Università degli Studi della Basilicata

SCUOLA DI INGEGNERIA

Dottorato di ricerca in

Ingegneria per l'innovazione e lo sviluppo sostenibile

Curriculum metodi e tecnologie per il monitoraggio e la tutela ambientale

Titolo della tesi:

SPATIAL ANALYSES AND REMOTE SENSING FOR LAND COVER CHANGE DYNAMICS: ASSESSING IN A SPATIAL PLANNING

ICAR/20

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Sommario

ABSTRACT (EN)

Spatial planning is a crucial discipline for the identification and implementation of sustainable development strategies that take into account the environmental impacts on the soil. In recent years, the significant development of technology, like remote sensing and GIS software, has significantly increased the understanding of environmental components, highlighting their peculiarities and criticalities. Geographically referenced information on environmental and socio-economic components represents a fundamental database for identifying and monitoring vulnerable areas, also distinguishing different levels of vulnerability. This is even more relevant considering the increasingly significant impact of land transformation processes, consisting of rapid and frequent changes in land use patterns. In order to achieve some of the Sustainable Development Goals of the 2030 Agenda, the role of environmental planning is crucial in addressing spatial problems, such as agricultural land abandonment and land take, which cause negative impacts on ecosystems. Remote sensing, and in general all Earth Observation techniques, play a key role in achieving SDG 11.3 and 15.3 of Agenda 2030. Through a series of applications and investigations in different areas of Basilicata, it has been demonstrated how the extensive use of remote sensing and spatial analysis in a GIS environment provide a substantial contribution to the results of the SDGs, enabling an informed decision-making process and enabling monitoring of the results expected, ensuring data reliability and directly contributing to the calculation of SDG objectives and indicators by facilitating local administrations approaches to work in different development and sustainability sectors. In this thesis have been analyse the dynamics of land transformation in terms of land take and soil erosion in sample areas of the Basilicata Region, which represents an interesting case example for the study of land use land cover change (LULCC). The socio-demographic evolutionary trends and the study of marginality and territorial fragility are fundamental aspects in the context of territorial planning, since they are important drivers of the LULCC and territorial transformation processes. In fact, in Basilicata, settlement dynamics over the years have occurred in an uncontrolled and unregulated manner, leading to a constant consumption of land not accompanied by adequate demographic and economic growth. To better understand the evolution and dynamics of the LULCCs and provide useful tools for formulating territorial planning policies and strategies aimed at a sustainable use of the territory, the socio-economic aspects of the Region were investigated. A first phase involved the creation of a database and the study and identification of essential services in the area as a fundamental parameter against which to evaluate the quality of life in a specific area. The supply of essential services can be understood as an assessment of the lack of minimum requirements with reference to the urban functions exercised by each territorial unit. From a territorial point of view, the level of peripherality of the territories with respect to the network of urban centres profoundly influences the quality of life of citizens and the level of social inclusion. In these, the presence of essential services can act as an attractor capable of generating discrete catchment areas. The purpose of this first part of the work was above all to create a dataset of data useful for the calculation of various socio-economic indicators, in order to frame the demographic evolution and the evolution of the stock of public and private services. The first methodological approach was to reconstruct the offer of essential services through the use of open data in a GIS environment and subsequently estimate the peripherality of each municipality by estimating the accessibility to essential services. The study envisaged the use of territorial analysis techniques aimed at describing the distribution of essential services on the regional territory. It is essential to understand the role of demographic dynamics as a driver of urban land use change such as, for example, the increase in demand for artificial surfaces that occurs locally. Social and economic analyses are important in the spatial planning process. Comparison of

socio-economic analyses with land use and land cover change can highlight the need to modify existing policies or implement new ones. A particular land use can degrade and thereby destroy other land resources. If the economic analysis shows that the use is beneficial from the point of view of the land user, it is likely to continue, regardless of whether the process is environmentally friendly. It is important to understand and investigate which drivers have been and will be in the future the most decisive in these dynamics that intrinsically contribute to land take, agricultural abandonment and the consequent processes of land degradation and to define policies or thresholds to mitigate and monitor the effects of these processes.
Subsequently, the issues of land take and abandonment of agricultural land were analysed by applying models and techniques of remote sensing, GIS and territorial analysis for the identification and monitoring of abandoned agricultural areas and sealed areas. The classic remote sensing methods have also been integrated by some geostatistical analyses which have provided more information on the investigated phenomenon. The aim was the creation of a quick methodology that would allow to describe the monitoring and analysis activities of the development trends of soil consumption and the monitoring and identification of degraded areas. The first methodology proposed allowed the automatic and rapid detection of detailed LULCC and Land Take maps with an overall accuracy of more than 90%, reducing costs and processing times. The identification of abandoned agricultural areas in degradation is among the most complicated LULCC and Land Degradation processes to identify and monitor as it is driven by a multiplicity of anthropic and natural factors. The model used to estimate soil erosion as a degradation phenomenon is the Revised Universal Soil Loss Equation (RUSLE). To identify potentially degraded areas, two factors of the RUSLE have been correlated: Factor C which describes the vegetation cover of the soil and Factor A which represents the amount of potential soil erosion. Through statistical correlation analysis with the RUSLE factors, on the basis of the deviations from the average RUSLE values and mapping of the areas of vegetation degradation, relating to arable land, through statistical correlation with the vegetation factor C, the areas were identified and mapped that are susceptible to soil degradation. The results obtained allowed the creation of a database and a map of the degraded areas to be paid attention to.

ABSTRACT (IT)

La pianificazione territoriale è una disciplina cruciale per l'identificazione e l'attuazione di strategie di sviluppo sostenibile che tiene conto degli impatti ambientali sul suolo. La pianificazione territoriale è una disciplina cruciale per l'identificazione e l'attuazione di strategie di sviluppo sostenibile che tengano conto degli impatti ambientali sul suolo. Negli ultimi anni il notevole sviluppo tecnologico, come il telerilevamento e software GIS, ha notevolmente aumentato la comprensione delle componenti ambientali, evidenziandone le peculiarità e le criticità. Le informazioni georeferenziate sulle componenti ambientali e socio-economiche rappresentano un database fondamentale per l'identificazione e il monitoraggio delle aree vulnerabili, distinguendo anche diversi livelli di vulnerabilità. Ciò è ancora più rilevante se si considera l'impatto sempre più significativo dei processi di trasformazione del suolo, costituiti da rapidi e frequenti cambiamenti nei modelli di uso del suolo. Al fine di raggiungere alcuni degli Obiettivi di Sviluppo Sostenibile dell'Agenda 2030, il ruolo della pianificazione ambientale è cruciale nell'affrontare i problemi territoriali, come l'abbandono dei terreni agricoli e il consumo di suolo, che causano impatti negativi sugli ecosistemi. Il telerilevamento, e in generale tutte le tecniche di Osservazione della Terra, giocano un ruolo chiave nel raggiungimento degli SDG 11.3 e 15.3 dell'Agenda 2030. Attraverso una serie di applicazioni e indagini in diverse aree della Basilicata è

