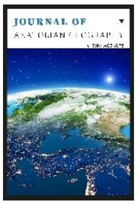
Journal of Anatolian Geography

https://dergipark.org.tr/tr/pub/jag

e-ISSN: 3023-8978



FAO veri setini kullanarak çevresel izleme için R'de istatistiki analiz

Polina Lemenkova[1,2,3*]

[1]*Bureau de Recherches Géologiques et Minières (BRGM), Orléans, Centre-Val de Loire, France*
[2]*LE STUDIUM, Institut d'Etudes Avancées du Val de Loire, Orléans, Centre-Val de Loire, France*
[3]*La Technopole d'Orléans, Orléans, Centre-Val de Loire, France*

Anahtar Kelimeler
Arazi planlaması,
Çevresel izleme,
Uzaktan algılama

Araştırma Makalesi
Geliş: 03.09.2025
Kabul: 22.11.2025
Yayınlanma: 25.04.2026

check for updates

Özet

Sınırlı kaynaklara sahip dağlık ülke bölgelerinde doğa koruma uygulamaları ve tarım sistemleri sürdürülebilirlik zorluklarıyla karşı karşıyadır. Tarım ve doğa arasındaki dinamikler, tarım sistemlerinin doğa koruma politikası ve biyofiziksel faktörlerdeki değişimlere verdiği tepkileri yansıtan karmaşık etkileşimleri içerir. Dahası, iklim değişikliği su kaynaklarının kontrolü ve toprak verimliliği yoluyla biyolojik çeşitliliği etkiler. İtalya'da dağlık alanlar son yıllarda sosyoekonomik değişimler yaşadı ve bu da geleneksel tarımsal ormancılık faaliyetlerini etkileyerek orman genişlemesine yol açtı. Bu çalışma, İtalya'daki tarım sistemlerinin ve orman koruma alanlarının sürdürülebilirlik performansını incelemektedir. 1990-2025 yılları arasındaki mevcut FAO verileri, sosyo-ekonomik, iklimsel ve çevresel açılardan arazi kullanımı ve arazi örtüsü (LULC) değişimlerindeki dinamikleri analiz etmek için kullanılmıştır. Veri analizi, R dilinin istatistik ve hesaplama kütüphaneleri kullanılarak gerçekleştirilmiştir: readr, ggplot2, reshape2, tidyverse, gridExtra, stats, plotly, latticeExtra, ggpubr bunlardan başlıcalarıdır. Sonuçlar, İtalya'da doğa koruma ve sosyo-ekonomik faaliyetlerde sürdürülebilir kalkınmayı gösteren yeniden ormanlaştırma (orman alanlarında %9, çalılık alanlarında %21 artış), iklim ısınması (buzul ve kar çekilmesi %34), kentleşme (yapay yüzeylerin artışı %5,8) ve tarım faaliyetlerinin yoğunlaşması (ekim alanlarında istikrarlı artış %2) eğilimlerini ortaya koymuştur.

Statistical analysis in R for environmental monitoring using FAO dataset

Keywords
Land planning,
Environmental monitoring,
Remote sensing.

Research Article
Received: 03.09.2025
Accepted: 22.11.2025
Published: 25.04.2026

Abstract

Nature protection practices and agricultural systems face sustainability challenges in mountainous countries regions with limited resources. The dynamics between agriculture and nature involves complex interactions that reflects the responses of farming systems to shifts in nature conservation policy and biophysical factors. Moreover, climate change impacts biodiversity through control of water resources and soil fertility. In Italy, mountain areas have experienced socio-economic changes in recent decades, which has affected traditional agro-forestry activities and resulted in forest expansion. This study examines the sustainability performance of farming systems and forest protection areas in Italy. Existing FAO data on 1990-2025 were used to analyse the dynamics in land use and land cover (LULC) changes in context of social-economic, climate and environmental aspects. The data analysis was performed using R language by its statistical and computing libraries such as readr, ggplot2, reshape2, tidyverse, gridExtra, stats, plotly, latticeExtra, ggpubr as the main ones. The results demonstrated trends in reforestation (increase of forest areas on 9% and shrubland on 21%), climate warming (glacier and snow retreat on 34%), urbanization (increease of artificial surfaces on 5.8 %) and intensification of agriculture activities (stable increase in cropland on 2 %), which indicates sustainable development in nature protection and social-economic activities of Italy.

(*) Sorumlu Yazar/Corresponding Author

*Assoc. Prof. Dr., polina.lemenkova@tech-orleans.fr, ORCID 0000-0002-5759-1089

Kaynak Göster (APA)

Atıf/Citiation: Lemenkova, P. (2026). Statistical analysis in R for environmental monitoring using FAO dataset. *Journal of Anatolian Geography*, 5:1. https://doi.org/10.65652/jag.1777704

1. Introduction

The factors that determine sustainable development that balances agriculture growth and nature conservation are fundamental for land management (Marković & Marković, 2012; Popov, 2014; Jevtić et al., 2024; Lemenkova, 2022a). Understanding reasons of environmental dynamics plays a key role for proper land management policy and predictive ecosystem modelling (Coll et al., 2011; Peng et al., 2025a; Li et al., 2025a). Agriculture and nature conservation are increasingly intertwined with conservation methods showing that sustainable practices of agriculture can lead to higher crop yields and increased profits while benefiting the environment (Allegrezza et al., 2025; Lemenkova, 2025b; Stamou et al., 2025; Keşanlı et al., 2025).

Balancing agriculture and nature is achieved through sustainable practices that work with natural processes (Gliessman, 2022; Cash et al., 2003). These measures aim at both nature conservation and agriculture development (Runhaar, 2017). A balance should be maintained between harmonized agricultural development and nature protection (Altieri, 1999; Batáry et al., 2015). The land allocation between protected land and agricultural areas should be maintained (Grupp et al., 2023).

Nature conservation includes diverse measures on protection of precious and vulnerable areas: creating protected areas (Shi et al., 2025), national parks (Schlagloth et al., 2025; Peng et al., 2025b), restoring degraded habitats through programs and restrictions (Yuan et al. 2025), smart resource management (Sayn-Wittgenstein et al., 2025), and implementing sustainable practices through reforestation and renewable energy (Jiang et al., 2025).

Forest serves as crucial environmental and climate regulators. Forest stands contribute to dampening the effects from climate acting as carbon sinks (Pu et al., 2025; Li et al., 2025a) and absorbing CO_2 (Pugh et al., 2019). Nevertheless, the emissions from deforestation, decomposition and degradation release stored carbon back into the atmosphere, contributing to climate change. The emissions of N_2O and CO_2 as major greenhouse gases released to the atmosphere require environmental analysis.

On the other hand, agriculture is crucial for societal development. Agriculture provides food security, drives economic growth, as it reduces poverty, creates jobs in agriculture sector, contributes to economic growth, and supports environmental sustainability. Therefore, nature protection should be in balance with economic development and well-being of society. The growth of ecologically intensive agriculture is crucial for balanced socio-economic advancement (Doré et al., 2011). Advantages of strong agriculture sector include increased purchasing power for goods and services and strengthened capital through increased farm income. Agriculture development methods include functional agrobiodiversity approaches, techniques of crop rotation, no-till farming to protect soil health, while also protecting and restoring natural habitats (Altieri et al., 2015). During recent decades, the landscapes of Italy have changed significantly due to the cumulative effects of land use and land cover (LULC) and climate (Turconi et al., 2025; Khachoo et al., 2024; Arcidiaco & Corongiu, 2025). Anthropogenic factors affect landscapes and reshaped land cover patterns, related to social-economic development (Marino et al., 2023). Recently, LULC patterns underwent a process of polarization: lowlands are converted to urban areas with intensive agricultural practices with the loss of the last remnants of natural natural elements (hedgerows, ditches).

Recent societal pressures induce a decline in rural population in Italy, degradation of agriculture and abandonment of marginal land (Pellegrino et al., 2016). The standardization and of LULC practices and simplification of pastures to low-productivity agricultural fields led to the expansion of forests, which caused habitat homogenization and decrease in landscape diversity (Anđelković & Radulović, 2022; Klaučo et al., 2013; Thompson et al., 2018). This finally led to regeneration of landscapes, including (semi-)natural habitats. Such processes restored landscape connectivity (Prigioni et al., 2008; Raia, 2004; Morini et al., 2016).

Climate change has important role as a driver of LULC changes (Kedward et al., 2022; Klaučo et al., 2017; Boersema et al., 2009). It has effects at various rates in different areas both in forest and agricultural areas. Climatic impacts vary across vulnerable communities (Oldfather et al., 2025; Lemenkova, 2025c).

Modelling links between climate and environmental factors is needed to identify vulnerable areas and habitats (Masini et al., 2025; Lemenkova, 2024a). Spatially explicit modelling allows predicting trends in agricultural-nature LULC balance under a range of plausible scenarios of social-economic development. However, most research focuses on spatial scales with regard to protected areas (e.g., Kerkez Janković et al., 2024). Fine-scale applications of these models are required to provide relevant information for ecosystem services. In this study, we contribute to the analysis of trends in agriculture and natural protection in Italy based on statistical quantitative analysis using FAO data.

2. Materials and Methods

For study area, we gathered a set of potential factors affecting agriculture and land use dynamics, making use of available FAO data such as agriculture and forest statistics. To achieve a deeper understanding of the multiple pressures driving environmental change in the study area, we performed quantitative estimations to capture qualitative data analysis. The data were collected from the 3 types of sources: 1) descriptive data; 2) statistical data from FAO; 3) cartographic and remote sensing (RS) data in open access, Figure 1.

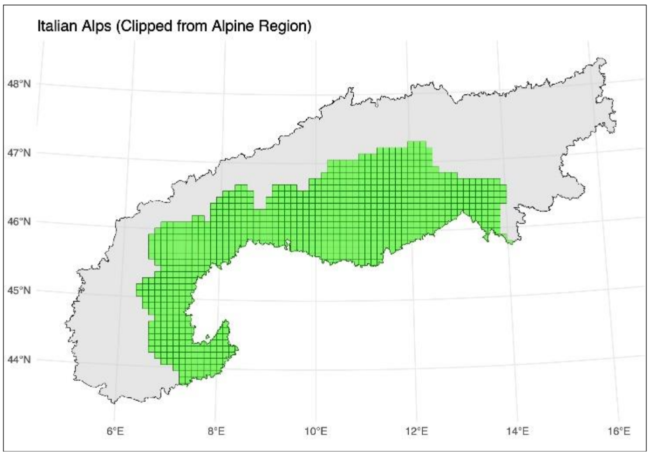


Figure 1. Location of RS data on the northern part of the study area: green squares show the location of the Landsat satellite images covering study area of Alps, Italy.

