRA, SINAnet Portal, CLC2018 shapefile).

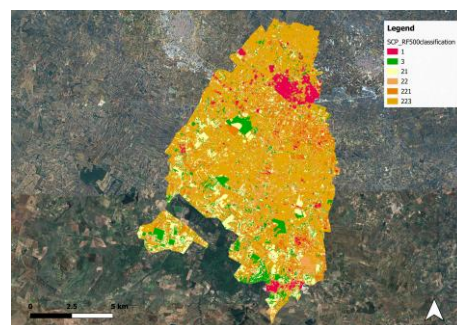


Figure 9. A1 map (source: generated by authors based on Copernicus Sentinel-2 imagery, May 2024).

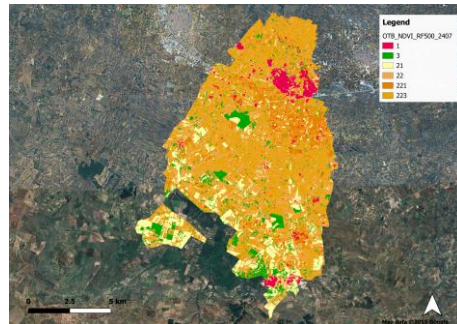


Figure 10. A2 map (source: generated by authors based on Copernicus Sentinel-2 imagery, July 2024).

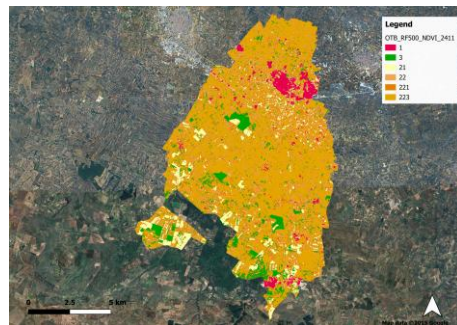


Figure 11. A3 map (source: generated by authors based on Copernicus Sentinel-2 imagery, November 2024).

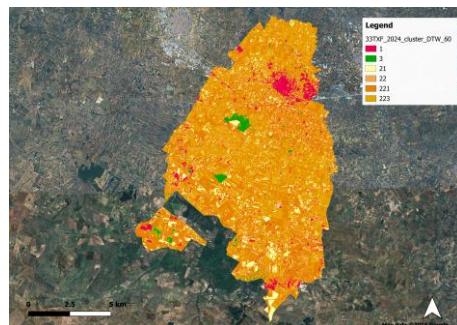


Figure 12. B1 map (source: generated by authors based on Copernicus multi-temporal Sentinel-2 imagery, 2024).

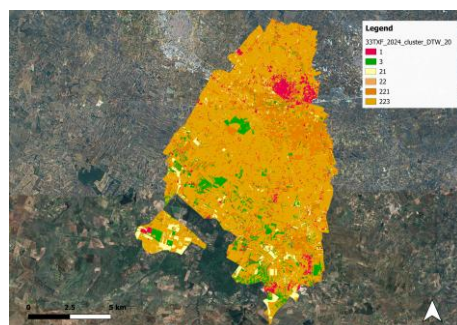


Figure 13. B2 map (source: generated by authors based on Copernicus multi-temporal Sentinel-2 imagery, 2024).

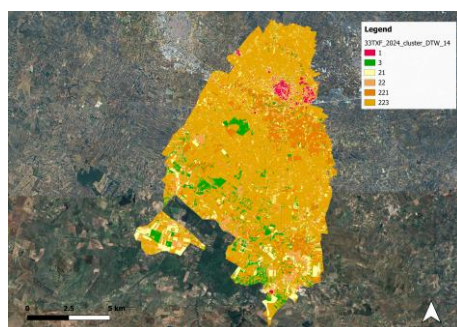


Figure 14. B3 map (source: generated by authors based on Copernicus multi-temporal Sentinel-2 imagery 2024).

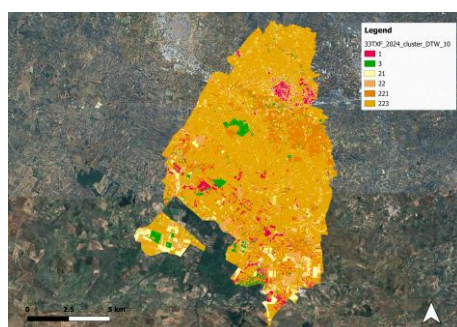


Figure 15. B4 map (source: generated by authors based on Copernicus multi-temporal Sentinel-2 imagery 2024).