stato dimostrato come l'ampio utilizzo del telerilevamento e l'analisi spaziale in ambiente GIS fornisce un contributo sostanziale per il raggiungimento degli Obiettivi SDG dell'Agenda 2030 consentendo un processo decisionale informato, migliorando l'accuratezza dei dati, garantendo l'affidabilità dei dati e contribuendo direttamente al calcolo degli obiettivi e degli indicatori SDG, facilitando, infine, gli approcci delle amministrazioni locali a lavorare in diversi settori di sviluppo e sostenibilità. In questa tesi sono state analizzate le dinamiche di trasformazione del suolo in termini di consumo di suolo ed erosione del suolo in aree campione della regione Basilicata, che rappresenta un interessante caso esemplificativo per lo studio del cambiamento di uso del suolo (LULCC). I trend evolutivi socio-demografici e lo studio della marginalità e della fragilità territoriale sono aspetti fondamentali nell'ambito della pianificazione territoriale, in quanto importanti driver dei LULCC e dei processi di trasformazione del territorio. In Basilicata, infatti, le dinamiche insediative nel corso degli anni sono avvenute in maniera incontrollata e non regolamentata, determinando un costante consumo di suolo non accompagnato da un'adeguata crescita demografica ed economica. Per meglio comprendere l'evoluzione e le dinamiche dei LULCC e fornire strumenti utili per formulare politiche e strategie di pianificazione territoriale finalizzate ad un uso sostenibile del territorio, sono stati indagati gli aspetti socio-economici della Regione. Una prima fase ha riguardato la creazione di una banca dati e lo studio e l'individuazione dei servizi essenziali sul territorio come parametro fondamentale rispetto al quale valutare la qualità della vita in un determinato territorio. L'erogazione dei servizi essenziali può essere intesa come una valutazione della mancanza dei requisiti minimi con riferimento alle funzioni urbane esercitate da ciascuna unità territoriale. Dal punto di vista territoriale, il livello di perifericità dei territori rispetto alla rete dei centri urbani influenza profondamente la qualità della vita dei cittadini e il livello di inclusione sociale. In questi la presenza di servizi essenziali può fungere da attrattore in grado di generare bacini discreti. Lo scopo di questa prima parte del lavoro è stato soprattutto quello di creare un dataset di dati utili al calcolo di diversi indicatori socio-economici, al fine di inquadrare l'evoluzione demografica e l'evoluzione dello stock di servizi pubblici e privati. Il primo approccio metodologico è stato quello di ricostruire l'offerta dei servizi essenziali attraverso l'utilizzo di dati aperti in ambiente GIS e successivamente stimare la perifericità di ciascun comune stimando l'accessibilità ai servizi essenziali. Lo studio ha previsto l'utilizzo di tecniche di analisi territoriale volte a descrivere la distribuzione dei servizi essenziali sul territorio regionale. È essenziale comprendere il ruolo delle dinamiche demografiche come motore del cambiamento dell'uso del suolo urbano come, ad esempio, l'aumento della domanda di superfici artificiali che si verifica a livello locale. Le analisi sociali ed economiche sono importanti nel processo di pianificazione territoriale. Il confronto delle analisi socio-economiche con l'uso del suolo e il cambiamento della copertura del suolo può evidenziare la necessità di modificare le politiche esistenti o implementarne di nuove. Un particolare uso del suolo può degradare e quindi distruggere altre risorse del suolo. Se l'analisi economica mostra che l'uso è vantaggioso dal punto di vista dell'utilizzatore del suolo, è probabile che continui, indipendentemente dal fatto che il processo sia rispettoso dell'ambiente. È importante comprendere e indagare quali driver sono stati e saranno in futuro i più determinanti in queste dinamiche che contribuiscono intrinsecamente al consumo di suolo, all'abbandono agricolo e ai conseguenti processi di degrado del suolo e definire politiche o soglie per mitigare e monitorare il effetti di questi processi.

Successivamente sono stati analizzati i temi del consumo di suolo e dell'abbandono dei terreni agricoli applicando modelli e tecniche di telerilevamento, GIS e analisi territoriali per l'individuazione e il monitoraggio delle aree agricole abbandonate e delle aree impermeabilizzate. I classici metodi di telerilevamento sono stati integrati anche da alcune analisi geostatistiche che hanno fornito maggiori informazioni sul fenomeno indagato. L'obiettivo era la creazione di una metodologia veloce che permettesse di descrivere le attività di monitoraggio e analisi dei trend di sviluppo del consumo di suolo e il monitoraggio

e l'identificazione delle aree degradate. La prima metodologia proposta ha consentito il rilevamento automatico e rapido di mappe LULCC e Land Take dettagliate con un'accuratezza complessiva superiore al 90%, riducendo costi e tempi di elaborazione.
L'identificazione delle aree agricole abbandonate in degrado è tra i processi di LULCC e Land Degradation più complicati da identificare e monitorare in quanto guidato da una molteplicità di fattori antropici e naturali. Il modello utilizzato per stimare l'erosione del suolo come fenomeno di degrado è la Revised Universal Soil Loss Equation (RUSLE). Per identificare le aree potenzialmente degradate, sono stati correlati due fattori del RUSLE: il Fattore C che descrive la copertura vegetale del suolo e il Fattore A che rappresenta l'entità della potenziale erosione del suolo. Mediante analisi statistica di correlazione con i fattori RUSLE, sulla base degli scostamenti dai valori medi di RUSLE e mappatura delle aree di degrado vegetazionale, relative ai seminativi, mediante correlazione statistica con il fattore vegetativo C, sono state individuate e mappate le aree che sono suscettibili al degrado del suolo. I risultati ottenuti hanno consentito la creazione di una banca dati delle aree degradate da attenzionare.

Foreword

1.1 Introduction

In last decades, due to the growth of the global population and the rapid development of urbanization, a significant proportion of rural regions are being transformed into urban areas, leading to an increment in land take[1–3]. The population moves from rural areas to cities, equipped with more services and opportunities, as stated in the World Urbanization Prospects, "the percentage of the world's population living in urban areas is expected to increase, reaching 66% by 2050” [4]. As a result, the land rush for the expansion of urban areas and the resulting land consumption and abandonment of agricultural areas has emerged as a critical problem in recent decades. The United Nations’ adoption of the 17 sustainable development goals (SDGs), under the 2030 Agenda for Sustainable Development, urged the scientific community to generate sound information with the aim of supporting planning and monitoring of socioeconomic development interlinking with environmental sustainability dimensions [5–9]. SDGs 11 and 15 refer to targets which commend direct consideration of land resources.

In particular SDG 11.3 refers to one of the goals of Sustainable Development Goal 11, which focuses on making cities and human settlements more sustainable. The specific goal of SDG 11.3 is to improve urbanization and make it sustainable by 2030 [5]. In other words, this goal aims to ensure that urban areas are developed in a sustainable, inclusive and participatory way, counteracting land take[1,10,11]. This includes efforts to reduce urban sprawl, improve access to basic services, and ensure that urban planning takes into account the needs and perspectives of all community members. This includes efforts to reduce urban sprawl, improve access to basic services, and ensure that urban planning takes into account the needs and perspectives of all community members.

SDG 15.3 refers to the third target under Sustainable Development Goal 15, which aims to protect, restore, and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, halt and reverse land degradation, and halt biodiversity loss [5,7,8,12]. This target recognizes the importance of protecting and restoring terrestrial ecosystems and halting land degradation, which are essential for achieving sustainable development and addressing climate change. The target calls for efforts to combat desertification, restore degraded land and soil, and achieve a land degradation-neutral world, where the amount of degraded land is balanced by an equal or greater amount of land that is restored or improved. To achieve this target, actions should focus on preventing and reversing land degradation, improving soil health and fertility, promoting sustainable land use and management practices, enhancing resilience to drought and other natural disasters, and supporting sustainable livelihoods for local communities. This will require coordinated efforts at all levels, from local communities to national governments and international organizations, and the participation of all stakeholders, including local communities, landowners, governments, civil society, and the private sector. Mainly the methods of evaluation and monitoring of land take and the neutrality of land degradation, for the achievement of the SDGs, provide for a multidisciplinary analysis approach which involves the use of territorial indicators and analyses.

The monitoring of the SDGs can be disaggregated into different aspects: study of urban sprawl, land consumption and abandonment of agricultural areas, soil degradation and land transformation dynamics, and socio-demographic dynamics. For the aspects concerning the Land Use Land Cover Change (LULCC), the use of the different algorithms and remote sensing techniques available, can provide synoptic views in space and time for the periodic monitoring of the territory. A variety of remote sensing data can provide sources of land use data. There are many studies in the literature that have seen the analysis of these issues applied to different territorial contexts: from megalopolises and large industrial areas to provincial areas[1,11,13–18]. For the second aspect, the determination of the exact population within a built-up area requires the existence of updated databases and metadata that follow the trend of the expansion of the built-up area that takes into account the evolutionary trends of the population and of all the socio-economic aspects that represent the drivers of the transformation processes of the territories with direct impacts on the soils[19–22]. The doctoral activities outlined in this thesis fit into this context, which involved a first phase of cognitive analysis on research topics focused on the dynamics of changes in the LULCC. The research project proposes the application of combined remote sensing and spatial analysis techniques for the assessment of relevant environmental components with respect to the construction of spatial governance tools. Anthropogenic land use and land cover change (LULCC) is a major cause of global environmental change [23]. The conversion of natural lands to human-dominated landscapes has accelerated dramatically over the past two to three decades and is expected to continue to increase dramatically. The transition of forests and grasslands to cropland and pasture is the most important of these changes, linked to increasing demand for food with impacts on climate. Land use and land cover are interconnected intrinsically, but are nevertheless conceptually distinct; drawing clear distinctions between the two is not easy, as there are multiple relationships within and between land cover and land use categories [24]. Land use and land cover are two extremely interrelated areas in the analysis of the phenomena and processes that characterize land evolution. These transformations have substantial consequences on human well-being and the state of the environment at global, regional and local levels, so there is a need for the development of monitoring support tools capable of supporting the implementation of appropriate sustainable land governance and management policies[25]. In this sense, although some dynamics, such as land take and agricultural land abandonment, are well known, the availability of an integrated monitoring and assessment system for the status and evolutionary dynamics of land cover and land use has historically been limited in our country. The growing need for high spatial temporal and thematic resolution information, which is essential for the description of complex contemporary land dynamics, has led to the creation of numerous independent products at the global, European, national and local levels, characterized by specific classification systems, different level of geometric detail and based on different relationships between land use and land cover. There are many papers in the literature by authors who have published investigations in the field of LULCC. Over the decades, scientific literature has defined 'land use' and 'land cover' in various ways, depending on the specific area of interest [22,24,26–30]. Generally, land use and land cover can be defined separately, where land use refers to the purpose for which the land is used, e.g., agricultural or recreational use. In contrast, land cover indicates specific landscape patterns and characteristics. While the terminologies for LULCC can be used interchangeably, the definition focuses on human use, over time and space, of the various physical, chemical and cultural factors of the soil resource. Land use and land cover are key physical elements that observe the earth's surface and classification systems are needed to differentiate them. These classification models and algorithms provide the tools for classifying and identifying spatial data. The use of remote sensing data is a consolidated approach in this field of research [27,31,32], particularly due to its ability to provide regular data (spatially and temporally) over large areas. Satellite images, therefore, offer the opportunity to extract significant information and study the territory, especially regarding the impacts of human activity on land use and land cover. One of the main problems associated with the use of Earth observation systems, however, is related to the quantitative interpretation of the signal and the time gap of the images due, for example, to the presence of clouds that do not allow for analysis. In the literature, different types of classification have been applied for mapping LULCC using satellite images [33–39]. Some