2.1. Objectives and Goals

The objective of this research is statistical analysis of ecosystem and agriculture change in Italy. The agricultural monitoring data are scarcely integrated and scattered. Some datasets essentially require integrating different data, expertise, and time series, for dynamic analysis. Integrating economic surveys on agricultural statistical with data that is available with complete spatial coverage, such as FAO repositories, is a necessary step for ecosystem survey. But interpreting changes in forest-agriculture shifts requires considering spatio-temporal dynamics based on statistical analysis. Only a qualitative-quantitative approach, for instance, R- or Python based allows modelling patterns and trends of agricultural change and also to highlight their trends (Be et al., 2025; Lemenkova, 2019b; Li et al., 2022a). To this end, the goal is the land use impacts and agriculture-forest shares in land use pattern using integrated methods of statistical analysis and modelling.

The overall objective of this study is to understand the spatiotemporal trends and future outlooks of land use and ecosystems in Italy. There are two specific objectives within the overall objective:

1) the statistical analysis of ecosystem and agricultural change in Italy based on FAO data;

2) the geospatial analysis of landscape dynamics in Italy based on RS data.

To this end, we aim to evaluate the RS and FAO data. The RS data are widely accepted reliable sources of geo-information that are reported in variety of papers (Tompolidi et al., 2025; Ghirardi et al., 2023; Longo-Minnolo, et al., 2025). In our study, we used data from MODIS with spatial resolution of 500 m. The second type of data includes the land use domain over Italy, which contains data on 21 land use categories and 23 categories of irrigation and agricultural practices.

MODIS images were selected due to coverage and environmental applicability of this sensor which contains several datasets that map the land cover with annual time steps. MODIS presents a reputable source of information widely used in environmental and climate-related studies (Ghaderpour et al., 2024). The evaluated data are available yearly at regional and global levels. The domain includes land use indicators providing information on the percentage of agricultural and forest land, and share of their sub-components, including irrigated areas and areas under organic agriculture, within a country land use pattern.

The goal is to evaluate the data available at country, regional and global level, for the following elements: i) Share in Land area (%); ii) Share in Agricultural land (%), iii) Share in Cropland (%); and iv) Share in Forest land (in ha/pc) v) Area per capita (%).

The specific objectives are the following ones:

i. to assess how temporal changes in land cover structure affected the composition and spatial distribution of agricultural and forest shares within the total land category of Italy, highlight categories of maximum changes and quantify the proportion of agriculture products for which dynamics is substantially improved the outlook for 1990-2025;
ii. to reveal the main triggers driving habitats and environmental changes and develop narratives for their interpretation by analysis of recent shifts;
iii. to analyse recent trends in LULC types for spatio-temporal dynamics that impacts economic development in agricultural sector.

The data analysis was based on R programming and statistical language (R Core Team, 2021). This tool was selected due to its numerous applications in ecological studies which proved its robustness and applicability. The main advantages of R as a statistical and graphical tool for data analysis include the wide possibilities of statistical modelling reported in existing studies through diverse libraries (Duggan, 2018; Duggan 2019; Lemenkova, 2019a; Cosmulescu et al., 2022; Theobold et al., 2021; Baumer et al., 2014), as well as presented specific novel R packages (Schwalb-Willmann et al., 2020; Hallett et al., 2016; Wu et al., 2023; Lam et al., 2024).

The R programming language and statistical software provide a flexible framework for supporting environmental modelling. In particular, R contains a suit of libraries, including the unparalleled collection of packages “tidyverse” and “ggplot2”, which contain a variety of functions. They are designed to process multi-variant data and with rows as individual observations and columns as variables. Such structure fits the organization of FAO data.

Here, we employ the functionality of R for diverse types of data manipulation, including import from external sources reformatting (.csv tables), aggregating and reshaping, processing and extracting information, highlighting variables. The flexibility of R for data analysis and modelling is based on diverse packages with extended functionality for scientific modelling and visualization.

To mention the most representative packages of R libraries, we used the following ones, among others: readr, ggplot2, reshape2, scales, RColorBrewer, tidyverse, gridExtra, stats, plotly, latticeExtra, ggpubr.

R libraries were employed for statistical tests, finding correlations between variables, stacked bar charts to show the grouped variables in clusters, dumbbell chart showing the change between two data points for distinct categories, time series analysis (1990-2025), and advanced statistical modeling. Hence, this study integrates the R-based algorithms for environmental analysis of trends in agriculture and forestry.

2.2. Data

The data were obtained from the Food and Agriculture Organization (FAO) statistical repository (FAO, 2025). There are many cases of the use of FAO data in environmental modelling due to its global reach, detailed coverage of agriculture, forestry, and its use in informing environmental policy and supporting decision-making (Li et al., 2022b; Lausch et al., 2025; Zolotnytska et al., 2025; Diaz-Chavez, 2025). Therefore, in this study, we used FAO data as a reputable and reliable source of information.

Data include the FAO categories on forest, climate, environment, economic-social sector, soil and agriculture sectors. Of these, the FAO land use classes included the major categories used in this research: "Agricultural Land’, ‘Land area’ and ‘Forest Land’ as inputs to the computations of Sustainable Development Goals (SDG) indicators based on paragraphs 2.4.1 and 15.1.1, 2030 SDG Agenda. The data were analysed with regards to land use and economics. The FAO dataset included the ‘Land Use’ category for 1990-2025 and included the parameters:

- Carbon stock and living biomass
- Land Use Indicators:

1. Share in forest land (in %)
2. Share in agricultural land (in %)
3. Share in cropland (in %)
4. Share in land area (in %)
5. Area per capita (ha/per person)
6. Value of agricultural production per area ($)

To evaluate the climate-environmental links, the land use and change category included the following categories:

- Emissions from forests
- Emissions from drained organic soils (as 2 classes: organic soils from cropland and grassland.

Forest data were analysed with the following categories:

1) Forest area as a share of total land area (%);
2) Forest area under an independently verified forest management certification scheme (1000 ha)
3) Forest area in absolute values (1000 ha)
4) Forest emissions: carbon stock in living biomass of forest as CO_2 and N_2O.

The data were collected and organized as several .csv tables which were imported into the R statistical software.

2.3. Workflow

The workflow consists of 2 parts: 1) geospatial analysis and 2) statistical analysis. First, we performed mapping and geospatial analysis of land cover types in Italy using CORINE and MODIS data processed in Geographic Information System (GIS) as the 1st part of the workflow. Afterwards, as the 2nd part of the workflow, we performed the statistical analysis. To this end, we created a series of plots using R statistical library "ggplot2" (Wickham, 2016) and database on environmental and forestry situation in Italy from FAO. Using FAO data, we evaluated the percentage of several classes separated within different categories, to detail the environmental analysis of land use system, The FAOSTAT Land Use domain was analysed for data on regional coverage of Italy with 21 land use categories, 23 categories of irrigation and agricultural practices and 5 indicators of land use.

The LULC analysis was based on data extracted from Moderate Resolution Imaging Spectroradiometer (MODIS) satellite-based sensor used for earth and climate measurements. Here, major classes were selected and their dynamics were visualised as trend for 1990-2025 and generalized using RS data based on the original dataset from Coordination of Information on the Environment (CORINE) EU initiative, Figure 2.

The data in Figure 2 were analysed for the country area and regrouped using the MODIS data into 9 (nine) most important classes, Figure 3.

2.3.1. Share in forest areas

Share in forest areas was analysed for 3 classes 1) forest land; 2) naturally regenerating forest; 3) planted forest. The computation is based on the formula in Equation (1):