3.2. Calculation of the Indicators of Diversity at Landscape Level

The landscape-level analysis was carried out using the best-performing classified map. Fourteen landscape indicators were calculated, as described in Section 2, and grouped into composition (Table 5), fragmentation (Table 6), and connection metrics (Table 7).

Table 5. Composition indicators.

Region of Interest	RR-MA	RR-EN	RR-AN	RR-CPRR-CE	RR-CA	RA-MA	RA-EN	RA-AN	RA-CP	RA-CE	RA-CA	LUS (%)	CEC
A2	2.76	0.00	10.31	75.53	11.40	0.00	4.03	0.00	7.52	75.50	12.95	0.00	5.83

Note: RR = Relative Richness Number; RA = Relative Richness Area; LUS = Land Use Sustainability; CEC = Crop Ecotone Composition. MA, EN, AN, CP, CE, and CA denote the macrocategories of land use and cover classes in Table 1.

Table 6. Fragmentation indicators.

Region of Interest	PAA	PAA-MA	PAA-EN	PAA-AN	PAA-CP	PAA-CE	PAA-CA	PD	PD-MA	PD-EN	PD-AN	PD-CP	PD-CE	PD-CA	SES	CEC
A2	0.25	0.37	0.00	0.18	0.25	0.28	0.00	399.86	273.52	0.00	548.18	400.02	352.12	0.00	0.09	8.00

Note: PAA = Patch Average Area; PD = patch density; SES = Sustainability of Ecotone System; CEC = Crop Ecotone Composition.

Table 7. Connection indicators.

Region of Interest	EL	EL-MA	EL-EN	EL-AN	EL-CP	EL-CE	EL-CA	EI	EI-MA	EI-EN	EI-AN	EI-CP	EI-CE	EI-CA
A2	0.20	0.19	0.00	0.16	0.22	0.18	0.00	489.78	530.08	0.00	641.78	464.56	561.11	0.00

Note: EL = ecotone length; EI = ecotone intensity.

4. Discussion

The rationale for testing two classification approaches was to assess whether a repeatable, cost-effective, and updatable land-use/land-cover monitoring workflow could be developed for a heterogeneous Mediterranean agricultural landscape.

Such monitoring frameworks are increasingly recognized as essential for supporting landscape-scale agroecological planning, where repeated and spatially explicit observations are required to assess landscape heterogeneity, ecological connectivity and agricultural sustainability [17,18].

In this perspective, the comparison between Approach A and Approach B should not be interpreted only as a technical exercise, but as a way to evaluate the trade-off between operational accuracy and reduction in dependence on a priori labeled data. Approach A, based on supervised pixel-based classification supported by UAV-derived training data, represents the multi-operational solution in the present study. Approach B, based on an unsupervised multi-temporal GEOBIA workflow, was instead tested as a more exploratory strategy aimed at reducing the need for training samples while preserving the capacity to capture phenological and spatial patterns from Sentinel-2 imagery.

The results clearly indicate that the supervised approach provided the most reliable cartographic output. The best-performing map (A2) reached an overall accuracy of 91.76% and a Kappa coefficient of 0.81, values that are above the commonly adopted minimum benchmark for land-use/land-cover mapping and support the use of this product for subsequent landscape-metric calculations [19].

This performance is consistent with previous studies and reviews showing that Sentinel-2 data, particularly when combined with machine-learning classifiers such as Random Forest and trained with representative reference samples, routinely achieves overall accuracies above 85–90% in heterogeneous agricultural landscapes [20–22]. Recent reviews further demonstrate that the integration of Sentinel-2 data with machine-learning approaches substantially improves the discrimination of crop types whose spectral signatures vary according to phenological stage and management practices [22]. In this study, the use of UAV-derived training and validation data strengthened the reliability of the supervised workflow, while the inclusion of the Digital Terrain Model helped account for topographic variability within the municipal territory.

Object-based image analysis has been widely recognized for its ability to incorporate spectral, spatial, textural, and contextual information while reducing the salt-and-pepper effect that commonly affects pixel-based classifications [23]. More recent studies have shown that GEOBIA can improve land-cover mapping in agricultural environments when objects correspond to meaningful ecological or management units; however, its performance strongly depends on segmentation quality and landscape structure [21,22,24].

Moreover, clustering of vegetation-index time series (multi-temporal) has been successfully applied in other contexts for mapping broad vegetation dynamics [25], although its performance decreases in highly fragmented agricultural mosaics characterized by strong within-class variability [22].