of these classifications are based on mono-temporal images[40], multitemporal [10,14]) or in combination with auxiliary data (e.g., [11,15,16]). Single date classification is widely used in the literature (e.g. [6,12,17,18]); this analysis focuses on a single date image for LULCC mapping. The processing of a single-date image is faster than multi-temporal classification. In multi-temporal classification, bands of multiple dates, seasons or years are combined and classified [19]. Free satellite imagery, such as Landsat, MODIS or Sentinel, is also increasingly used because it offers a wide range of options and possible applications. In addition, the constant supply of images with the same spatial and temporal resolution ensures highly relevant standard processing in spatial and ecological studies. However, the use of these data and methodologies is often limited to the academic or national arena and little is done locally. This happens because there is a lack of technical expertise, but also because the methodologies are often too complex and time-consuming to be exploited at the practical level in local planning. Remote sensing (RS) technology obtains geographic data through satellite images (optical and/or radar) or aerial photographs that can be examined in a GIS environment. Land use and land cover are important aspects in spatial planning. In fact, LULCC data are essential in environmental studies, decision making, land use planning and design, and the definition of natural resource management policies. Urban and territorial planning and the decision-making process for sustainable development need high spatial resolution data to study the relationships between the socio-economic performance of the urban and territorial system and their impact on the land cover. Land use changes are deeply connected to social and economic determinants, thus also depending on the territorial policies and financial incentives put in place by government bodies, also in implementation of EU regulations. In Italy in the last thirty years, among the actions that have had the greatest impact on land use and land cover phenomena, we find the Community economic policy such as the Common Agricultural Policy (CAP).
The CAP, through the disbursement of funds through the Rural Development Programmes, has profoundly influenced the choices of agricultural entrepreneurs.
Among the different dynamins and types of land use and land cover change, in this thesis we have chosen to analyse two types of LULCC: land take and the degradation of abandoned agricultural land in the form of erosion. Land take from soil sealing is the leading cause of soil degradation in Europe, the negative impacts of which on the environment lead to an increased risk of flooding, threatens biodiversity, causes the loss of fertile agricultural land and natural and semi-natural areas, contributes together with urban sprawl to the progressive and systematic destruction of the landscape, especially rural landscapes, and to the loss of the capacity to regulate natural cycles and mitigate local thermal effects. (European Commission, 2012). Detailed analysis of land transformations resulting from land take is the main planning reference and the fundamental tool for achieving the goal of zero land take. Soil degradation, on the other hand, is the phenomenon of altered soil conditions due to the reduction or loss of biological or economic productivity due primarily to human activity. In addition to productivity, other factors such as water erosion can be used to assess soil degradation. The present research concerns practical studies on the time series of land consumption, land abandonment and erosion, carried out through remote sensing data from the Landsat and Sentinel Mission, with the objective of providing accurate information of the phenomena in Basilicata and relating them to demographic dynamics, settlement by taking a look at government actions acting on the territory. The methods used in this thesis work are mainly based on the use of historical land use data to derive time series of changes in the LULCC. These information series were then used to feed classification models to estimate changes in the LULCC. Finally, the results were compared with population data. The study of the main territorial changes was accompanied by the evolution of demographic dynamics linked to changes in the regional production system, in the various sectors, highlighting and understanding any implications with the degree and type of pressures in terms of land consumption and land degradation soil and trying to grasp any

connections between economic activities and demographic aspects with the increase in soil degradation and the consequent territorial marginalization.

1.2 Main research objectives

The research project proposes the application of combined techniques of remote sensing and analysis spatial for the assessment of relevant environmental components with respect to the construction of spatial government tools.

The state of the research proposes a series of applications based on change detection techniques to significant domains that characterize the contemporary urban and land use planning debate: land take, land abandonment and degradation. Applications referring to sample spatial domains take into account the availability of data spatial organized also with respect to time series useful for recording evolutionary trends of the phenomena considered. Both the choices of case studies, the organization of applications compose a heterogeneous pool of results that has been useful to test the applicability of techniques at different scales of land assessment in order to consolidate an analytical competence and thick ex-ante transferability to broader contexts in order to achieve a unified and integrated reading of the territory.

Contexts of interest for the development of the research are: the regional dimension referred to for landscape planning actions in the context of the Basilicata Region; the urban areas of the Lucanian capitals and the main sites of industrial settlement for the reading of the relationships between anthropic settlements and climatic forcings and land use alterations; areas with a specific agricultural vocation, in which to assess relationships between forms of land degradation and agricultural uses related to the programming of regional rural development policies; rural and urban-agricultural interface areas in which to assess the phenomenon of soil erosion as a form of land degradation due to anthropogenic actions.

The choice of the study area was dictated by the fact that in the Basilicata region the phenomenon of land abandonment is very present, while the phenomenon of land take in the main cities shows an increasing trend in contrast with the demographic dynamics.

The research consisted of several stages, the preliminary stages consisted of a territorial framework from the socio- demographic point of view where the issues of depopulation, endowment of essential services and territorial fragility of the analysed area were analysed. The first part of the work involved a great deal of work in the research and construction of spatial data to assess the dynamics of LULCC in the Basilicata region from the 1990s to 2020.

Subsequently, the issue of land take and agricultural land abandonment was analysed by applying remote sensing, GIS and spatial analysis models and techniques for the identification and monitoring of abandoned agricultural areas and sealed areas. The classical remote sensing methods were also complemented by some geostatistical analyses that provided more information about the investigated phenomenon. Geostatistics represents a possibility of exhaustive reading of the territory, the techniques of spatial statistics and autocorrelation methods were used, through global and local indicators, for a more detailed analysis of the investigated phenomena.

It is critical to understand, investigate, and monitor what have been and will be in the future the most influential drivers on these dynamics that inherently contribute to land consumption and land degradation and to define directions to curb the associated degradation phenomena.

1.3 General structure of the thesis

The thesis was organized as follows: 4 chapters introduced by an abstract presenting the main objectives and main results obtained, as well as continuity with the previous chapter. Specifically, the research consisted of several phases of work, the results of which are reported in the chapters of which this thesis is composed. The first cognitive phase is aimed at defining the scientific frame of reference on the topic of land use land cover (Chapter 1). This is a topic of particular interest in the field of land use planning, partly as a result of European strategies and regional guidelines aimed at limiting land consumption and land degradation, as well as the urban planning instruments that currently regulate land management at the national and European levels. The characters and dynamics of population, territorial marginalization as expressed through accessibility analyses have been flanked by substantial sets of historiographic, sociological, political and economic data that have been summarized in Chapter 2. The compendium of these qualitative elements will then also serve as the basis for determining suitable indicators for measuring the processes analysed.
The second part of the thesis work consists of a methodological and experimental phase involved the application of models and techniques for the qualitative - quantitative estimation of land transformations of land take (Chapter 3) and the qualitative and quantitative estimation of agricultural abandonment and its consequences on land degradation (Chapter 4). Finally, the last chapter on the conclusions of the thesis and considerations on the issues addressed. The thesis includes an appendix that consists of methodological and technical attachments, as well as a glossary with definitions of the key terms used throughout the text, which are emphasized in bold italics.