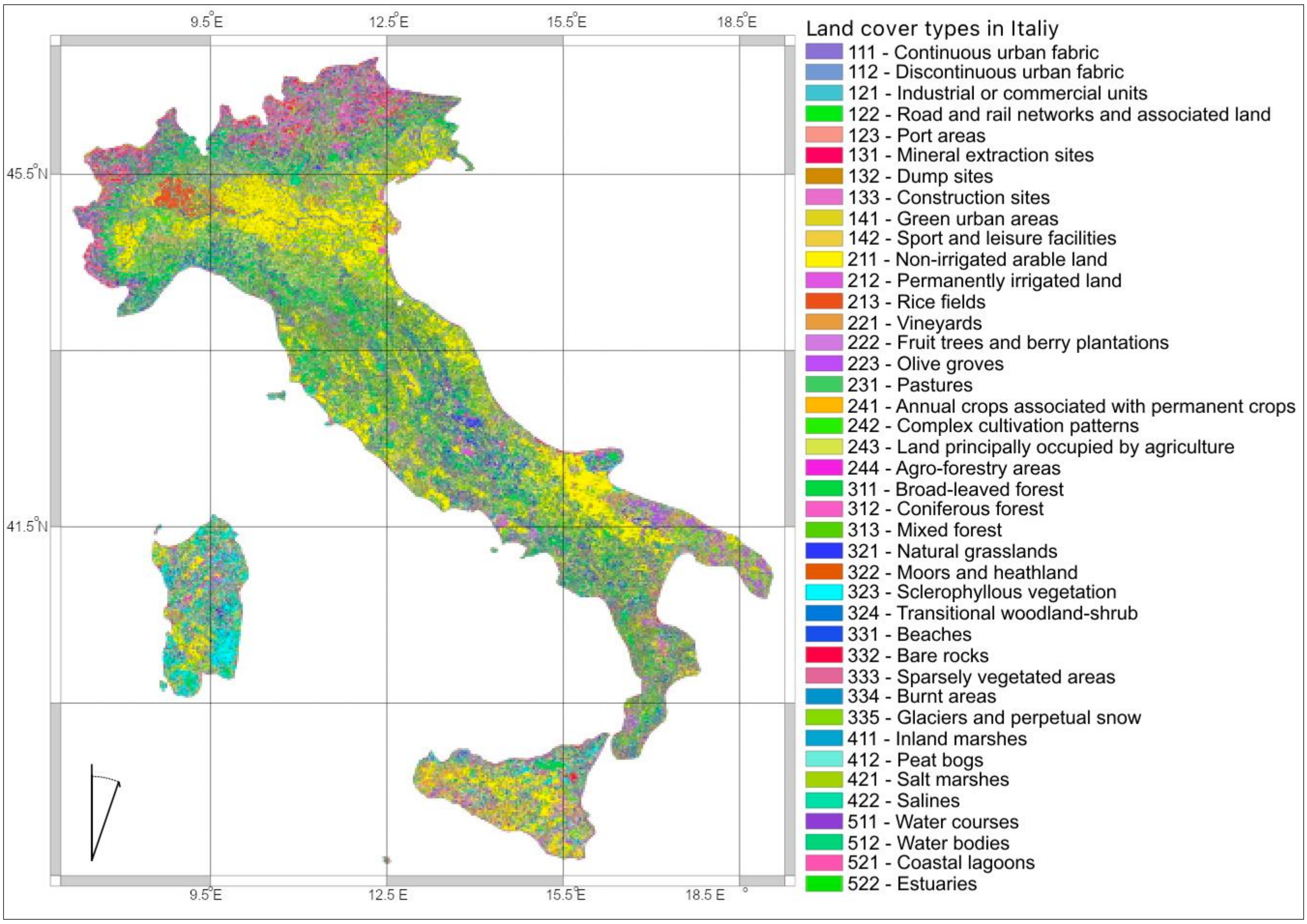


Figure 2. Land cover types classification based on the CORINE dataset: original ungrouped data. Map software: QGIS. Source: author.

$$Shareofforestland_{(i,C,Y)} = \left(\frac{Area_{(i,C,Y)}}{Forestland_{(C,Y)}}\right)x100$$

where C is country, Y is year and i is land use type "I"; area is given in 1 000 ha. The same variables are given in formulas of Equations (2) and (3), respectively.

Changes in share of area from total land are (%) were compared to assess the dynamics of re- and deforestation with regard to the total land area. Here, we compared the share (%) of two classes – "Naturally regenerating forest" and "Planted forest" for the category "Share in forest land", to assess the dynamics of forest regeneration activities on 1990-2025. For category "Forest land", the dynamics in carbon stock in living biomass was evaluated for the same period following existing reports (Li et al., 2025b), to show the contribution to the carbon cycle (carbon in live trees, dead wood, litter, and soil) as indicators of the ecological balance.

2.3.2. Share in agricultural areas

Share in agricultural area was analysed for the classes: 1) Cropland; 2) Arable land; 3) Permanent crops; 4) Permanent meadows and pastures. The computation is based on the formula in Equation (2):

$$Shareofagriculturalland_{(i,C,Y)} = \left(\frac{Area_{(i,C,Y)}}{Agriculturalland_{(C,Y)}}\right)x100$$

where variables are identical to those in Equation (1). The percentage of these classes was compared to evaluate their spatial-temporal dynamics. To analyse the agricultural value of the produced crops, we visualized the dynamics of value of agricultural production (Int. $) per Area which shown the economic benefits of the cultures.

2.3.3. Share in cropland areas

Share in cropland was evaluated with regard to irrigation for the category of land area equipped for irrigation (in percentage) and availability of land for population per capita. These dynamics showed the use of irrigation technologies in agriculture and water supply. The calculation followed the formula in Equation (3):

$$Shareofcropland_{(i,C,Y)} = \left(\frac{Area_{(i,C,Y)}}{Cropland_{(C,Y)}}\right)x100$$

where variables are identical to those in Equation (1). Additionally, the dynamics of the area per capita was evaluated for croplands (ha/cap) within the country, to analyse the intensity of agriculture activities for 1990 to 2023 (using the available data in this category). The Value of agricultural production per area was evaluated in USD ($) PPP/ha. To show the economic growth based on the agriculture production, the trends in growth of agricultural production were visualised for the given period.

Share in land area (as a total of country) was evaluated in % for the following four classes: 1) agricultural land, 2) cropland, 3) permanent meadows and pastures, 4) forest land. The dynamics of these classes and their spatio-temporal changes were compared for the period 1990-2025.

The next step complements environmental analysis through climate data from FAO TIER 1 as net carbon emissions and removal of CO_2 in kt in the forest's areas. This enabled to fill in the gaps in climate-environmental links to facilitate multi-temporal comparisons. The datasets on net forest conversion and forest land areas for CO_2 emissions were evaluated separately to compare inputs.

The next step uses the FAO data on climate and emissions from land as three variables: N_2O, net stock change and emission of CO_2. The comparative analysis of these three categories enabled to perform a spatially explicit model quantifying the impact of cropland organic soils and grassland organic soils affected by agriculture practices and climate-induced processes in land cover patterns.

The qualitative data collected from FAO were processed by R and models were interpreted through comparative analysis using embedded functions of R (Buttrey, 2017). The quantitative analysis of the impacts of climate-induced LULC change and emission dynamics in forest and agricultural areas were evaluated for 25 years.

3. Results and Discussion

By comparing the relative importance of land cover and climate factors, we evaluated the drivers of vegetation change and model the agricultural shifts and landscape dynamics under the effects of climate change.

The land cover type was detected and reclassified using MODIS RS data, Figure 3. These maps show the major land cover types in Italy. Recently, landscape dynamics in Italy is characterized by urban expansion, as the main driver of land fragmentation in plains and coastal areas: northern Emilia-Romagna and Veneto, central Tuscany, Lazio, and Campania, and the southern regions of Calabria and Apulia. Mreover, spontaneous reforestation is also occurring on the RS data in mountainous and rural areas (regions of Trentino-Alto Adige, Alps along the northern border, and the Apennines). Such changes are leading to a decrease in grasslands and open habitats.

Recent trends in LULC for 1990-2025 are dominated by the conversion of land to urban, forest regeneration and moderate increases in lands for agricultural use, Figure 4. The data analysis demonstrated the following findings. The area occupied by the artificial surfaces demonstrated increase on 5.8 % (from 1567,77 to 1587,51 ha), which indicated urbanization. Areas covered by barren land showed decrease on 16% (178,7 to 148,03 ha), which indicates the intensification of constructions.

Key dynamics and drivers of land cover change in Italy include the following factors. First, urbanization is the most significant driver of land cover change, leading to the fragmentation of agricultural land and loss of coastal habitats. In Italy, urban areas are expanding, particularly in plains and along the coasts. This process negatively impacts biodiversity and ecological processes. On the other hand, we noted the processes of reforestation, which can be visible on the statistical graph showing the gradual increase in forest area, according to MODIS data, Figure 4. Thus, spontaneous reforestation is a major trend, particularly in mountainous regions like the Apennines.

In our previous work, we reported the issues of reforestation in Italy, which is often a result of rural depopulation and the abandonment of agricultural land, such as grasslands and open habitats in central regions of the country (Lemenkova, 2025a). In such cases, the rate of forest expansion in Italy is significant, with 25 years (since early 2000s) being enough for canopy closure of the forests in selected cases in the northern regions of the country, e.g., Trentino-Alto-Adige (South Tyrol).

Another important issue is related to climate warming which affects the glaciers and snow coverage in high Alps. The decrease in permanent areas covered by snow in glaciers on 34% (from 28,04 to 9.64 ha) indicated climate change and the rise in temperatures in recent decades. The increase in forest areas on 9% (from 12748,35 to 13937,72 ha) showed the positive processes of restoration of forests.

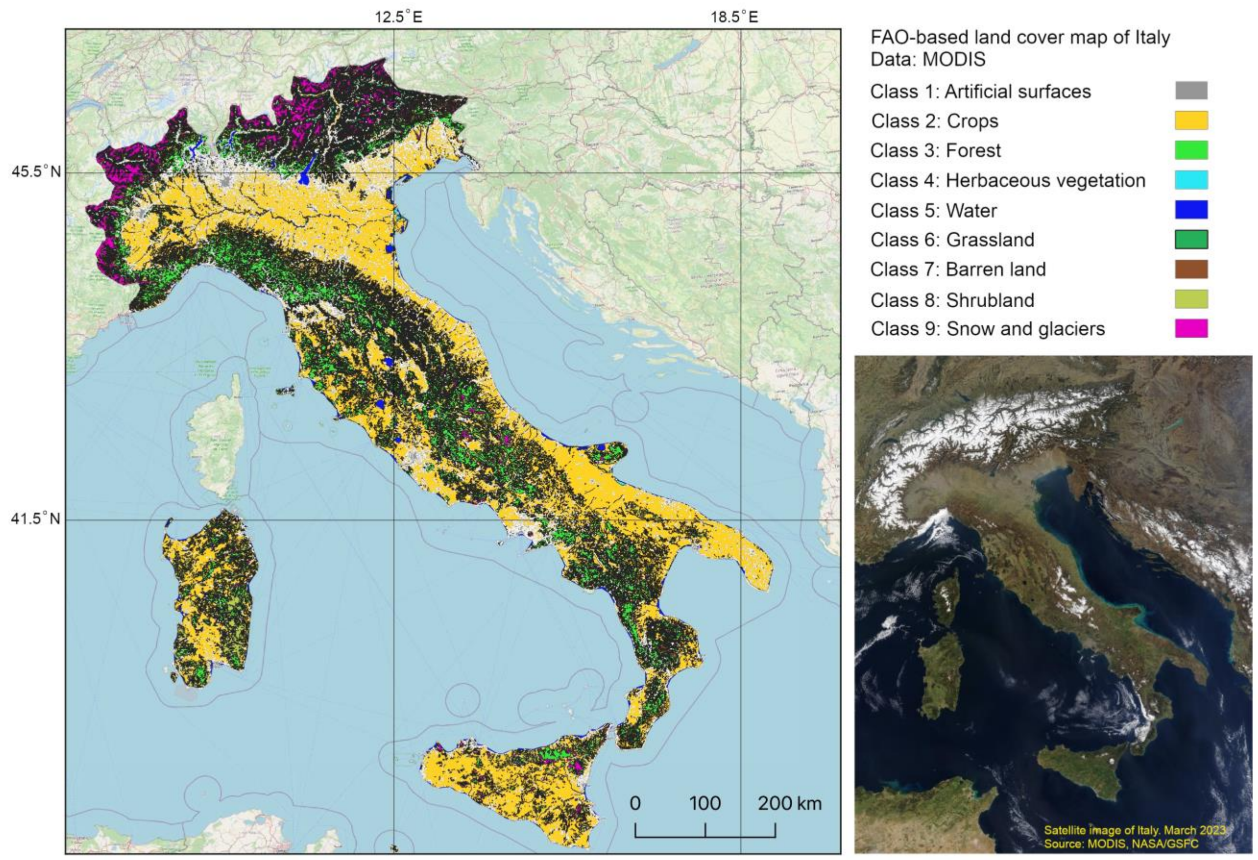


Figure 3. Reclassified CORINE-based land cover types in Italy using RS dataset MODIS. Map software: QGIS. Source: author