About the discrepancies in terms of classification performances, Refs. [26,27] emphasize the fact that supervised classifications generally show higher results than unsupervised. GEOBIA unsupervised pipeline, in fact, strongly depends on how the pixels are clustered together, leading to an inevitable loss of accuracy from a pure pixel-level perspective: the geometries are based on the similarity of the area pixel, while the clustering of groups of pixels is determined by zonal statistics.

In the Ruvo di Puglia case study, the k-means configurations tested within the GEOBIA framework did not produce land-cover clusters that could be easily translated into stable and interpretable classes. This result suggests that, in highly fragmented Mediterranean agroecosystems, the benefits of object-based segmentation may be constrained

when object boundaries and spectral groupings do not correspond to agronomically or ecologically meaningful units.

Several factors help explain the weaker performance of Approach B. First, UAV observations and terrain information revealed frequent altitudinal variation, even within individual plots. This variability can generate different NDVI responses among neighboring trees belonging to the same crop and variety, producing spectral noise that complicates both segmentation and clustering. Second, management heterogeneity strongly affects the spectral response of permanent crops.

Similar limitations have been reported in Mediterranean perennial cropping systems, where differences in canopy architecture of olive groves, vineyards and orchards, soil exposure, irrigation and pruning practices generate substantial intra-class spectral variability and reduce the separability of olive groves, vineyards and orchards. [20,21]. In addition, in the area targeted by the present analysis, vineyards covered with plastic sheets for phenological management or hail protection may be spectrally confused with artificial surfaces or other non-agricultural classes. These conditions explain why the supervised approach, guided by labeled reference samples, was more robust than the unsupervised GEOBIA workflow in this specific landscape.

Nevertheless, the lower performance of Approach B should not be interpreted as a rejection of unsupervised or object-based approaches. Rather, it highlights the need for further methodological refinement before these workflows can be used operationally in complex agricultural mosaics.

Future developments could test alternative clustering strategies, such as Gaussian Mixture Models and Affinity Propagation, or hybrid frameworks combining unsupervised segmentation with limited supervised labeling.

Recent reviews suggest that such hybrid strategies may represent one of the most promising directions for operational agricultural monitoring because they reduce field-data requirements while maintaining high classification accuracy [22].

Such approaches may be particularly useful where frequent map updates are required, but the systematic production of large training datasets is costly or impractical. From this point of view, the scientific contribution of the present work is also methodological: it identifies both the potential and the operational limits of reducing dependence on *a priori* labeled samples in a real Mediterranean bio-district context.

The role of UAV data deserves specific attention. In many remote sensing workflows, UAV imagery is mainly used to produce training samples or to support multi-scale comparison and validation between very-high-resolution observations and satellite products. In this study, UAV data also served as an independent source for validation and post-classification quality control. This distinction is important because it supports a more scalable monitoring strategy: satellite imagery provides repeated, low-cost and spatially continuous observations, while UAV surveys can be scheduled selectively to verify uncertain classes, validate outputs and improve the interpretation of fine-scale elements such as field margins, ecotones, small semi-natural patches and crop discontinuities.

This integrated use of Sentinel-2 and UAV observations is consistent with the rapidly growing literature on satellite-UAV data fusion, which recognizes UAV imagery as an effective bridge between field observations and satellite products by providing high-resolution reference information for classifier training, validation and interpretation of landscape elements that cannot be adequately captured by medium-resolution satellite imagery [21,22].

The analysis of data from the 2024 classification and the 2018 official cartography suggests a structural transformation of the agricultural landscape of the Ruvo di Puglia.

Similar trends toward increasing perennial crop specialization and progressive simplification of Mediterranean agricultural landscapes have recently been documented in

several European regions, where agricultural intensification has altered the composition and spatial configuration of landscape mosaics with important consequences for ecosystem services and ecological resilience [17,18].

The results indicate a decrease in total agricultural area, an expansion of permanent crops and a marked reduction in arable land. These changes point to a process of specialization in perennial production systems, especially olive, vine, and fruit crops, together with a partial increase in natural and semi-natural areas. However, these trends must be interpreted cautiously because the datasets used as a reference differ in spatial resolution, minimum mapping unit and classification rules. As also highlighted by broader assessments of land-cover products, differences between maps may reflect both real land-use changes and cartographic-scale effects [28,29]. A harmonized multi-year Sentinel-2 time series would therefore be needed to separate actual transition trajectories from differences related to mapping scale and thematic detail.

