

Enhanced Map Composition and Diachronic Land Cover Classification of Landsat Data in Google Earth Engine

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Abstract. Understanding how habitats in the European Natura 2000 network change over time and space is crucial to evaluating the effectiveness of protective measures and developing sustainable management practices. Satellite remote sensing through Earth observation offers a cost-effective, timely, reproducible vegetation analysis. This study aims to analyze the changes in grassland habitats (types 6210 and 6230*, Annex I, European Directive 92/43/EEC) within the Natura 2000 network's areas in Umbria (Central Italy) between 2000 and 2020. The goal is to gather spatial information to develop more sustainable planning and management strategies. In this direction, we selected a three-year time window in two periods (1999–2001 and 2019–2021). We applied an enhanced dataset composition, including cloud-filtering, topography correction, and textural analysis on Landsat 7 and 8 surface reflectance images available in Google Earth Engine (GEE). Additional morphometric features were derived from the digital elevation model of the area. Using machine learning classification (Random Forest – RF), we obtained the land cover maps for the two periods under investigation with high overall accuracy (87 and 88%). Only shrublands showed a lower classification accuracy due to the varied nature of this land cover class and the limited resolution of Landsat data. On this basis, we identified transformations that occurred in the study areas. The results confirmed the effectiveness of enhanced map composition and RF in GEE for diachronic land cover classification. The final spatial information can help identify areas where conservation measures related to the Natura 2000 network have been more or less effective and develop more appropriate management strategies for grasslands of European concern.

Keywords: grasslands dynamics · google earth engine · remote sensing · machine learning · random forest · Landsat 7 · Landsat 8

1 Introduction

Permanent grasslands cover 34% of the European Union's agricultural area and are among Earth's most prominent land cover for human welfare and livestock [1]. Natura 2000 network is by far the most influential EU nature conservation effort implemented

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O. Gervasi et al. (Eds.): ICCSA 2023 Workshops, LNCS 14107, pp. 289–299, 2023.
https://doi.org/10.1007/978-3-031-37114-1_19

in Umbria. It is regulated mainly by the Habitat Directive (92/43/EEC, "The Habitats Directive - Environment - European Commission," 1992) [2] and the Birds Directive (2009/147/EC, "The Birds Directive - Environment - European Commission", 2009) [3]. The network includes two types of protected areas: Special Areas of Conservation (SACs) and Special Protection Areas (SPAs). Assessing habitat conservation status is crucial for managing Natura 2000 network according to international conventions such as the Convention on Biological Diversity or the European Biodiversity Strategy [4]. Mapping and monitoring grasslands' habitats are essential for implementing the European Directive 92/43/EEC and protecting and managing the Natura 2000 network [5]. Understanding land cover, landscape, and habitat dynamics in space and time, also considering the spatial gradients [6, 7], is very relevant for the definition of sustainable management practices [8–11] and protecting the ecosystem service flows [12, 13]. Field surveys are needed for collecting ground GIS data [14] and habitat detection and identification [15]; however, analyzing trends and processes requires gathering adequate spatial and temporal information, which is time-consuming and expensive, especially when dealing with large areas. Although its known limitations compared to on-field surveys, Earth observation by satellite remote sensing (RS) offers many possibilities for cost-effective, timely, and reproducible vegetation analysis [16]. Moreover, in the last decade, RS techniques and tools have become very efficient, especially with the advent of easily accessible and open-source data and software [17]. Grassland remote sensing research supports ecology studies because it utilizes multi-platform, multi-sensor, and multi-temporal satellite remote sensing data sources and ground observation data [18–20]. Landsat data have been broadly used for land-use land-cover (LULC) change detection and analysis (see, e.g., [21–23]). Despite its coarser spatial and temporal resolution than other satellites, it provides the most comprehensive free-access remote sensing data globally, thus offering the possibility to gain insights into past trends, which are fundamental for monitoring land cover changes [24, 25].

In recent years, RS data processing has progressively migrated to cloud-based platforms from traditional workstations. Users can rapidly access and analyze pre-processed geospatial data using user-friendly web-based interfaces and powerful scripting languages [26]. Among these technologies, Google Earth Engine (GEE) is a cloud-based geospatial analytic platform that enables users to effectively manage massive amounts of data, storage, processing, and analysis [27].