The agriculture activities experienced fluctuations from 12 % by 2015 (from 11859,17 to 10568,7 ha) following a stable increase during recent decade on 2 % by 2023 (10897,35 ha). Moreover, the analysis revealed that in some areas, particularly in the central Apennines, have seen a shift from barren land to agricultural land, caused by human activities like reclamation and irrigation. Such dynamics indicates recent intensification of agriculture activities and farming. A gradual increase in the land cover occupied by shrubland (by 21%, from 23.5 in 2001 to to 4,92 ha in 2023), herbaceous vegetation (drop by nearly 28%, from 284,73 ha to 201,67 ha in the same period) and fluctuations in grassland (by 3%, from 3220,95 to 3124,04 ha) illustrate positive dynamics in reforestation during recent two decades, according to MODIS, Figure 4. Land degradation, including the formation of quarries and salt-affected soils, has also been observed in certain areas of Italy, which is mostly related to human activities and land abandonment.

Such dynamics leads to a significant decrease in natural habitats such as forests and bare land which corresponds to the SDG. While the rate of net forest loss slowed regional increase between 1990 and 2015, the snow and glaciers have decreased which indicated the global warming and recent increase in temperature. Besides, urban sprawl has continued to accelerate due to population growth which is reflected in the increase of urban spaces (artificial surfaces).

Quantifying land cover changes in forest and dynamics in agricultural areas over long-time frame in consistent and reproducible way is necessary for ecological monitoring. This is possible using FAO statistics and comparative analysis of environmental variables.

The above-ground biomass in forest for the country experienced a slight increase from 95.2 in 2000, to 105.3 in 2010 and reached 110.6 t/ha in 2020 (FAO statistics). Such positive dynamics indicates the ongoing processes of regeneration and restoration of the forest areas in Italy.

Nevertheless, the dominating part of forest regeneration is taken by natural restoration rather than artificial plantations, Figure 5. Here, the share of naturally regenerated forest in Italy has the dominance over the planted forest for the period of 1990-2025.

The annual recession in forest area as change rate has also demonstrated positive dynamics in Italy. Thus, the detected changes of recession area from 0.76 % in 2010 to

0.58 % in 2020 (FAO statistics). Such values indicate the recession of forest cutting and, in contrast, regeneration of areas occupied by trees. It enables us to evaluate the proportion of forest area and crop areas with a long-term management plan for the sustainable development goals (SDG), Table 1.

According to recent FAO data on 2020 for Italy, the proportion of forest area within legally established protected areas and natural parks consists of 35.12 %, which indicates a positive dynamic compared to the value of 30.91 % in 2020 that corresponds to the SDG (FAO). Forest area that is covered by the independently verified forest management certification scheme has demonstrated positive dynamics with the increase up to 1044.66 T ha compared to the initial data on 14.32 in 2000 (FAO), Table 1.

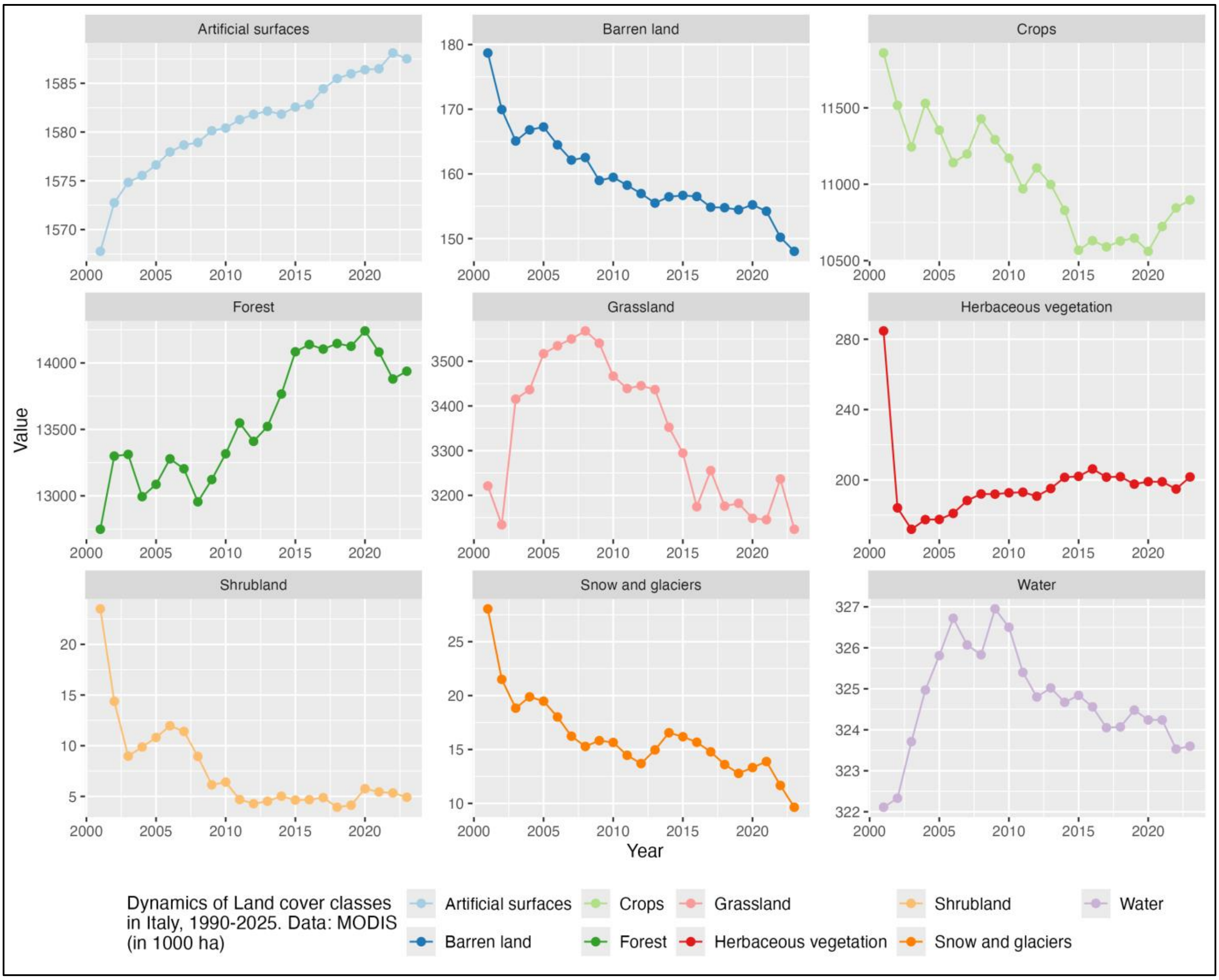


Figure 4. Dynamics of and cover classes in Italy (1000 ha), 1990-2025.RS data: MODIS. Sofware: R. Source: author.

Table 1. Forest indicators of Sustainable Development Goals (SDG) in Italy: FAOSTAT statistics.

Forest area as a share of total land area (%)							
2000	2010	2015	2016	2017	2018	2019	2020
28.3	30.53	31.44	31.62	31.8	31.98	32.17	32.35
Forest area under an independently verified forest management certification scheme (1000 ha)							
2000	2010	2015	2016	2017	2018	2019	2020
14.32	626.52	536.56	828.34	819.91	840.11	818.27	865.94
Forest area in 1000 ha							
2000	2010	2015	2016	2017	2018	2019	2020
8369.25	9028.04	9297.08	9350.89	9404.7	9458.51	9512.32	9566.13
Carbon stock in living biomass of forest							
2000	2010	2015	2016	2017	2018	2019	2020
496.3	593.14	614.59	620834	627078	633322	639566	645.81

The computational analysis and graphical output improved the understanding of the effects of climate drivers on LULC change and for assessments of environmental risks to climate change. We employed statistical data analysis allowing a characterization of the proportion of forests with regards to shares of human-based regenerated and naturally regenerated, Figure 5.

Forest land data were analysed based on the Forest Resource Assessment (FRA, 2025) data. These included the folloiwng categories covering Italy: ‘’Forest area’’ and ‘Carbon stock as below and above-ground biomass’. The area values were analysed for forest sub-category items, such as “Planted forest”, and “Naturally regenerating forest”. These categories were used as input to produce the corresponding plot showing dynamics for period 1990-2025, Figure 5.

The agricultural cropland per capita in Italy is ca. 0.18 ha per person (p/p), based on 2025 data. This value comes from dividing the total arable land of the country (6,601 T ha) by its population. The dynamics in data showing land share divided by all major land categories for country level is shown in Figure 6, and agriculture land share by sub-categories in Figure 7.

Explanatory modelling using combination of computing techniques and statistical data was performed through R-based statistical analysis for ecosystem modelling. We developed a framework to guide data analysis for detection and robust attribution of land cover changes in Italy using FAO statistics. Changes in land cover types were studied by comparison of data on several years (1990-2025).