1.4 Results in brief

The research project conducted during the PhD proposed an innovative methodological approach to land use change issues (land occupation and abandonment), based on a solid spatial and landscape study. The overall research was based on the use and integration of spatial analysis and remote sensing techniques for the study of land transformation processes.
The main results obtained are:

- The data collection process led to the identification of about 19,000 activities and services on the regional territory and the creation of a territorial dataset that allowed for the collection, analysis and organization in a synthetic form of territorial data on the stock of services present on the territory, useful for the planning and management of urban tools;
- The regional territory is mainly characterized by smaller centres that offer limited accessibility to essential services due to the significant distance from the main centres that provide essential services (education, health and mobility) and the poor road and infrastructure network;
- Between 1981 and 2021, the depopulation index in Basilicata is about 6%, with higher values in the province of Potenza (14.24%). In 2021, there are 67 municipalities in the region with a population under 2,000 and 40 with a resident population below 5 thousand inhabitants;
- Economic activities also record a decrease in the period between 2002 and 2021;

- The municipalities recording an inverse trend of socio-economic depopulation are the municipalities of Melfi and Policoro, the former being the hub of the region's main industrial centre and the latter the centre of agricultural and tourist activities in the Metapontine area;
- The Land Use and Land Cover classification model implemented involved the use of supervised classification algorithms (SVM) with the integration of auxiliary data (orthophotos, ground truth data). The LULCC maps obtained show an overall accuracy greater than 92%. The results show that the increase of impermeable areas (built-up areas) has occurred predominantly in areas away from urban centres, especially near industrial areas and rural areas;
- The installation of new renewable energy plants has produced a further increase in land take with a consequent increase in territorial fragmentation;
- Clustering of the RUSLE data, via Getis and Ord. autocorrelation algorithm, highlighted the areas showing permanent erosion during the period considered;
- The NDVI time series surveys for the period 1990-2020 identified areas that experienced agricultural abandonment (formerly agricultural areas) or agricultural transition;
- Through statistical correlation analysis with the RUSLE factors, on the basis of the deviations from the average RUSLE values and mapping of the areas of vegetation degradation, relating to arable land, through statistical correlation with the vegetation factor C, the areas were identified and mapped are susceptible to soil degradation. The results obtained were compared with data from various agricultural censuses and policy actions acting on the territory in order to identify the likely drivers of degradation and analyse their impacts (soil erosion).

Chapter 1: Land Cover/Land Use and Land Cover Change: an overview

Soil is a natural resource that performs a fundamental role in providing environmental, social and economic functions, that humans have utilized for life and various activities. Soil provides food, biomass and raw materials essential for human life and activity, it is a central element of the landscape and cultural heritage of a country. Soil is a limited resource whose formation times are extremely long, and for this reason we can define it as a substantially non-renewable resource. Soil is an essential, complex, multi-functional and vital ecosystem of critical environmental and socioeconomic importance, performing many key functions and providing services vital to human existence and ecosystem survival for current and future generations to meet their own needs (European Parliament, 2021). Due to these peculiarities, natural soil must be protected and conserved for future generations. The importance of protecting the soil, taking into account the persistent degradation of this non-renewable resource, also derives from the costs of inaction regarding soil degradation, with estimates that in the European Union exceed 50 billion euros per year (European Parliament, 2021). According to estimates between 60% and 70% of soils in the EU are not in optimal conditions, in fact soils and soils continue to be subject to processes of strong degradation such as erosion, compaction, reduction of organic matter, pollution, biodiversity loss, salinisation and sealing (European Commission, 2021). Europe, key LULC changes consist in land abandonment (sometimes with forest recovery), agricultural intensification and rapid (and often uncontrolled) expansion of urban areas [41]. The human use of terrestrial resources gives rise to the "land use", which varies according to the purposes such as food production, the extraction and processing of materials, the creation of new infrastructures and homes, as well as the biophysical characteristics of the territory itself [42]. Thus, land use is shaped under the influence of human needs and environmental characteristics and processes. The changes in land use that occur at various spatial levels and in various periods of time are the material expression of environmental and human dynamics and their interactions through the territory. These changes have impacts and effects, beneficial and harmful; the latter affect human well-being and health in various ways and are the subject of attention and study. The extent of land use change varies according to the time period examined and the geographical area concerned[43]. Knowledge of land use and land cover is essential for understanding land development, loss and degradation and energy security for the growing population, to simulate water and carbon cycles, learn about ecosystem dynamics and climate change, assess the environmental effects associated with land use and the impact on service provision ecosystems, consider land management that accounts for land cover change, change sensing analysis (e.g. where change occurs, what type of change and how it occurs), using monitoring tools for policy change, landscape monitoring and natural resource management of the environment. These activities have contributed to the observation, research, planning and implementation of policies that find a balance between the management of local resources, such as agriculture and urbanization[44]. United Nations Convention to Combat Desertification Aims for Land Degradation Neutrality by Addressing Sustainable Development Goals to Strengthen National Capacity and Quantitatively Assess Land Degradation. There are many works in the literature that have investigated the field of LULC; over the decades the scientific literature has defined “land use” and “land cover” in various ways. Depending on the specific area of interest Land Use and Land Cover can be defined separately, where land use refers to the purpose for which the land is used, for example, agricultural or urban use. In contrast, land cover indicates specific landscape patterns and features and focuses on human use of the land resource over time and space. LULC terminologies can be used interchangeably, they are key physical elements that observe the Earth's surface. To distinguish between land use and land cover classification systems are needed which provide the essential functions of structuring tools for classifying, naming and identifying objects on land [45]. Classification systems have incorporated mapping and spatial data as an essential function for the analysis and evaluation of land observations.

1.1 Land Use - Land Cover Definition

Generally, land is usually classified with respect to its use or its cover. In addition to its use in landscaping, in planning, this information is used in predictive models of environmental protection (e.g., biodiversity, habitat fragmentation) and in economic planning. In cartographic implementations, the choice between Land Use (LU) and Land Cover (LC) is determined by the specific end use of the cartography produced, although in most cases hybrid classifications are adopted [29,46,47]. The terms “land use” and “land cover” are widely used, they are not synonymous and the literature draws attention to their differences, so use them correctly. Indeed, confusion between the two concepts has existed in the literature for at least 30 years [29,48]. The lack of a universally recognized definition of LU and LC is certainly the main cause of this confusion. The most common definitions of LU and LC are those adopted in the Land Cover Classification System by FAO [49,50]. LU is the intended use of a specific area of land by humans, i.e., its socio-economic function. LC is the observed biophysical coverage of the Earth's surface, the type of surface layer of a specific area of land, including vegetation, bare soil, open bodies of water and artificial surfaces observable in the field and recorded by orthophotos. Both definitions are consistent with Directive 2007/02/EC. In fact, while the definition of LC coincides with that of the Directive, according to the definition of LU, the classification of a territory should be based on the functional dimensions or on the socio-economic intention and on the plan for the future, as indicated by the Directive. Land use implies the way in which the biophysical attributes of the territory are manipulated, states that land use is the way and the purpose with which human beings use the territory and its resources [23,29]. FAO states that “land use concerns the function or purpose for which soil is used by the local human population and can be defined as human activities which are directly related to the soil, which use its resources or that have an impact on them”[50]. Land use, therefore, is a reflection of the interactions between man and land cover and constitutes a description of how the land is used in human activities. Directive 2007/2/EC defines it as a classification of the territory based on the functional dimension or socio-economic destination present and planned for the future (for example: residential, industrial, commercial, agricultural, forestry, recreational). A land use change (and even less a land use change envisaged by an urban planning instrument) could have no effect on the real state of the soil, which could keep its functions and its ability to provide services intact ecosystems. While the definitions of land use previously reported mostly refer to wider territorial scales, on an urban scale the interest is concentrated on other aspects of the term. In the words of Chapin and Kaiser [51]: "At spatial scales involving large areas, there is a strong predisposition to think of soil in terms of the yield of the raw materials needed to sustain people and their businesses. At these scales, 'land' is a resource and 'land use' means 'use of the resource' On the contrary, at the urban scale, instead of characterizing the territory in terms of the productive potential of its soils, the emphasis is more on the potential of use of the land surface for the location of various activities". This connotation of the term "land use" is implicit in many other texts dealing with land use in the context of urban and regional planning and analysis. Therefore, by land cover we mean the biophysical cover of the earth's surface, including artificial surfaces, agricultural areas, woods and forests, semi-natural areas, wetlands, water bodies, as defined by Directive 2007/2/CE. Land use refers to land cover in various ways and affects it with various implications, “A single land use can correspond quite well to a single land cover. On the other hand, a single cover class can support multiple uses (forest used for timber combinations, slash-and-burn agriculture, hunting/gathering, firewood collection, recreation, nature preserve, and watershed and soil protection) and a single land use system may involve maintaining several distinct covers (because some agricultural systems combine farmland, woodland, improved grazing, and settlements). Land use change is likely to cause land cover change, but land cover may change even if land use remains unchanged' [51,52]. The importance and need to distinguish between land use and land cover is most evident in analyses of the environmental impacts of land cover changes. The distinction between land use and land cover, therefore, although it is relatively simple in concept, is not so simple in practice since it is not always possible to distinguish clearly between use and cover. LU and LC changes are dynamic processes that are closely connected to direct or indirect human activities. These changes are able, among other things, to influence the climate at a regional and global scale[53,54] . Knowledge of transitions between different categories of LU and LC is essential for addressing issues such as urban sprawl, loss of croplands and, more generally, all of the changes entailing the alteration of the balance and functionality of ecosystems.