Machine learning (ML) algorithms generally produce better results than traditional classifiers in the categorization of LULC. Classification and Regression Trees (CART), Random Forest (RF), and Support Vector Machine (SVM) are non-parametric ML classifiers that have been shown to generate exceptionally accurate LULC classification results from remotely sensed imagery [28]. The RF classifier has been widely used in the GEE for RS data classification [29, 30], even in object-based approaches [31–33] due to its non-parametric structure, ability to handle dimensionality and overfitting, and superior performance to other classifiers. However, the unknown splitting rules are one of its most known inherent flaws [22].

This study aims to perform a long-term analysis of vegetation within the Natura 2000 network's areas in Umbria (Central Italy). The analysis focuses on transformations in grassland habitats (Annex I, types 6210 and 6230*) to identify areas where significant degradation phenomena related to reduced green biomass due to erosion or invasion of shrub and tree species can be observed in the last 20 years.

2 Materials and Methods

2.1 Study Areas

The Umbrian Natura 2000 network includes 102 sites: 5 SPAs and 97 SACs. The network protects 41 habitats of Annex I to the Habitats Directive, i.e., habitats of community interest, of which 11 are defined as priorities due to their particular importance, 143 animal species (4 priority), and eight plant species (1 priority). Grassland habitats (Annex I, types 6210 and 6230*, Directive 92/43/EEC) are very relevant to the Umbrian Natura 2000 network sites, especially within the sites falling along the Apennine mountains. Our study area includes the higher altitude (over 700 m a.s.l.) Natura 2000 areas of Umbria. We defined the proper altitude threshold to select the most critical grassland areas in the Natura 2000 network and include all the montane grasslands, traditionally used as pastures and affected in recent decades by a massive decline due to land depopulation [34].

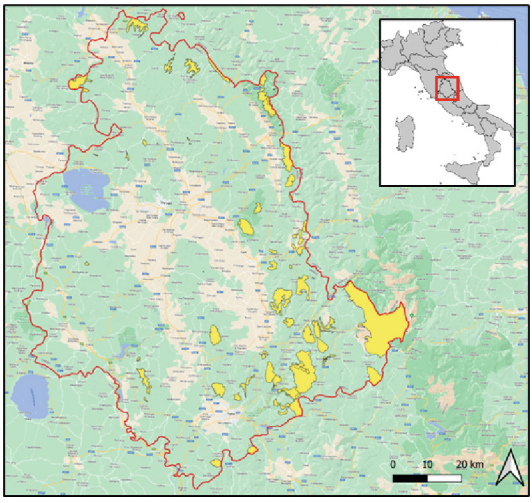


Fig. 1. The geographical location of the study areas.

2.2 Methodology

We tested a diachronic land cover classification in Google Earth Engine (GEE) to assess the main changes in grassland areas between 2000 and 2020, focusing on the sensible decrease of grasslands' biomass and the increase of shrubs and trees. We defined five main land cover classes (Table 1) and spatially compared their extents in the two classifications. As with every typical LULC (Land Use/Land Cover) classification procedure, our workflow includes a) data composition and pre-processing, b) image classification, c) accuracy assessment, and d) LULC transition analysis.

Generating the base composite dataset is a crucial step in every LULC classification. In this regard, GEE offers a vast database of satellite imagery and computational power accessible to all users [35]. We used the Landsat 7 (L7) and the Landsat 8 (L8) data atmospherically corrected at the Surface Reflectance (SR) level in this application, available in GEE. According to Xi et al. [36], we filtered the L7 and L8 GEE datasets considering two sufficiently broad periods of interest (in this case, three years, from 1999 to 2001 and 2019 to 2021) were defined to create a more effective composite image for the subsequent classification. We applied a cloud cover filtering on the resulting dataset using the "pixel_qa" band, which allowed us to almost entirely mask pixels occupied by dense and cirrus clouds and their on-ground shadows [37].

Table 1. Land cover classes used in the classification.