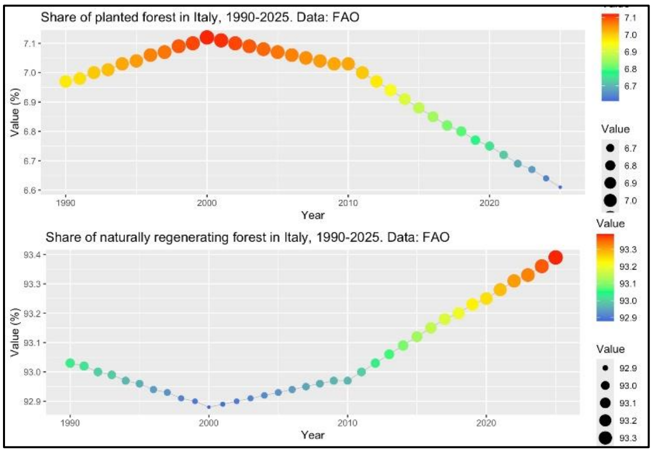


Figure 5. Forest regeneration in Italy, 1990-2025: share of planted forest and naturally regenerated forest. Software: R. Plot source: author.

The analysis of the agricultural land area (cropland) per capita in Italy (ha/person) is shown in Figure 8. It demonstrates trends in both land area (increase of the land occupied by croplands and arable lands and population change over time. Compared to the global average data (FAO Statistics), the situation in Italy shows positive trends in availability of arable land for population. Hence, the global average for agricultural cropland per capita is ca. 0.2 ha p/p, according to recent available data on 2021. This value has decreased falling by ca. 18% since 2000.

The FAO data were imported into an R environment for further post-processing. After defining the database and metadata structure, the tables were read in R using library(readr). As a result, the dataset presented an internally coherent, complementary and strongly interrelated project. Coherence stems from the common natural substrate of the three study areas located across different ecoregions.

A series of plots highlighted climate-environmental links, to produce plots of LULC dynamics as exposure to climate change. By interpreting graphs, we evaluated current situation in trends in agricultural sector of Italy and LULC dynamics in roughly 3 decades (1990-2025).

Complementarity of this research relates from the different expertise (GIS mapping, statistical analysis, RS data integration, data from FAO on agriculture, climate, socio-economic development and environment). The interrelation depends on the main expertise and applications of data analysis in forest, crop and agriculture. Besides, we applied techniques of scripts (Lemenkova, 2022b, 2024b) for data automation.

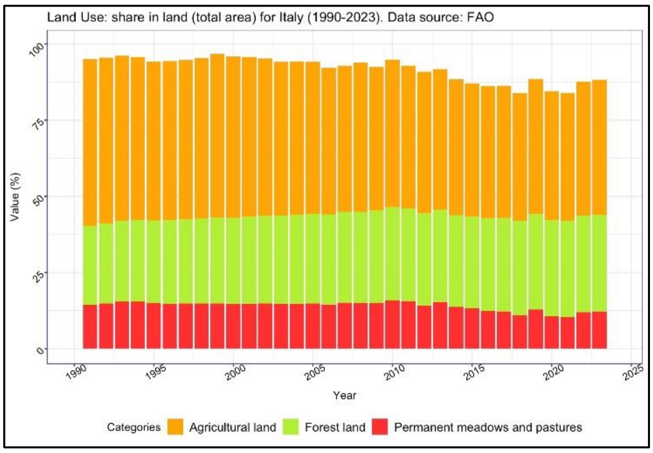


Figure 6. Land use trends in Italy (1990-2023): share by land categories). Software: R. Plot source: author.

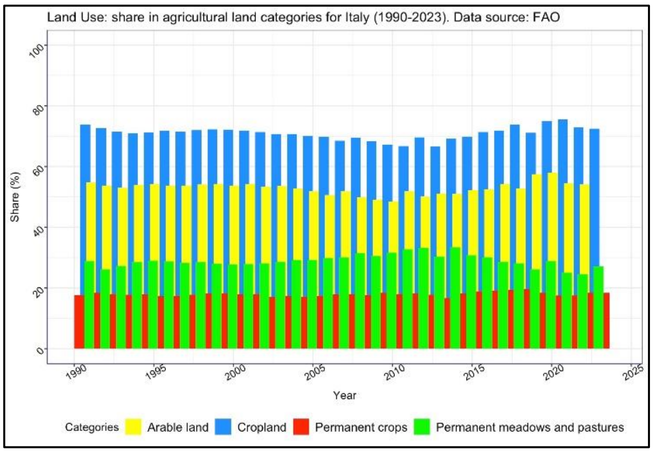


Figure 7. Land share by categories: agriculture land use in Italy (1990-2023). Software: R. Plot source: author.

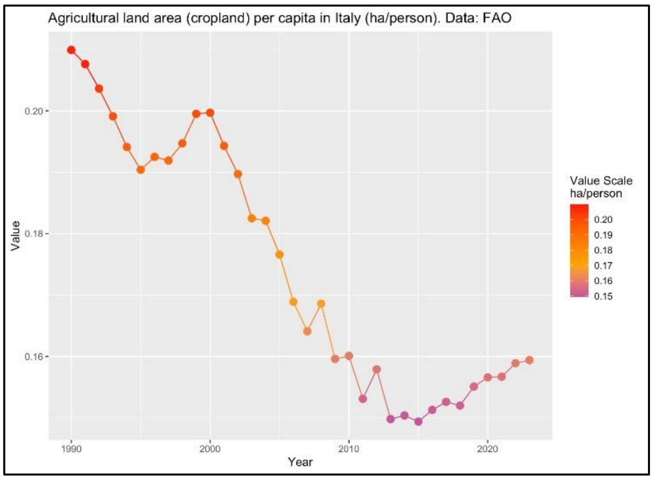


Figure 8. Agricultural land area (cropland) per capita in Italy (ha/person). Data: FAO. Software: R. Plot source: author.

Forest regeneration in Italy triggered profound changes. Many areas underwent a process of landscape restoration. These areas can be seen as a benchmark for assessing how nature regeneration performs in improving resilience of natural ecosystems and agriculture stability. Agriculture and environmental analysis was performed by R to effectively implement the qualitative aspects. The data were modelled using multiple statistical methods to highlight the links between environmental variables, climate and food availability. The correlations between variables (land use structure and changes) was modeled to highlight the effects of climate on land cover, we used FAO dataset on LULC.

This study achieved the following main conceptual and methodological advances, together with the relevance and technological readiness.

(a) Multi-temporal FAO-based database
(b) Statistical models by R integrating data.
(c) Qualitative-quantitative data analysis.

Quantitative modelling of FAO-based datasets was performed by R to interpret the long-term processes within forest stands (areas occupied by forests, carbon emissions, processes of regeneration).

Figure 8 shows the decrease in agricultural land area per capita reflects the effects of factors contributing to this trend. First of all, population growth naturally affects the share of the total cropland, which becomes smaller along with the increase of the population. As a result, a significant factor driving the per capita decrease. Second, cropland expansion explains that the changes in the rate of expansion has not kept pace with population growth. While the total global cropland area has expanded, the population growth has higher rate of increase which makes the allocation per person smaller. Third, the imbalance in cropland area per capita between different regions of Italy has increased due to the contrasting processes of urbanization on the one hand and intensification of agriculture on the other, particularly affecting developing rural regions of south of the country.

In contrast, value of agricultural production in Italy (Int. $) per area (USD_PPP/ha) demonstrated the increase in recent decades, Figure 9. This can be explained by the growing market value of land and the increase of value of the actual crops produced in Italy, both demonstrate the positive dynamics which proves the inclusion of smart technologies that enable to obtain more yield and optimize the agriculture activities. The increase in highly valuable production is notable for central regions with intensification of crop and type of farmland.

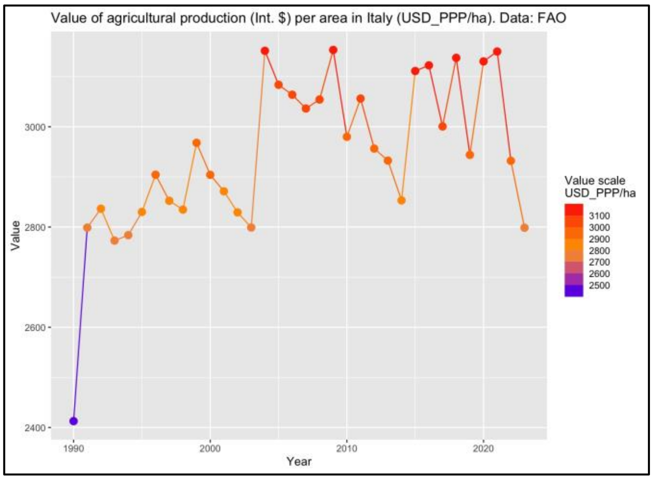


Figure 9. Value of agricultural production in Italy (Int. $) per area (USD_PPP/ha). Data: FAO. Software: R. Plot source: author.

For instance, Italy leads in EU agriculture value due to its diverse horticultural sector, where olives have high values making Italy as the second-largest global producer. Besides, specific crops grown in Italy for commercial value have a major impact. These include wine grapes, fruits, and vegetables (tomatoes), rice and wheat (in the southern regions). The value of agricultural production per area in Italy differs by region, influenced by climate, soil quality, and infrastructure that generally contrast for southern and northern regions of the country. Overall, Italy is one of the key countries for the EU agricultural production, Figure 9.

Figure 10 shows the dynamics in the degraded mountain land in Italy, which is primarily a result of the abandonment of traditional farming and forestry. The processes of restructuring in LULC and agriculture sector lead to a decline in landscape diversity and an increase in soil erosion. Besides, depopulation of mountain areas in the Apennines, Dolomites and higher Alps has caused a loss of traditional land management practices, such as terracing and chestnut orchards.