In analysing land use and land cover change, it is first necessary to conceptualize the meaning of change in order to be able to identify it in real-world situations. At a very basic level, land use and land cover change are understood to mean (quantitative) changes in the areal extent (increases or decreases) of a given land use or land cover type, respectively. It is important to note that the detection and measurement of change depends on the spatial scale; the higher the level of spatial detail, the more changes in areal extent of land use and land cover that can be detected. However, both in the case of land cover and land use, the meaning and conceptualization of change is much broader. In the case of land cover change, the relevant literature distinguishes two types of change: land conversion and land modification [23,29,52].

Land cover conversion involves changing from one cover type to another. Land cover modification involves alterations of structure or function without a total change from one type to another; could result in changes in productivity, biomass or phenology. Land cover changes are the result of natural processes such as climatic variations, volcanic eruptions, changes in river channels or sea levels, etc. to land uses for production or settlement. The modification of a particular land use can lead to changes in the intensity of that use and alterations of its characteristic qualities/attributes. In the case of agricultural land use, land use changes: consist of intensification, extensification, marginalization and abandonment.

The reason why the link between land use and land cover change is emphasized is that the environmental impacts of land use change and their contribution to global change are mediated, to a considerable extent, by land cover changes. Therefore, their analysis requires examining how land use relates to land cover changes at various levels of spatial and temporal detail. The specification of the spatial and temporal levels of detail is of crucial importance for the analysis of both changes, because:

- guides the selection of land use and land cover types that will be analysed;
- determines the drivers and processes of change and the level of spatial and temporal detail of the changes that can be detected;
- it affects the identification and explanation of links between land use and land cover within particular spatial-temporal frames.

As regards the latter aspect, the point is that land use changes at the local level may not produce significant land cover changes (and, consequently, significant environmental impacts). However, they can accumulate over space and/or time and produce significant land cover changes at higher levels (e.g., regional or national).

This is the case, for example, with the conversion of agricultural land to urban uses, which results from the decision of individual land owners to convert agricultural land to non-agricultural uses. Similarly, changes in land use may be more qualitative than quantitative at the lowest levels of spatial and temporal detail, but manifest as quantitative changes at the highest levels and over the long term. For example, gradual and incremental changes in farm-scale crop types or in the quality of land management can lead, in the long run, to farmland abandonment or severely degraded farmland (in other words, a change in category from productive to non-productive land). A simplified scheme for classifying the possible land cover transformations is the one proposed and described by the European Environmental Agency, through the image of the transition triangle, shown below (Fig. 1) in the reworking of the National Observatory on Soil Consumption (ONCS, 2009), which later became the Research Centre on Soil Consumption (CRCS) Information sources for monitoring land take.

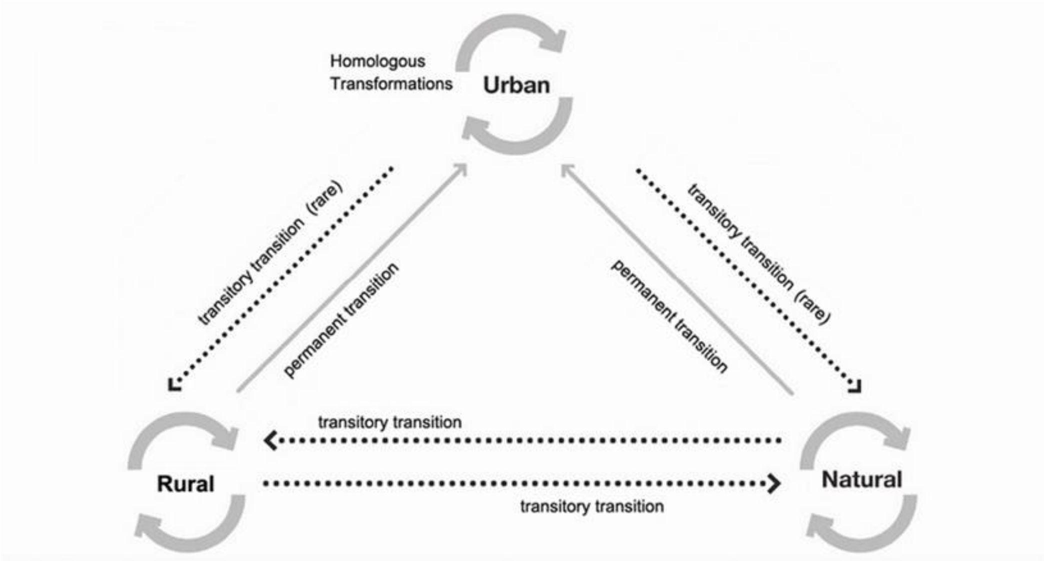

Figure 1. Transition triangle by ONCS (2009).

At the vertices of the triangle are the three macro-categories of land cover (natural, agricultural, urban), while the possible changes in the use of the cover "transit" along the sides, distinguished by type, duration (temporary-permanent) and outcome (agricultural-urban-natural) and indicated by the arrows. The circular arrows represent homologous transformations, i.e., those occurring in the same macro-classes of land cover; the linear arrows represent transitions from one macro-class to another. The dashed arrows represent transitory transformations and the continued arrows represent permanent/irreversible transformations [43,55].

On the basis of the three variables considered, the transformations assume different characters and can therefore be classified differently. For example, the transition from an agricultural cover to an urban cover is classified according to this scheme as a non-homologous transformation (i.e., one that does not occur within the same category), permanent and artificial, while the transition from a natural cover to an agricultural one will be catalogable as a transitory, non-homologous and semi-natural transformation. Strictly speaking, only in the first case should we speak of soil consumption both for the duration of the (permanent) transformation and for the impacts deriving from it. The transition triangle represents an absolutely simplified scheme that needs to be integrated by other qualitative-quantitative measures that are able to characterize the soil transformation processes in greater detail and therefore support the territorial government choices. At national and European level, the offer of land cover/land use data is vast but extremely fragmented; the main, and often only, land-use information available is censuses, while land-cover information is usually deduced from cartographies derived mainly from aerial photos or satellite images[24,56–58]. The purpose of the Copernicus program is to collect information on the earth's surface and organize it according to criteria that allow different data to be compared, to exchange data between EU countries and to increase the number of users. The Copernicus Land Monitoring Service (CLMS) allows researchers to obtain geographic information about soils and numerous related variables (such as the state of vegetation or the water cycle), supporting applications in a wide variety of sectors, such as spatial planning, management of water and forest resources, agriculture and food security. CORINE Land Cover is one of the main products belonging to CLMS. It has guaranteed information for the whole European territory since 1990, with 44 land cover and use classes and geometric detail of 25 hectares. It aims to provide detailed information on environmentally critical areas, which require specific and detailed monitoring. Currently, this Copernicus component offers land cover and land use maps in vector format, with high spatial resolution and 6-year update frequency for four area categories. The Urban Atlas refers to the CLC classification system, which describes in more detail the land cover and land use characteristics of urban areas, while the Riparian Zone and Natura 2000 use the ecosystem types defined in the Mapping Assessment of Ecosystems and their Services (MAES) [59]. In order to coordinate data flows from a thematic point of view, the EAGLE group (EIONET Action Group on Land monitoring in Europe) was created. It aims at defining a conceptual methodology to describe land cover and land use information in a consistent data model. EAGLE is not a classification system but a tool to describe classes of a given classification system by tracing them to the segments related to the three categories. This allows to better understand the characteristics, the overlaps and the possible conversions between different classification systems and provides a basis to define new ones. The EAGLE model aims at separating the land cover and land use components through data modelling systems applicable at different scales and in different contexts, while maintaining compatibility with existing databases. The problem of interoperability and non-homogeneity between data is also evident at a national level. The National Land Consumption Map offers national coverage, with annual update and EAGLE compliant classification system, while most of the data available at the regional level are inconsistent, not updated and difficult to relate to each other. Despite the large amount and variety of land cover and land use data available at national and European level, currently CLC is the only product capable of supporting an assessment of LULCC on a national scale [59,60], since it guarantees the mapping of the entire national territory and has a thematic detail suitable for the purpose. However, the low spatial resolution and the presence of mixed classes reduce the reliability of the assessments based on them.