LULC Class	Description
Woodland	Forest vegetation dominated by different tree species
Shrubland	Shrubs and scrublands, including the types 4060, 4090, and 5130 of Annex I, Directive 92/43/EEC (usually dominated by brooms, juniper, blackthorn, and hawthorn)
Grassland	Grassland vegetation dominated by grasses, forbs, and small shrubs in variable proportion, from dense and continuous to sparse and discontinuous, including both primary and semi-natural secondary grasslands (in particular, habitat types 6210 and 6230*, Annex I, Directive 92/43/EEC)
Cropland	Agricultural mosaic is mainly composed of annual crops
Sparse/ No vegetation	Areas characterized by highly sparse and discontinuous vegetation cover, with a remarkable presence of rocky substrate, or persistently non-vegetated areas characterized by bare soil or built-up areas

A topographic correction in mountainous areas is ordinarily necessary to reduce the topographic effect before calculating spectral indices and image classification (Richter et al., 2009). To this aim, using the 30m Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM), we applied a Sun-Canopy-Sensor + C (SCSc) correction method [38, 39] successfully applied in previous studies [23, 40, 41], already implemented in a GEE script [42]. To correct some noise and aberrations observed on the first SCSc outputs, we smoothed the DEM convolving with a 2-cell radius low-pass filter. Adding spectral indices generally increases the available information and improves the

final classification [43, 44]. In this regard, we computed three spectral indices for each image in the period of interest (Table 2).

Textural analysis by GLCM in GEE requires a grey-level 8-bit image as input to generate 18 different textural indices. The algorithm calculates statistical data of texture characteristics by analyzing the distribution of intensity combinations observed at specified positions relative to one another in the image up to the second order [45]. As performed in previous studies [23], we applied a weighted linear combination to median B3, B4, and B5 bands to generate the 8-bit input for the GLCM step in GEE. We selected the first eight metrics for the subsequent classification.

Table 2. Spectral indices and related formulas used in the research.

Index	Formula	Author
BSI	$\frac{(SWIR1+RED)-(NIR+BLUE)}{(SWIR1+RED)+(NIR+BLUE)}$	Rikimaru et al., 2002 [46]
NDVI	$\frac{NIR-RED}{NIR+RED}$	Rouse Jr. et al., 1974 [47]
GARI	$\frac{(NIR-(GREEN-(BLUE-RED)))}{(NIR-(GREEN+(BLUE-RED)))}$	Gitelson et al., 1996 [48]

Table 3. Area of land cover (LC) classes (km^2) in the two analysis periods (2000, 2020) and the increase/decrease percentage within the Natura 2000 sites.

LC classes	2000	2020	Var. %
Woodland	332	359	+ 8.1
Shrubland	44	34	−22.7
Cropland	20	19	−5.0
Grassland	112	98	−12.5
Sparse/No Vegetation	31	30	−3.2

To compose the 30-m resolution base Data Cube (BDC), we calculated the median images for the L8 and the L7 bands and that of the derived spectral indices in GEE. We added the 30m SRTM DEM for altitude and the derived slope and aspect layers to consider the morphological features crucial for an area of interest with complex morphology, such as the Umbria territory.

We computed the land cover classification using the Random Forest (RF) machine learning classifier. RF utilizes bootstrap aggregation (bagging) to build multiple decision trees to combine the results employing a majority voting method to make a more accurate prediction [49, 50].

We collected 1200 randomly distributed points in the two periods, with a reciprocal minimum distance of 200 m, to train the classifier and validate the LULC classification results. These points were classified in QGIS, visually integrating information from high-resolution orthophotos from 2000 and 2020. The classification accuracy was assessed

using the confusion matrix method, a widely used approach based on comparing the classification outputs with the ground truth data [51, 52].

3 Results and Discussion

The two final LULC classifications gathered a high overall accuracy (87 and 88%). Classification of shrublands was more problematic due to the varied nature of this land cover class and the limited resolution of Landsat data. Concerning our analysis of changes, the region we examined is situated at high elevations and predominantly composed of natural and semi-natural habitats, with forests and grasslands being the primary land cover types (Table 2). The area covered by forests has increased over the past two decades, while there has been a decrease in the coverage of grasslands. Natural transitional flows from shrubland areas characterized the forests in the area. These phenomena, typical of inner Italian marginal areas, are in counter-tendency compared to those typical of peri-urban areas [53].

Conversely, grasslands have suffered significant losses due to the transition into shrubs or forests, as illustrated (Fig. 2). Shrublands have experienced inflows from grasslands and outflows to forests. Still, despite these transitions, the area covered by shrublands has declined over the past 20 years. Agricultural areas experienced a slight decline in the same period. Non-vegetated and eroded areas decreased only marginally during the analysis period.