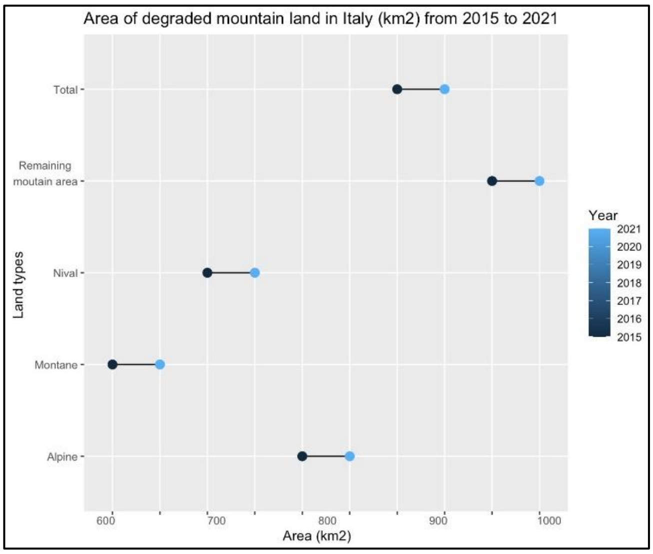


Figure 10. Dumbbell chart showing the area (km^2) of the degraded mountain land in Italy from 2015 to 2021 as discrete values by categories. Data: FAO. Software: R. Plot source: author.

Land degradation increased the risk of desertification, which is particularly notable in southern regions where the effects of climate warming accelerate these processes.

The demonstrated results provide the environmentalists with a clearer understanding of the socio-ecological and climate drivers in LULC of Italy. Data analysis supported by R improves the decision-making process for allocation of resources to protect habitat and detect trends in agriculture resources through a statistical approach to LULC processes, which internalizes uncertainties linked to global change. The statistical analysis by R enabled to reveal shares in LULC for the country level (Italy) and level-based hierarchical subdivisions as follows.

a) The components of forest and agriculture were analysed as parts of total shares for Italy.

b) The agriculture share was analysed as components (arable land, croplands, meadows and permanent crops).

c) The LULC shares were analysed as time series

d) The social-economic factor was analysed as financial revenues from agriculture and division of available agricultural land for population per capita.

R-based data analysis enabled us to highlight trends in nature protection and agriculture management. The outcomes of this study are applicable for professionals in agricultural production, food sustainability, land managers, nature protection and conservation practitioners. The presented a case study of R-based environmental data analysis are applicable in a diverse pool of environmental research areas where data processing and modelling are required. Therefore, this report can be leveraged for getting applications in environmental projects and data science.

4. Discussion

Influencing factors for land cover change in Italy include three major drivers: socio-economic, climate-environmental and regional geographic ones.

First, the socio-economic factors comprise the urbanization (Khachoo et al., 2023), policies on land ownership fragmentation, and agricultural intensification, which all play a role in land cover changes.

Second, the environmental factors combine climate change (Limoncella et al., 2025) which results in rise in temperature, water availability (Chiesa Turiano et al., 2025) and precipitation patterns that affect vegetation (Falanga Bolognesi et al., 2020). Another driving force is provided by geological hazards (landslides in the mountainous regions). The combination of these factors plays a crucial role in landscape dynamics with some areas showing warming and changes in precipitation patterns.

Third, regional differences of Italy are important factor, because the environment of this country is diversified with contrasting setting in the northern, central and southern regions. Here, the specific dynamics vary according to the regional setting. For example, southern Italy experiences soil erosion (Minervino Amodio, et al., 2023) and wildfire events during hot and dry summers (Parente et al., 2023), which can drastically alter land cover types, while central areas are more prone to occasional floods, and northern Italy experience melt of glaciers and snow in the Alps.

Here, we integrated geospatial and statistical data to evaluate recent land cover changes in Italy with focus on situation of forests. In this way, this paper contributed to analysis of forest, agriculture and environmental dynamics of Italy. Climate change and LULC have an intertwined nature and has consequences on Earth and inhabitants (Čavlović et al., 2012). Given its essential role for societal well-being and agriculture development, tackling these crises is important issue. To foster transformative change of the economic, social and environmental systems, it is necessary to better understand the consequences of global change on food security (Faz et al., 2025). This is possible using advanced research methods that integrate spatial analysis, statistical modelling, RS data and mapping.

In this study, we demonstrated such integration through combination of spatial visualization and statistical analysis. We showed the cartographic processing of environmental datasets and RS data and demonstrated the extraction from FAO repositories using R. that R libraries provide excellent possibilities for such analysis through diversity of modelling tools and embedded statistical algorithms. This study has shown the application of such techniques through R libraries (ggplot2 and others) to the environmental analysis of multi-format data from FAO.

Using the data from FAO on sustainable development, conservation, ecology, food management and LULC, we performed a study on eco-informatics and habitat interpretation using both statistical and geospatial analysis. Trends in food security and LULC dynamics in Italy were evaluated using FAO database through R-based data analysis, while landscape maps were presented based on RS data processed in GIS. With respect to the coherence with the forest recovery, this study highlights the need of balance between ecological protection, nature conservation, and agricultural development for food security.

5. Conclusions

5.1. Summary

This study integrated expertise in data science, R modelling, eco-informatics, agriculture and landscape ecology. Such multi-disciplinary aspects of this project are faced towards the land use science, and environmental modelling supported by R. The specific tasks implemented in this study are based on the interdisciplinary extension. To this end, the FAO-based statistical surveys investigated the LULC with climate change, evaluating correlations and modelling impacts and risks.

This study also monitored links between societal development, dynamics of forest and agriculture through the statistical data analysis (revenues from agriculture sector). In line with the strategy of agriculture development and nature protection, we contributed to enhancing measures on sustainable land management.

Besides the environmental aspects, we demonstrated the important technical aspect in data science. This study strengthens the capacity of R libraries and GIS for implementation of statistical and geospatial analysis of large datasets, such as FAO data, as an advanced and integrated tool for environmental monitoring systems.

5.2. Limitations

Possible limitations of this study may include the issues related to data collection, such as statistical data acquisition, geographic extent of the GIS layers, size and quality of the satellite images, availability of the cloudless RS data and statistical survey on the FAO repository. The lack of suitable data with required extent and parameters can significantly affect data-driven research. Hence, data availability is an important factor for research design.

Second, when selecting R libraries, the data should be checked for potential bias in surveys and social-economic analysis. The methodological limitations of GIS can also arise from the research design itself, such as mapping methods and limitations in GIS functionality. Hence, the selection of reliable methods improves the generalizability, validity, and replicability of the findings.

Third, integrated analysis that includes statistical data, RS images and GIS layers requires the development of the optimized stepwise workflow, as we demonstrated in this study. Nevertheless, possible constraints in similar research can be easily overcome through selection of robust data and methods. The dataset processed by the advanced methods improves the credibility and utility of the results to provide a framework for evaluating the outcomes.

5.3. Future directions

The approach of the research presented can be extended for future studies which can use its major benefits:

(I). It benchmarks the ecosystem-level effectiveness of forest restoration through R-based modelling, providing evidence of increase of tree-covered areas.

(ii). It brings clear methodological innovation by merging statistical modelling, qualitative data collection and LULC analysis in the climate-environmental context.

Similar research can develop environmental and agriculture analysis using multi-source data integration on other regions and territories. The next research can be performed at different scales of socio-ecological context, using diverse components computed from official FAO statistics and analysed for varied periods as time series.

Future studies can increase the knowledge of the environmental and agriculture dynamics in other countries. In this regard, this study presents the example of the multi-disciplinary analysis which can be followed up in similar studies. The developed framework of the environmental and statistical analysis can focus on the sustainability issues, agriculture and food security and climate change effects in diverse regions worldwide.

Author Contributions

Polina Lemenkova: Literature review, modeling, manuscript writing, editing, and analysis.

Conflict of Interest Statement

The author declares that there is no conflict of interest.

References

Allegrezza, M., Tesei, G., Francioni, M., Giovagnoli, D., Bianchini, M., & D'Ottavio, P. (2025). The Effects of Different Management Intensities on Biodiversity Conservation in the Wooded Grasslands of the Central Apennines. *Forests*, 16(7), 1034. https://doi.org/10.3390/f16071034

Altieri, M. A. (1999). The ecological role of biodiversity in agroecosystems. Agriculture, Ecosystems and Environment, 74(1–3), 19–31. https://doi.org/10.1016/S0167-8809(99)00028-6

Altieri, M. A., Nicholls, C. I., Henao, A., & Lana, M. A. (2015). Agroecology and the design of climate change-resilient farming systems. Agronomy for Sustainable Development, 35(3), 869–890. https://doi.org/10.1007/s13593-015-0285-2

Anđelković, A., & Radulović, S. (2022). The role of riparian areas in alien plant invasions. *Acta herbologica*, 31(2), 93-104. https://doi.org/10.5937/actaherb2202093A

Arcidiaco, L., & Corongiu, M. (2025). Analysis of LULC Change Dynamics That Have Occurred in Tuscany (Italy) Since 2007. Land, 14(3), 443. https://doi.org/10.3390/land14030443

Batáry, P., Dicks, L. V., Kleijn, D., & Sutherland, W. J. (2015). The role of agri-environment schemes in conservation and environmental management. Conservation Biology, 29(4), 1006–1016. https://doi.org/10.1111/cobi.12536

Baumer, B., Cetinkaya-Rundel, M., Bray, A., Loi, L., and Horton, N. J. (2014). R Markdown: Integrating a Reproducible Analysis Tool Into Introductory Statistics. *Technology Innovations in Statistics Education*, 8, 1–22. https://doi.org/10.5070/T581020118

Be, M. C., Randrianantenaina, A. S., Kanneh, J. E., Han, Y., Lei, Y., Zhi, X., Xiong, S., Jiao, Y., Shang, S., Ma, Y., Yang, B., Tao, L., & Li, Y. (2025). Comparative Analysis of Machine Learning Algorithms for Object-Based Crop Classification Using Multispectral Imagery. Drones, 9(11), 763. https://doi.org/10.3390/drones9110763

Boersema, J., Blowers, A., & Martin, A. (2009). Biodiversity loss, poverty and climate change: can one solution fit all? *Journal of Integrative Environmental Sciences*, 6(4), 239–245. https://doi.org/10.1080/19438150903432701

Buttrey, S. (2017). R Data, Part 2: More Complicated Structures. In A Data Scientist's Guide to Acquiring, Cleaning and Managing *Data in R*, S. Buttrey (Ed.). https://doi.org/10.1002/9781119080053.ch3

Cash, D., Clark, W., Alcock, F., Dickson, N. M., Eckley, N., Guston, D. H., Jäger, J., Mitchell, R. B. (2003). Knowledge systems for sustainable development. Proceedings of the National Academy of Sciences, 100, 8086–8091. https://doi.org/10.1073/pnas.1231332100