1.2 Land Use – Land Cover Change: Drivers and Impacts

Land use/land cover change (LULCC) has aroused great concern over the years in many countries also due to the negative impacts on the environment and the consequent repercussions on the economies and social dynamics in the various nations [23,61–63].

The analysis of land use change revolves around two central and interconnected questions: "What drives and causes land use change?" and "what are the (environmental and socio-economic) impacts of land use change?". This section addresses the first of these questions. The precise meaning of the 'drivers' or 'determinants' or 'driving forces' of land use change is not always clear. Often, some driving forces are emphasized over others and there is confusion as to the semantic categories to which these causes of land use change belong. Two principal distinctions are made in the following. The first regards the origins of the drivers of land use-cover change. It is almost unanimously accepted that there are two main categories: biophysical and socio-economic drivers and they are extremely interconnected: the former cause the latter which then affect biophysical factors potentially causing successive cycles of land use change. A common example of a domino effect of environmental and socio-economic impacts of land use change is that of itinerant farmers: the sequence of land use change begins with forest clearing; follows cultivation, intensive grazing and finally land abandonment and movement to another location where the sequence is repeated [64]. Biophysical drivers include the characteristics and processes of the natural environment, such as: climatic and meteorological variations, landform, topography and geomorphic processes, soil types and processes, drainage patterns, availability of natural resources. Socio-economic drivers include demographic, social, economic, political and institutional factors and processes such as population and demographic changes, industrial structure and changes, technology and technological changes, etc. It should be noted that biophysical factors usually do not directly cause land use change, whereas anthropogenic one's cause land cover change(s) which, in turn, can influence land use decisions. The second central issue that land use change analysis deals with concerns the impacts (environmental and socio-economic) of land use change. Five main types of driving forces can be identified: socio-cultural, economic, natural, demographic and agricultural driving forces (Fig 2).

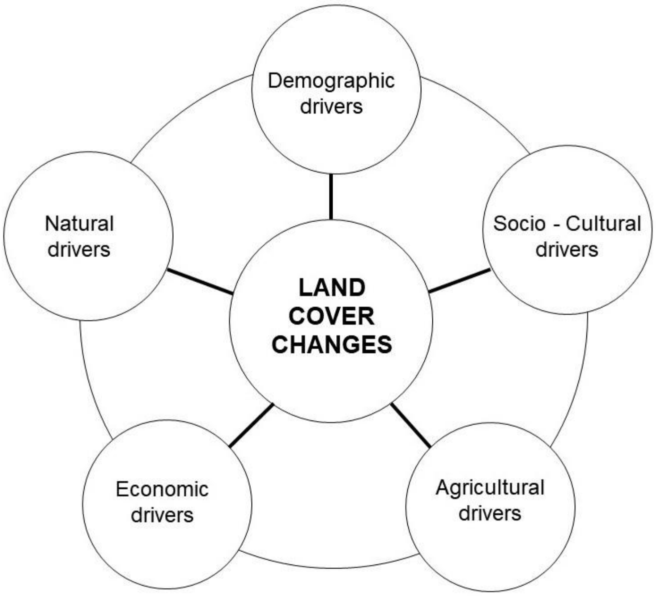

Figure 2. Principal drivers of land use - land cover change.

Usually, the anthropic development of the Land Use Land Cover Change (LULCC) consists of two main macro-groups: direct actions and indirect ones, consequence of the first ones. The former explains the direct action of man on local territorial coverage and include the expansion of agriculture, the unsustainable exploitation of forest resources and the development of infrastructure[65]. Indirect forces, such as economic, institutional, technological, cultural and demographic changes, accelerate man's effect on the use of natural resources.

Land cover change refers to the change of some continuous land characteristics, such as vegetation type, soil properties, etc., while land use change consists of an alteration in the way in which a given area of land is used or managed by humans. Interestingly, this change is responsible for a number of local and global effects, including biodiversity loss and associated effects on human health, as well as loss of habitat and ecosystem services. The phenomenon is mainly driven by urban growth and is particularly important today for developing and underdeveloped countries. However, natural causes can result in land cover change, but land use change requires human intervention[24]. Land use change causes a multitude of environmental impacts at lower spatial levels in urban, suburban, rural areas and spaces widely studied by the scientific community. Particularly important are land use changes occurring in the periphery of large urban concentrations that are subject to the pressures of urbanization and industrialization and often result in losses of agricultural raw land and tree cover. Their environmental impacts include changes in the hydrological balance of the area, increased risk of floods and landslides, air pollution, water pollution, etc. Other local impacts of land use changes include soil erosion, sedimentation, contamination and salinization of soil and groundwater, erosion and coastal pollution. The significance of these impacts is not restricted to the local area of concern as they are often cumulative resulting from the decisions of many individual land and property owners to act in their narrow self-interest, the environmental impacts of which may also play out in distant areas. For example, the urbanization or tourist development of an area increases the demand for water which, however, is supplied by another territory. Excess water abstraction reduces the water available for agriculture and plant growth in the latter area and can induce saltwater intrusion into coastal areas[19,66].

In addition to the environmental impact, the socio-economic impacts of land use change are equally significant and raise serious concerns at all territorial levels. The global socio-economic impacts concern food security issues, water scarcity, population displacement and, more generally, the problem of human security and vulnerability to natural hazards. Problems related to food security and water scarcity can arise from the reduction of agricultural land area and the decrease in available water resources that result from soil erosion, land degradation, desertification, industrialization, urbanization, from suburbanization and, above all, from the mismanagement of environmental resources. The regional socio-economic impacts of land use change are more diverse and reflect the variety of regional contexts in which these changes occur. Even these, however, derive from the same processes discussed above and evolve around issues such as land availability for regional food production, changes (reduction) in land productivity and, consequently, (reduced) profitability and changes in industrial structure, employment/unemployment, poverty and quality of life.

1.3 LULCC Classification and Monitoring

The LULCC analysis is critically dependent on the chosen land use and land cover classification system. The extent and quality of land use change is expressed in terms of specific land use or land use/land cover types. The assessment of the environmental and socio-economic impacts of land use change is only possible when the particular environmental and socio-economic characteristics of the chosen land use/cover types are specified. If this requirement is not met, then, the analysis will be of limited value in guiding policy and decision-making, especially at smaller scales. Hence, the need to discuss the available land use and land cover classification systems and consider their suitability for the analysis of land use change at various spatial and temporal levels. Land use change models can play an instrumental role in assessing the environmental and/or socio-economic impact of past or future activities. This use has two facets; on the one hand, it may concern the assessment of qualitative and/or quantitative changes in land use caused by autonomous or planned changes of one or more of its determinants; on the other hand, it may concern the assessment of the environmental and socio-economic impacts of land use changes (such as land degradation, desertification, food security, health and safety risks, unemployment, etc.). Land use change models have been and are currently being used to prescribe "optimal" land use models for sustainable use of land resources and development, in general. In this case, they are usually based on optimization techniques used to produce land use configurations that meet specific objectives as well as a variety of environmental and socio-economic constraints. One such constraint is the availability of land. Optimization models are commonly used in planning and management contexts. Evaluation is an end use of the model associated with the last three uses mentioned: forecasting, impact assessment and prescription. Land use change models for assessment purposes per se do not exist as assessment is an activity that can be performed on any set of alternatives that need to be assessed against specific criteria. Therefore, in the particular case of land use change analysis, the model-generated land use alternatives (for forecasting, impact assessment or prescription purposes) can be evaluated using any of the available evaluation techniques.