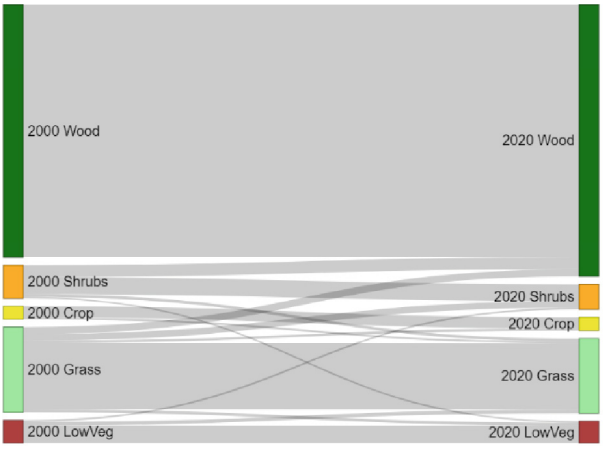


Fig. 2. Sankey's diagram showing the land cover transitions between 2000 and 2020.

The proposed methodology identified the grassland areas in the Umbrian Natura 2000 network where the most relevant degradation phenomena occurred. These phenomena are partly related to biomass reduction (primarily due to the increase of erosion or over-grazing) and partly (the majority) to the invasion of shrubs or trees (Fig. 3). This information helps detect the areas where the conservation measures related to the

Natura 2000 network have been more (or less) effective and address more appropriate management strategies. On the one hand, specific spatially explicit management measures aimed to reduce over-grazing or erosion phenomena and reduce invasion by shrub or tree species (often related to under-grazing) could be defined to increase grassland ecosystem protection.

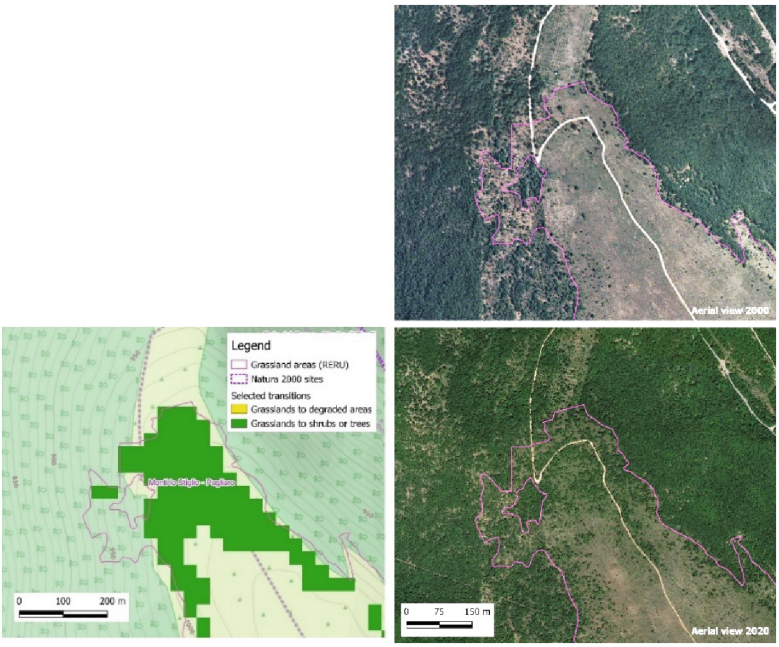


Fig. 3. Example of the diachronic land cover analysis output showing a grassland area occupied progressively by shrubs or trees during the investigated period.

4 Conclusions

This research developed a diachronic land cover analysis of Natura 2000 areas to identify areas where significant degradation phenomena (reduction of the grasslands' biomass or invasion by shrubs or trees) occurred during the 2000–2020 period, generating a loss of grassland areas. The machine learning-based land cover classification in GEE produced high overall accuracy results. However, shrublands classification was more problematic due to the varied nature of this land cover class and the limited resolution of Landsat data. Preliminary results of the diachronic analysis focused on the specific transitions of grassland areas. The green biomass reduced considerably only in a few areas, mainly due to increased erosion phenomena or rarely to over-grazing. The spatial information helps detect the areas where the conservation measures related to the Natura 2000 network have been more (or less) effective and address more appropriate management strategies for protecting grasslands of European concern.

Acknowledgments. This research was developed within the LIFE Project "LIFE IMAGINE UMBRIA" LIFE19 IPE/IT/000015 funded by the European Union.

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