Čavlović, D., Obratov Petković, D., Ocokoljić, M., & Đurđević, V. (2012). Climate change impact on wetland forest plants of SNR Zasavica. *Glasnik Šumarskog fakulteta*, 105, 17-34. https://doi.org/10.2298/GSF1205017C

Chiesa Turiano, N., Tuninetti, M., Laio, F., & Ridolfi, L. (2025). Evaluating Country-Scale Irrigation Demand Through Parsimonious Agro-Hydrological Modeling. Hydrology, 12(9), 240. https://doi.org/10.3390/hydrology12090240

Coll, J., Bourke, D., Skeffington, M. S., Sweeney, J., & Gormally, M. (2011). Developing a predictive modelling capacity for a climate change-vulnerable blanket bog habitat: Assessing 1961–1990 baseline relationships. *Irish Geography*, 44(1), 27–60. https://doi.org/10.1080/00750778.2011.615165

Cosmulescu, S., Ștefănescu, D., & Stoenescu, A.-M. (2022). Variability of Phenological Behaviours of Wild Fruit Tree Species Based on Discriminant Analysis. *Plants*, 11(1), 45. https://doi.org/10.3390/plants11010045

Diaz-Chavez, R. (2025). Socio-Economic Assessment of the Agriculture Sector and the Bioeconomy in East Africa—A Gender-Focused Approach. *Agriculture*, *15*(18), 1933. https://doi.org/10.3390/agriculture15181933

Doré, T., Makowski, D., Malézieux, E., Munier-Jolain, N., Tchamitchian, M., & Tittonell, P. (2011). Facing up to the paradigm of ecological intensification in agronomy: Revisiting methods, concepts and knowledge. *European Journal of Agronomy*, 34(4), 197–210. https://doi.org/10.1016/j.eja.2011.02.006

Duggan, J. (2018). Input and output data analysis for system dynamics modelling using the tidyverse libraries of R. *System Dynamics Review*, 34: 438-461. https://doi.org/10.1002/sdr.1600

Duggan, J. (2019), Using R libraries to facilitate sensitivity analysis and to calibrate system dynamics models. *System Dynamics Review*, 35: 255-282. https://doi.org/10.1002/sdr.1638

FAO, 2025. FAOSTAT Land Use Statistics. FAO, Rome, Italy.

Falanga Bolognesi, S., Pasolli, E., Belfiore, O. R., De Michele, C., & D'Urso, G. (2020). Harmonized Landsat 8 and Sentinel-2 Time Series Data to Detect Irrigated Areas: An Application in Southern Italy. Remote Sensing, 12(8), 1275. https://doi.org/10.3390/rs12081275

Faz, A., Kabas, S., Zornoza, R., Martínez-Martínez, S., & Acosta, J. A. (2025). Multifunctional Greenway Approach for Landscape Planning and Reclamation of a Post-Mining District: Cartagena-La Unión, SE Spain. *Land*, 14(8), 1657. https://doi.org/10.3390/land14081657

Gliessman, S. (2022). Balancing nature and agriculture. *Agroecology and Sustainable Food Systems*, 46(2), 163–164. https://doi.org/10.1080/21683565.2022.2009171

Ghaderpour, E., Mazzanti, P., Bozzano, F., & Scarascia Mugnozza, G. (2024). Trend Analysis of MODIS Land Surface Temperature and Land Cover in Central Italy. Land, 13(6), 796. https://doi.org/10.3390/land13060796

Ghirardi, N., Pinardi, M., Nizzoli, D., Viaroli, P., & Bresciani, M. (2023). The Long-Term Detection of Suspended Particulate Matter Concentration and Water Colour in Gravel and Sand Pit Lakes through Landsat and Sentinel-2 Imagery. Remote Sensing, 15(23), 5564. https://doi.org/10.3390/rs15235564

Grupp, T., Mishra, P., Reynaert, M., & van Benthem, A. A. (2023). An evaluation of protected area policies in the European Union. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4665580

Hallett, L.M., Jones, S.K., MacDonald, A.A.M., Jones, M.B., Flynn, D.F.B., Ripplinger, J., Slaughter, P., Gries, C. and Collins, S.L. (2016), codyn: An r package of community dynamics metrics. *Methods in Ecology and Evolution*, 7: 1146-1151. https://doi.org/10.1111/2041-210X.12569

Jevtić, M., Gajić, T., & Vukolić, D. (2024). Theoretical review and literature analysis of the role of the environment in health tourism. *Turističko poslovanje*, 34, 69-79. https://doi.org/10.5937/turpos0-53295

Jiang, L., Zhang, J., Wang, S., Zhang, J., & Li, X. (2025). Spatiotemporal Dynamics of Eco-Environmental Quality and Driving Factors in China's Three-North Shelter Forest Program Using GEE and GIS. Sustainability, 17(17), 7698. https://doi.org/10.3390/su17177698

Kedward, K., Ryan-Collins, J., & Chenet, H. (2022). Biodiversity loss and climate change interactions: financial stability implications for central banks and financial supervisors. *Climate Policy,* 23(6), 763–781. https://doi.org/10.1080/14693062.2022.2107475

Kerkez Janković, I., Vilotić, D., Nonić, M., Maksimović, F., & Šijačić Nikolić, M. (2024). Genepool of woody species in the Strict Nature reserve "Felješana". *Sustainable Forestry: Collection*, 89-90, 1-15. https://doi.org/10.5937/SustFor2490001K

Keşanlı, Z., Dikmen Deliceırmak, F., & Seraj, M. (2025). The Impact of Technology, Economic Development, Environmental Quality, Safety, and Exchange Rate on the Tourism Performance in European Countries. *Sustainability*, 17(15), 7074. https://doi.org/10.3390/su17157074

Khachoo, Y. H., Cutugno, M., Robustelli, U., & Pugliano, G. (2023). Unveiling the Dynamics of Thermal Characteristics Related to LULC Changes via ANN. Sensors, 23(15), 7013. https://doi.org/10.3390/s23157013

Khachoo, Y. H., Cutugno, M., Robustelli, U., & Pugliano, G. (2024). Impact of Land Use and Land Cover (LULC) Changes on Carbon Stocks and Economic Implications in Calabria Using Google Earth Engine (GEE). Sensors, 24(17), 5836. https://doi.org/10.3390/s24175836

Klaučo, M., Gregorová, B., Stankov, U., Marković, V. & Lemenkova, P. (2013). Determination of ecological significance based on geostatistical assessment: A case study from the Slovak Natura 2000 protected area. *Open Geosciences*, 5(1), 28-42. https://doi.org/10.2478/s13533-012-0120-0

Klaučo, M., Gregorová, B., Koleda, P., Stankov, U., Marković, V. & Lemenkova, P. (2017). Land planning as a support for sustainable development based on tourism: A case study of Slovak rural region. *Environmental Engineering and Management Journal*, 16(2), 449-458. https://doi.org/10.30638/eemj.2017.045

Lam, O. H. Y., Kattge, J., Tautenhahn, S., Boenisch, G., Kovach, K. R., & Townsend, P. A. (2024). 'rtry': An R package to support plant trait data preprocessing. Ecology and Evolution, 14, e11292. https://doi.org/10.1002/ece3.11292

Lausch, A., Bumberger, J., Jung, A., Pause, M., Selsam, P., Zhou, T., & Herzog, F. (2025). Monitoring Agricultural Land Use Intensity with Remote Sensing and Traits. *Agriculture*, *15*(21), 2233. https://doi.org/10.3390/agriculture15212233

Lemenkova, P. (2019a). Statistical analysis of the Mariana Trench geomorphology using R programming language. Geodesy and Cartography, 45(2), 57-84. https://doi.org/10.3846/gac.2019.3785

Lemenkova, P. (2019b). Testing Linear Regressions by StatsModel Library of Python for Oceanological Data Interpretation. Aquatic Sciences and Engineering, 34(2), 51-60. https://doi.org/10.26650/ASE2019547010

Lemenkova, P. (2022a). Evapotranspiration, vapour pressure and climatic water deficit in Ethiopia mapped using GMT and TerraClimate dataset. Journal of Water and Land Development, 54(7-9), 201--209. https://doi.org/10.24425/jwld.2022.141573

Lemenkova, P. (2022b). Command-Line Cartographic Data Processing for Geophysical Plotting of Rwanda Using GMT and R Scripts. Romanian Journal of Physics, 67(7-8), 1-21. https://doi.org/10.5281/zenodo.7113414

Lemenkova, P. (2024a). Artificial Intelligence for Computational Remote Sensing: Quantifying Patterns of Land Cover Types around Cheetham Wetlands, Port Phillip Bay, Australia. Journal of Marine Science and Engineering, 12(8), 1279. https://doi.org/10.3390/jmse12081279

Lemenkova, P. (2024b). Support Vector Machine Algorithm for Mapping Land Cover Dynamics in Senegal, West Africa, Using Earth Observation Data. *Earth*, *5*(3), 420-462. https://doi.org/10.3390/earth5030024

Lemenkova, P. (2025a). Gathering predictors of biodiversity change and reconstructing land cover history in Central Apennines using machine learning and remote sensing data. *Journal of Anatolian Geography*, 2(1), 36-47. https://doi.org/10.5281/zenodo.15767237

Lemenkova, P. (2025b). Machine Learning Algorithms of Remote Sensing Data Processing for Mapping Changes in Land Cover Types over Central Apennines, Italy. *Journal of Imaging*, 11(5), 153. https://doi.org/10.3390/jimaging11050153

Lemenkova, P. (2025c). On forest hydrology in South Tyrol: Processes, modelling and assessment. *Agriculture and Forestry*, 71(2), 7-22. https://doi.org/10.17707/AgricultForest.71.2.01

Li, K.-Y., Sampaio de Lima, R., Burnside, N. G., Vahtmäe, E., Kutser, T., Sepp, K., Cabral Pinheiro, V. H., Yang, M.-D., Vain, A., & Sepp, K. (2022a). Toward Automated Machine Learning-Based Hyperspectral Image Analysis in Crop Yield and Biomass Estimation. Remote Sensing, 14(5), 1114. https://doi.org/10.3390/rs14051114