LULCC assessment is much needed to sustain, monitor and plan natural resource use [34,67]. Indeed, the LULCC classification has a direct impact on the atmosphere, soil erosion and water, while it is indirectly related to global environmental problems [37,68,69]. To this end, remote sensing images and their processing have helped to provide large-scale and up-to-date information on surface conditions. LULC classification is the process of naming land cover classes to pixels and classifying them. For example, water, subways, woodlands, horticulture, buildings, woodlands, agriculture, grasslands, mountains, and highlands [70,71]. The overall goal of image grouping is to naturally arrange all pixels of an image into land cover classes or subjects. That is, different types of components exhibit a distinctive blend of dependence on their inherent otherworldly reflectance. LULC maps play a significant and primary role in planning, managing and monitoring programs at the local, regional and national levels. It is necessary to monitor the ongoing process of LULC models for a certain period of time. In recent years, land-use and land-cover (LULC) classification using remote-sensing imagery plays an important role in many applications like land use planning (growth trends, suburban sprawl, policy regulations and incentives), agricultural practice (conservation easements, cropping patterns and nutrient management), forest management (harvesting, health, resource-inventory, reforestation and stand-quality) and biological resource (fragmentation, habitat quality and wetlands) [72].

Successful remote sensing classification is an essential source for many application processes, because many environmental, social and economic applications rely on classification results [73]. Also, to achieve successful classification, a proper classification system is required. Therefore, the presentation of research objectives, questions and problems is required by the end user before using the classification. On the other hand, there are many factors that need to be taken into consideration when choosing a classification method to use, such as the spatial resolution of remote sensing data, different data sources, a classification system, and the availability of classification software. Appropriate. In general, the purpose of image classification is to predict any entered image category using its characteristics [74]. Remote sensing is a well-known alternative to evaluate the LULCC process on a large scale. Much progress has been made in land use and land cover change (LULCC) mapping using geographic information systems (GIS) and remote sensing, e.g., with the multi-year 30m Landsat, RapidEye or Sentinel high-resolution [75,76] and moderate resolution MODIS images [77]. LULC classification methods and classification techniques for extracting accurate land use and land cover data from remote sensing images are very versatile. The accuracy of classification techniques is influenced by factors such as the choice of test preparation, the heterogeneity of the study area, the sensors, the number of classes to be characterized [78]. Classifiers can be classified into different classes based on the methodology and technologies used, for example, supervised and unsupervised classification, hard and soft (ambiguous) classification, or pixel-based classifications. Image processing and classification approaches can affect classification success, because remote sensing classification is a complex process and requires consideration of a number of factors. Various types of algorithms are used to provide adequate classification accuracy. In the past two decades many advanced classification approaches have been applied for image classification such as artificial neural networks (ANN) [79], support vector machine [80,81], decision trees (DTs) [82], spectral angle classifiers and rule-base evidential reasoning for building expert and decision making system. These methods are non-parametric classifiers, which do not use statistical parameters to calculate class separation. The ideal map is one which has been well validated and implemented and which should take into consideration a number of factors such as methods for collecting landmarks, classification scheme, sampling method collection, size and sample units and calculation of accuracy rating. Additionally, other important elements of accuracy evaluation can be derived from the confusion matrix such as manufacturer accuracy, user accuracy, and overall kappa statistics. However, getting the accuracy assessment is more difficult than classification. MLC, SVM and RF are some of the most widely used classification methods to classify multispectral images.

Chapter 2: Assessing the spatial marginality of Basilicata Region to support land use planning

Land use planning, in the context of land use and land cover change, is the systematic evaluation of land potential, land use scenarios and economic and social conditions in order to select and adopt the best land use options. Its aim is to select and implement land uses that best meet the needs of the population while safeguarding resources for the future. All types of land use are involved in the process: agriculture, forestry, wildlife conservation, urban and industrial expansion, tourism and services. We can understand it as an iterative and continuous process, the aim of which is to make the best use of land resources. Research in this field requires intensive fieldwork and a wide range of tools such as information management, systems analysis, decision support systems, multi-criteria analysis, geographic information systems, remote sensing, image analysis, modelling techniques, neural network technology, land evaluation. All these tools need to be considered as part of a broad and integrated approach related to rational land use planning, resource conservation, environmental impact and socio-economic effects. The goal is to create the conditions for obtaining a form of land use that is ecologically correct, socially and economically appropriate. It is estimated that more than 50% of the world's population lives in urban areas, and this percentage will reach 69.6% by 2050 (United Nations, 2010) [4]. This implies an increase in demand for land for various uses such as urbanization and industrial development, infrastructure, and agricultural activities. Population structure and dynamics are important factors in land use. Rapid and intensive urbanization is an example of human-induced land use/land cover change (LULCC), which has exacerbated ongoing impacts on the climate system [83]. For this reason, land use changes have become an important part of spatial planning, as it is based on an interdisciplinary approach which pays attention to all the functions of the territory and involves all users through participatory processes. It is essential to understand the role of demographic dynamics as a driver of urban land use change such as, for example, the increase in demand for artificial surfaces that occurs at the local level. Social and economic analyses are important in the spatial planning process. Comparison of socio-economic analyses with land use and land cover change can highlight the need to modify existing policies or implement new ones. A particular land use can degrade and thereby destroy other land resources. If the economic analysis shows that the use is beneficial from the point of view of the land user, it is likely to continue, regardless of whether the process is environmentally friendly. To formulate and implement spatial planning policies and strategies it is essential to collect, process and disseminate timely and reliable information and to use modern land evaluation technologies, in order to create solid scientific knowledge for adequate decision support. This section presents some analytical applications for the investigation of time series of different demographic and socio-economic trends at the regional scale to discuss, in the following chapters, the relationships between LULCC, urban sprawl and demographic trends. In the following chapters, in fact, the territorial transformations that involve a significant change of intended use and land cover will be analysed, such as the increase in sealing and the transitions that bring natural and semi-natural land to artificial and/or degraded land. Knowing the changes in land use and land cover, for example from natural to artificial, is important to understand the interactions between human activities with the environment.

2.1 Evaluation of territorial variables connected to the provision of essential services in the Basilicata Region

Demographic change and the study of territorial marginality and fragility are becoming increasingly important in policy and planning discussions, as they are considered important factors for the future development of land use and urbanization across Europe. Through the years, the topic of 'inland areas' has also become central in the European debate on inequality and territorial fragmentation, which focuses on inequalities and opportunities to exploit the territory's potential linked to the availability of primary resources and land [84–86]. The definition of the inner area in an urban settlement, officially introduced by Barca (2009), is related to the idea of distance and marginalization from a principal attracting pole [87]. Inland areas are, therefore, those settlements that are significantly distant from the central poles, rich in natural and cultural resources but lacking in services (e.g., high schools or medical centres), and characterised by emigration flows. Inland areas have been officially defined as sensitive contexts eligible for specific planning by the Italian National Agency for Territorial Cohesion (2014). The national strategy of internal areas (SNAI) [88] describes and identifies a vast set of areas that occupy about 60% of the Italian territory united by a vast marginalization compared to the centres offering essential services and by a low population density. In order to better understand the dynamics of the LULCC and the regional demographic trend and produce the first considerations in terms of impact on the soil of it is useful to frame the regional peculiarities from the point of view of settlement dynamics in the broader national context.

The national settlement dynamics over the years have occurred in an uncontrolled way, in fact the wild sealing has led to dynamics of fragmentation of the natural and artificial landscape, transforming vast areas into smaller isolated and not interconnected environments and habitats [65–67].

This phenomenon, a consequence of the uncontrolled and unregulated use of the territory, is associated with the excessive transformation of natural and semi-natural areas into artificial ones, for example passing from a semi-natural use of the territory to artificial use of a residential type not accompanied by an effective demand for new housing. In the literature, there are many authors who affirm the negative consequences of fragmentation on the distribution of essential services, infrastructure costs and landscape changes that also affect and fragment very often abandoned farmland, also increasing the risk of hydrogeological disruption [68–70]. Low-density urban forms associated with the geographical expansion of cities also tend to result in lower accessibility to local services and higher average transport distances [71,72].

2.1.1 Study Area

The Basilicata region is representative of the inland areas described by SNAI since it is characterized by various factors of fragility, such as, for example, the high territorial fragmentation and the constant demographic contraction. From a settlement point of view, Basilicata is characterized by the presence of small centres, even at high altitudes, poorly connected to each other and even less to the main regional and extra-regional road and railway junctions.

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demand for new housing. In the literature, there are many authors who affirm the negative consequences of fragmentation on the distribution of essential services, infrastructure costs and landscape changes that also affect and fragment very often abandoned farmland, also increasing the risk of hydrogeological disruption [92–94]. Low-density urban forms associated with the geographical expansion of cities also tend to result in lower accessibility to local services and higher average transport distances [95,96].
In Basilicata, in fact, the historical trend of urban and territorial development has led to the formation of medium-small urban centres (with a resident population of less than 5.000 units) geographically decentralized with respect to the main urban poles and dispersed in rural areas [97].
In addition to the several factors of territorial fragility linked to geomorphologic aspects, the Region's marginality and spatial peripherality are reflected in the poor endowment and accessibility to essential services of the various centres, most of which are small municipalities located in hilly and mountainous areas.
In this context, providing an appropriate definition of a spatial model is a challenge, since spatial data and information must be managed in order to understand the mechanisms that determine, on a local scale, the demand and supply of services. It consists of an interpretative approach to the dynamics of settlement, territorial, infrastructural endowments and organisational models of the territory that condition, for example, territorial accessibility, which lead citizens to self-determine residence and systematic movements according to criteria of optimising the ways of using space and territory.