The landscape indicators provide a complementary interpretation of these land-use dynamics. Composition metrics confirm the dominant role of permanent crops in the spatial identity of the local agroecosystem, while arable crops show both a reduction in total area and a tendency to persist in fewer and larger patches. Natural and semi-natural elements increased in area, but the fragmentation metrics indicate that they remain spatially discontinuous. The average patch size of approximately 0.25 ha and the high patch density describe a fine-grained and disaggregated mosaic.

Recent global evidence indicates that both landscape composition and configuration influence biodiversity responses, and that heterogeneous agricultural mosaics generally support higher levels of species richness and ecosystem services than simplified landscapes, although excessive fragmentation may reduce functional connectivity for many taxa [18].

Such a configuration may increase edge habitats and landscape heterogeneity, but it may also limit habitat continuity and reduce the stability of ecological processes for species and communities requiring connected or continuous habitats.

The indicators used in this study should therefore be interpreted as structural proxies describing the capacity of the landscape to support ecological processes rather than as direct measurements of biodiversity. This interpretation is consistent with the landscape agroecology framework, which considers landscape heterogeneity, habitat diversity and ecological connectivity as key determinants of ecosystem functioning and resilience, while recognizing that these variables cannot replace direct biological surveys [17,18,30].

Increased heterogeneity may support some components of biodiversity, especially species associated with woody vegetation, ecotonal environments and transitional habitats. At the same time, the reduction and discontinuity of open agricultural habitats may negatively affect species linked to herbaceous cover, cereal fields, and extensive arable systems, including many pollinators and other organisms dependent on open landscapes. Therefore, the observed increase in natural or semi-natural areas should not automatically be interpreted as an overall improvement in biodiversity conditions. Recent meta-analyses demonstrate that biodiversity responses depend not only on the quantity of semi-natural habitats but also on their spatial arrangement, habitat quality, and connectivity across the agricultural matrix [18].

Connectivity indicators, particularly ecotone length and ecotone intensity, are central for evaluating the agroecological potential of the landscape. High ecotone values around permanent crops and at interfaces with natural vegetation indicate opportunities for strengthening ecological networks. However, the functional role of these interfaces depends not only on their extent, but also on their vegetation structure, continuity, management intensity, and capacity to connect habitat patches across the agricultural matrix. The mapped natural areas do not correspond only to protected areas but rather to portions of

the municipal territory likely affected by secondary succession following land-use change. These dynamics may reflect both positive environmental awareness and less favorable socio-economic processes, such as marginalization or abandonment of agricultural plots. Overall, the discussion of the results suggests that agroecological planning in the Bio-Distretto delle Lame should move beyond the simple quantification of natural and semi-natural areas and focus on their spatial arrangement, ecological quality and management. Priority actions should include the restoration of hedgerows with native species, the maintenance of spontaneous vegetation strips, the protection of small natural patches acting as steppingstones, the enhancement of field margins and the adoption of low-disturbance practices in permanent crops. In this way, landscape management could support the competitiveness of specialized supply chains while also reconstructing functional ecological networks, thereby strengthening agroecosystem resilience and providing a stronger territorial basis for the agroecological transition.

Recent landscape-genetic studies further demonstrate that landscape connectivity cannot be inferred solely from the physical presence of habitat interfaces, because functional connectivity depends on the permeability of the agricultural matrix and species-specific movement patterns [31–33]. Consequently, future work should complement landscape metrics with direct biodiversity surveys or landscape-genetic approaches to better evaluate whether structurally connected landscapes also provide effective ecological connectivity.

5. Conclusions

This study fits within the growing body of research employing satellite remote sensing for updating land-use and land-cover (LULC) information, a field in which Sentinel-2 is now widely recognized as a highly effective data source due to its spatial resolution, revisit frequency, and free availability. The scientific literature has consistently highlighted the capacity of Sentinel-2 to improve monitoring of agricultural, forest, and natural land covers, while also recognizing limitations in heterogeneous and fragmented landscapes, where spectral and phenological variability may reduce class separability [34].

Compared with studies focusing primarily on land-use classification, the present work introduces an additional interpretative layer by integrating mapping with landscape ecology indicators and an agroecological assessment framework [17]. This aspect is particularly relevant because recent literature increasingly emphasizes that agroecological transition cannot be evaluated exclusively at farm scale but requires consideration of landscape structure, ecological connectivity [35], semi-natural habitats, and their capacity to sustain ecosystem services such as pollination, biological pest regulation, soil fertility, and water regulation [36].