Li, P., Xiao, C., & Feng, Z. (2022b). Swidden agriculture in transition and its roles in tropical forest loss and industrial plantation expansion. *Land Degradation & Development*, 33(2), 388–392. https://doi.org/10.1002/ldr.4152

Li, Q., Geng, Y., Fu, S., Zhang, Y., & Zhang, J. (2025a). How to Recognize and Measure the Driving Forces of Tourism Ecological Security: A Case Study from Zhangjiajie Scenic Area in China. *Land*, *14*(9), 1733. https://doi.org/10.3390/land14091733

Li, L., Feng, Y., He, J., Yang, Z., & He, Y. (2025b). Spatio-Temporal Evolution of Land Use and Carbon Stock Under Multiple Scenarios Based on the PLUS-InVEST Model: A Case Study of Chengdu. Sustainability, 17(21), 9903. https://doi.org/10.3390/su17219903

Limoncella, G., Feurer, D., Roye, D., de Hoogh, K., de la Cruz, A., Gasparrini, A., Schneider, R., Pirotti, F., Catelan, D., Stafoggia, M., de'Donato, F., Biscardi, G., Marzi, C., Baccini, M., & Sera, F. (2025). A Machine Learning Model Integrating Remote Sensing, Ground Station, and Geospatial Data to Predict Fine-Resolution Daily Air Temperature for Tuscany, Italy. Remote Sensing, 17(17), 3052. https://doi.org/10.3390/rs17173052

Longo-Minnolo, G., Consoli, S., & Tessitori, M. (2025). Evaluation of the Impact of Climate Change on *Fagus sylvatica Dieback*—A Combined Approach with ERA5-

Land Data and Landsat Imagery. Remote Sensing, 17(5), 873. https://doi.org/10.3390/rs17050873

Marino, D., Barone, A., Marucci, A., Pili, S., & Palmieri, M. (2023). Impact of Land Use Changes on Ecosystem Services Supply: A Meta Analysis of the Italian Context. Land, 12(12), 2173. https://doi.org/10.3390/land12122173

Marković, D., & Marković, S. (2012). The influence of different land uses on biodiversity. *Agroznanje*, 13(2), 309-316. https://doi.org/10.7251/AGRSR1202309M

Masini, P., Salerno, G., Rebora, M., Lupi, D., Colombo, W. D., & Azevedo, C. O. (2025). Molecular and Morphological Analyses for Delimiting Species Boundaries: The Case of Sclerodermus cereicollis Kieffer, 1904 (Hymenoptera: Bethylidae). *Diversity*, 17(9), 611. https://doi.org/10.3390/d17090611

Minervino Amodio, A., Gioia, D., Danese, M., Masini, N., & Sabia, C. A. (2023). Land-Use Change Effects on Soil Erosion: The Case of Roman "Via Herculia" (Southern Italy)—Combining Historical Maps, Aerial Images and Soil Erosion Model. Sustainability, 15(12), 9479. https://doi.org/10.3390/su15129479

Morini, P., Pinchera, F. P., Nucci, L. M., Ferlini, F., Cecala, S., Di Nino, O., & Penteriani, V. (2016). Brown bears in Central Italy: a 15-year study on bear occurrence. *The European Zoological Journal*, 84(1), 26–33. https://doi.org/10.1080/11250003.2016.1261190

Oldfather, M. F., Ennis, A., Miller, B. W., Clark-Wolf, K., Rangwala, I., Robe, H., & Littlefield, C. (2025). Climate change impacts and adaptation in U.S. Rocky Mountain high-elevation ecosystems. *Arctic, Antarctic, and Alpine Research*, *57*(1). https://doi.org/10.1080/15230430.2025.2450089

Parente, J., Tonini, M., Stamou, Z., Koutsias, N., & Pereira, M. (2023). Quantitative Assessment of the Relationship between Land Use/Land Cover Changes and Wildfires in Southern Europe. Fire, 6(5), 198. https://doi.org/10.3390/fire6050198

Pellegrino, D., Schirpke, U., & Marino, D. (2016). How to support the effective management of Natura 2000 sites? *Journal of Environmental Planning and Management*, 60(3), 383–398. https://doi.org/10.1080/09640568.2016.1159183

Peng, Z., Han, H., & Ma, J. (2025a). Research on a Short-Term Electric Load Forecasting Model Based on Improved BWO-Optimized Dilated BiGRU. Sustainability, 17(21), 9746. https://doi.org/10.3390/su17219746

Peng, W., Zhu, Z., Liu, J., Lin, Y., Zhao, Q., Yang, W., Wu, C., & Cai, W. (2025b). An Adaptive Management-Oriented Approach to Spatial Planning for Estuary National Parks: A Case Study of the Yangtze River Estuary, China. *Water*, *17*(20), 3002. https://doi.org/10.3390/w17203002

Popov, D. (2014). Protection, landscaping and regulation of agricultural land in Serbia. *Zbornik radova Pravnog fakulteta, Novi Sad*, *48*(3), 67-80. https://doi.org/10.5937/zrpfns48-7247

Prigioni, C., Balestrieri, A., Remonti, L., & Cavada, L. (2008). Differential use of food and habitat by sympatric carnivores in the eastern Italian Alps. *Italian Journal of Zoology*, 75(2), 173–184. https://doi.org/10.1080/11250000701885521

Pu, M., Yang, S., Chen, A., & Deng, Z. (2025). Research on Forest Carbon Sequestration and Its Economic Valuation: A Case Study of the Zixi Mountain Nature Reserve, Chuxiong Prefecture. Plants, 14(17), 2746. https://doi.org/10.3390/plants14172746

Pugh, T. A., Lindeskog, M., Smith, B., Abel, C., & Arneth, A. (2019). Role of forest regrowth in global carbon sink dynamics. Proceedings of the National Academy of Sciences (PNAS), 116(10), 4382–4387. https://doi.org/10.1073/pnas.1810512116

R Core Team (2021). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing. Vienna, Austria. https://www.R-project.org/

Raia, P. (2004). Morphological correlates of tough food consumption in large land carnivores. *Italian Journal of Zoology*, 71(1), 45–50. https://doi.org/10.1080/11250000409356549

Runhaar, H. (2017). Governing the transformation towards 'nature-inclusive' agriculture: insights from the Netherlands. *International Journal of Agricultural Sustainability*, 15(4), 340–349. https://doi.org/10.1080/14735903.2017.1312096

Sayn-Wittgenstein, F., de Mariz, F., & Leijonhufvud, C. (2025). Nature Finance: Bridging Natural and Financial Capital Through Robust Impact Measurement. *Risks*, 13(11), 213. https://doi.org/10.3390/risks13110213

Schlagloth, R., Santamaria, F., Cadman, T., McEwan, A., Danaher, M., McGinnis, G., Clark, I. D., Cahir, F., Cadman, S., & Dell, M. (2025). Community and Scientists Work Together to Identify Koalas Within the Plantations Inside the Proposed Great Koala National Park in New South Wales, Australia. *Wild*, *2*(4), 42. https://doi.org/10.3390/wild2040042

Schwalb-Willmann, J., Remelgado, R., Safi, K., Wegmann, M. (2020). moveVis: Animating movement trajectories in synchronicity with static or temporally dynamic environmental data in r. *Methods in Ecology and Evolution,* 11: 664–669. https://doi.org/10.1111/2041-210X.13374

Shi, S., Xu, S., & Meng, Z. (2025). Ecosystem Service Value Dynamics in the Yellow River Delta National Nature Reserve, China: Conservation Implications from Two Decades of Change. *Sustainability*, 17(20), 9291. https://doi.org/10.3390/su17209291

Stamou, A., Bakousi, A., Dosiou, A., Tsifodimou, Z.-E., Karachaliou, E., Tavantzis, I., & Stylianidis, E. (2025). Mapping Drought Incidents in the Mediterranean Region with Remote Sensing: A Step Toward Climate Adaptation. *Land*, 14(8), 1564. https://doi.org/10.3390/land14081564

Theobold, A. S., Hancock, S. A., & Mannheimer, S. (2021). Designing Data Science Workshops for Data-Intensive Environmental Science Research. *Journal of Statistics and Data Science Education*, *29*(sup1), S83–S94. https://doi.org/10.1080/10691898.2020.1854636

Thompson, M.S.A., Brooks, S.J., Sayer, C.D., et al. (2018). Large woody debris "rewilding" rapidly restores biodiversity in riverine food webs. *Journal of Applied Ecology,*; 55: 895–904. https://doi.org/10.1111/1365-2664.13013

Tompolidi, A.-M., Mantovani, L., Frigeri, A., & Nazzareni, S. (2025). Remote Sensing Applications for Geological Mapping in the Mediterranean Region: A Review. Geosciences, 15(11), 425. https://doi.org/10.3390/geosciences15110425

Turconi, L., Bono, B., Mambriani, C., Masotti, L., Stocchi, F., & Luino, F. (2025). Natural and Anthropic Constraints on Historical Morphological Dynamics in the Middle Stretch of the Po River (Northern Italy). *Sustainability*, 17(14), 6608. https://doi.org/10.3390/su17146608

Wickham, H. (2016). *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. ISBN 978-3-319-24277-4, https://ggplot2.tidyverse.org

Wu, N., Guo, K., Zou, Y., He, F., & Riis, T. (2023). SER: An R package to characterize environmental regimes. *Ecology and Evolution*, 13, e9882. https://doi.org/10.1002/ece3.9882

Yuan, B., Li, Y., & Yao, Z. (2025). The Habitat Fragmentation and Suitability Evaluation of Mrs Hume's Pheasant

Syrmaticus humiae in Northwestern Guangxi, China. *Biology*, *14*(10), 1345. https://doi.org/10.3390/biology14101345

Zolotnytska, Y., Kowalczyk, S., Sobiecki, R., Krupin, V., Krzyżanowski, J., Perkowska, A., & Żurakowska-Sawa, J. (2025). Drivers of Global Wheat and Corn Price Dynamics: Implications for Sustainable Food Systems. *Sustainability*, *17*(19), 8581. https://doi.org/10.3390/su17198581