From a methodological perspective, the comparison between the supervised pixel-based approach and the unsupervised GEOBIA workflow represents one of the key contributions of this study. The supervised approach produced the most robust results, achieving an overall accuracy of 91.76%, consistent with findings reported in previous studies indicating that supervised methods applied to Sentinel-2 imagery generally provide strong classification performance when representative training datasets are available. In complex agricultural landscapes, however, classification accuracy strongly depends on training data quality, adequate representation of land-cover classes, and the phenological consistency of input imagery.

The unsupervised GEOBIA workflow, although not achieving the same level of accuracy, retains substantial methodological relevance. Object-based approaches are widely recognized for their ability to incorporate spatial information and reduce the “salt-and-pepper” effect typically associated with pixel-based classifications, particularly when the objective is to characterize patches, field margins, and landscape elements. However, their

performance critically depends on segmentation quality, analysis scale, and the capability of generated objects to correspond to ecologically and agronomically meaningful units. In the present study, the strong heterogeneity of the Ruvo di Puglia landscape—including topographic variability, parcel-scale heterogeneity, intra- and inter-field spectral variability, and diversified agronomic practices—limited the interpretability and performance of the unsupervised classification, highlighting the need for further methodological developments before fully operational implementation in Mediterranean agricultural systems [37].

An additional element of originality concerns the role assigned to UAV surveys. Rather than being employed primarily for model training, UAV-derived information was integrated as an independent validation and quality-control component supporting satellite classification outputs. This approach strengthens mapping reliability and improves the characterization of fine-scale landscape elements such as ecotones, vegetated margins, small semi-natural patches, and agricultural discontinuities, which are often poorly represented in coarse-resolution or outdated official datasets. In this respect, the proposed workflow contributes to bridging the gap between institutional cartography and the operational requirements of local-scale agroecological planning.

The results reveal relevant land-use changes between 2018 and 2024, including an expansion of permanent crops and natural or semi-natural areas, accompanied by a reduction in arable land. These dynamics suggest the coexistence of two parallel processes: specialization of perennial farming systems and secondary re-naturalization processes affecting marginal or less intensively managed areas. Nevertheless, because the analyses relies on datasets characterized by different spatial resolutions, classification criteria, and thematic specifications, these findings should be interpreted as indicative territorial trends requiring further validation through harmonized multi-year monitoring frameworks.

From an ecological perspective, increased landscape heterogeneity may represent an opportunity to strengthen biodiversity conservation and ecosystem service provision, as demonstrated by studies highlighting the role of semi-natural habitats, hedgerows, vegetated margins, and diversified agricultural mosaics [38]. However, the current literature also indicates that heterogeneity alone does not automatically generate ecological benefits unless accompanied by adequate habitat continuity, structural quality, and ecological functionality. A more diversified but fragmented landscape may favor species associated with woody vegetation and ecotonal environments while negatively affecting organisms dependent on extensive and continuous open habitats [18].

Therefore, the principal scientific contribution of this work does not rely exclusively on producing an updated land-use/land-cover map but rather on proposing an integrated framework capable of linking satellite classification, UAV validation, landscape ecology metrics, and agroecological interpretation. Applied to the Bio-Distretto delle Lame context, this framework provides an operational knowledge base supporting local planning processes, identifying structural vulnerabilities of the agricultural mosaic, and informing actions aimed at strengthening ecological connectivity. Within this perspective, agroecological transition should not focus exclusively on increasing the quantity of natural and semi-natural elements but also on improving their spatial distribution, continuity, and ecological quality through measures such as native hedgerow restoration, conservation of spontaneous vegetation strips, protection of small natural patches, and adoption of low-disturbance practices within permanent cropping systems.

Overall, the study provides not only an updated land-use/land-cover assessment but also a methodological framework for comparing supervised and unsupervised classification strategies in heterogeneous Mediterranean agricultural landscapes. While the supervised pixel-based approach currently represents the most reliable operational solution,

the unsupervised GEOBIA workflow remains a promising exploratory pathway for reducing dependence on labeled training datasets, provided that further methodological refinements are introduced.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/land15071199/s1>, Annex S1: Sampling areas; Annex S2: Bio-diversity indicators.

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Abbreviations

The following abbreviations are used in this manuscript:

UAV	Unmanned Aerial Vehicle
NDVI	Normalized Difference Vegetation Index
GEOBIA	Geographic Object-Based Image Analysis
QGIS	Quantum Geographic Information System
DTM	Digital Terrain Model
DEM	Digital Elevation Model
RF	Random Forest
OTB	Orfeo ToolBox
SCP	Semi-Automatic Classification Plugin
CLC	Corine Land Cover
UA	User's Accuracy
MP	Megapixel

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