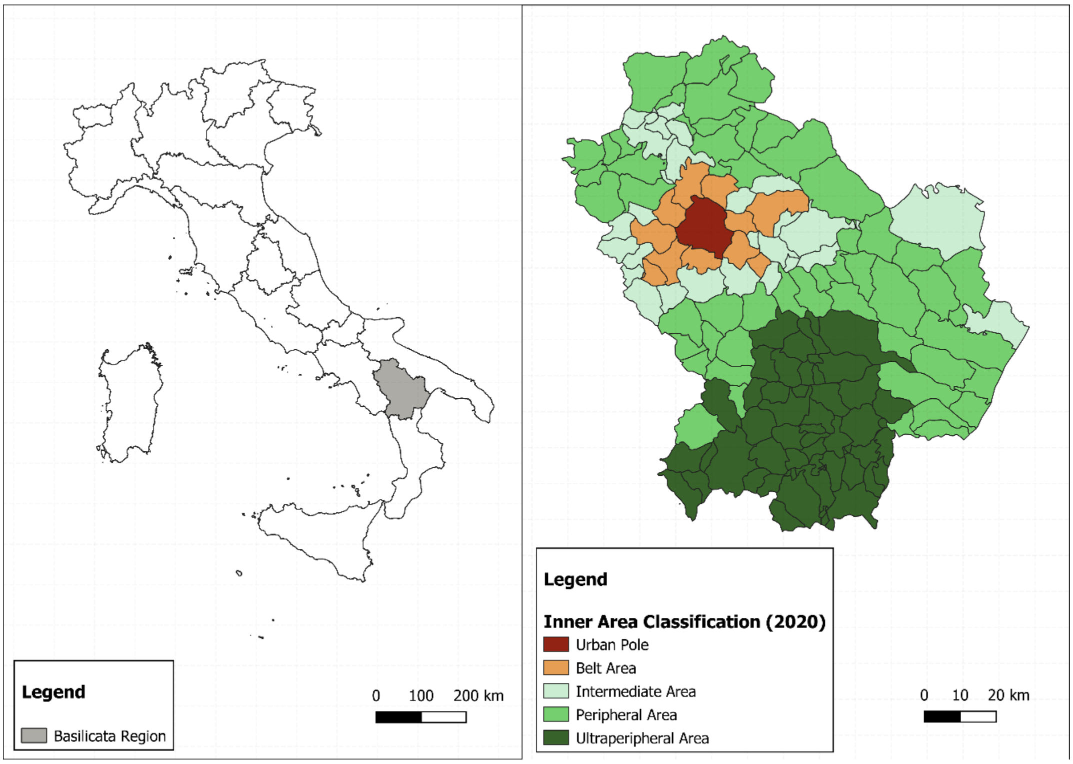


Figure 3. Geographic overview. On the left the map of Italy with the distinction of the Basilicata Region. On the right Basilicata with the identification of the inner areas and all the municipalities.

In recent decades, in Basilicata, spatial transformations connected to traditional settlement components have been associated with new types of land use and land cover. As a consequence of the global challenges on climate change and the related framework of international agreements on the reduction of CO2 emissions, a local policy has been promoted at different scales. Renewable energy sources (RES) represent an important component of the package of solutions adopted by public and private actors to address global climate change issues, orienting land development towards a low-carbon economy and sustainability principles [98]. This chapter includes the main elements of an initial experimentation of a methodology aimed at identifying and highlighting the marginality and high degree of isolation of the centres of the most inland areas located mainly in the south of the Region and to relate them to the socio-demographic aspects.

2.2 Material and Methods

2.2.1 The Stock of Services and Accessibility Estimation

The provision of essential services in a territory is a fundamental parameter against which to evaluate the quality of life in a specific territory. It can also be understood as a deficit assessment, i.e., the absence of minimum requirements for the supply of essential services with reference to the urban functions exercised by each territorial unit. From a spatial point of view, the level of peripherality of the territories with respect to the network of urban centres, home to a vast plurality of services, profoundly influences the quality of life of citizens and the level of social inclusion. In these, the presence of essential services can act as an attraction capable of generating discrete catchment areas [99–101]. The centre of the supply of essential services is identified in that municipality capable of simultaneously supplying all the school supplies, at least one hospital and one railway station[21,97,100,102,103]. The purpose of this chapter was first of all to create a dataset of data useful for the calculation of various socio-economic indicators, in order to frame the demographic evolution and the evolution of the stocks of public and private services. The first methodological approach was to reconstruct the supply of essential services through the use of open data and tools present in the Google suite in a GIS environment and subsequently estimate the peripherality of each municipality by estimating the accessibility to essential services. The study involved the use of spatial analysis techniques aimed at describing the distribution of essential services over the regional territory. The main categories of services examined for each study area (Fig 4), were extrapolated from Google My Maps using the Points of Interest function. The stock of services was also obtained by consulting online searchable public databases, business websites, lists of associations and/or public authorities. The service centroids were imported into the GIS environment and reclassified into 9 main categories.
Each category, in fact, has been divided into subcategories identified with the code L2:

- Commerce: CM01-Mini Market Shops; CM02-Supermarket; CM03-Butcher, CM04-Clothes Shop; CM05-Electronic Shops; CM07-Jewellery; CM08-Furniture; CM09-News Kiosk; CM10-Book Shop; CM11-Car and Motorcycle dealer shop; CM12-Bakeries; CM13-Florist, etc.
- Education: IF01-Nursery School; IF02-Elementary School; IF03-Secondary School; IF04-High School; IF05-Nursery; IF06-University; IF08-Musical School; IF09-Private training School; IF10-Research institute; IF11-Tecnology Park; IF14-Driving School; IF15-Language School.
- Services: S1-Refueling Station; SR02-Carpenters; SR03-Hardware store; SR04-Hydraulic; SR05-Elettrician; SR06-Graphical Designers; SR07-Beauty center; SR09-Freight transport; SR10-Estate

agency; SR11-, Professional Study (engineers, geologist, architets, etc); SR12-Lawers; SR13-Notaries; etc.

- Public Services: SP01-City Hall; SP02-Post office; SP03-Library; SP04-Public Office; etc.
- Turism: TR01-Hotel 5stars; TR02-Hotel 4 stars; TR03-Hotel 3 stars; TR04-Hotel 2 stars; TR05-Hotel 1 star; TR06-Farm Holidays; TR07-B&B; TR08-Camping; TR09-Restaurants; etc
- Culture and art: CA01-Teathre; CA02-Cinema; CA03-Museum; etc.
- Sport and free time: ST01-Stadium; ST02-Gym; ST03-Pool; ST04-Bar and pubs; ST05-Sport associations; ST06-Bar; ST08-Night club; etc;
- Healt: HE01-Hospital; HE02-Clinics; HE03-Emergency Room; HE04-Pharmacy, etc;
- Safety: SA01-Army; SA02-Traffic Police; SA03-Carabinieri; SA04 Financial guard; etc;
- Financial service: FR01-Bank; FR02-ATM/Bancomat; FR03-Insurance Agencies; etc.

The urban services that guarantee an elementary level of performance at the basic centre are reclassified by subdividing each macro-category, identified with the Level 1 code, into sub-categories assigned the Level 2 code, as summarised in the table (table 1).

Table 1: List of services and equipment.

REFERNCE CODE Level 1	**TYPE OF SERVICE Level 1**	**REFERENCE CODE Level 2**
CM	Commerce (CM)	$\sum_{n=0}^{\infty} CM$
CU	Culture and Art (CU)	$\sum_{n=0}^{\infty} CU$
ED	Education (ED)	$\sum_{n=0}^{\infty} ED$
HE	Healt (HE)	$\sum_{n=0}^{\infty} HE$
S	Services (S)	$\sum_{n=0}^{\infty} S$
FS	Financial Services (FS)	$\sum_{n=0}^{\infty} FS$
PS	Public Services (PS)	$\sum_{n=0}^{\infty} PS$
SA	Safety (SA)	$\sum_{n=0}^{\infty} SA$
SF	Sport and free time (SF)	$\sum_{n=0}^{\infty} SF$
TR	Turism (TR)	$\sum_{n=0}^{\infty} TR$

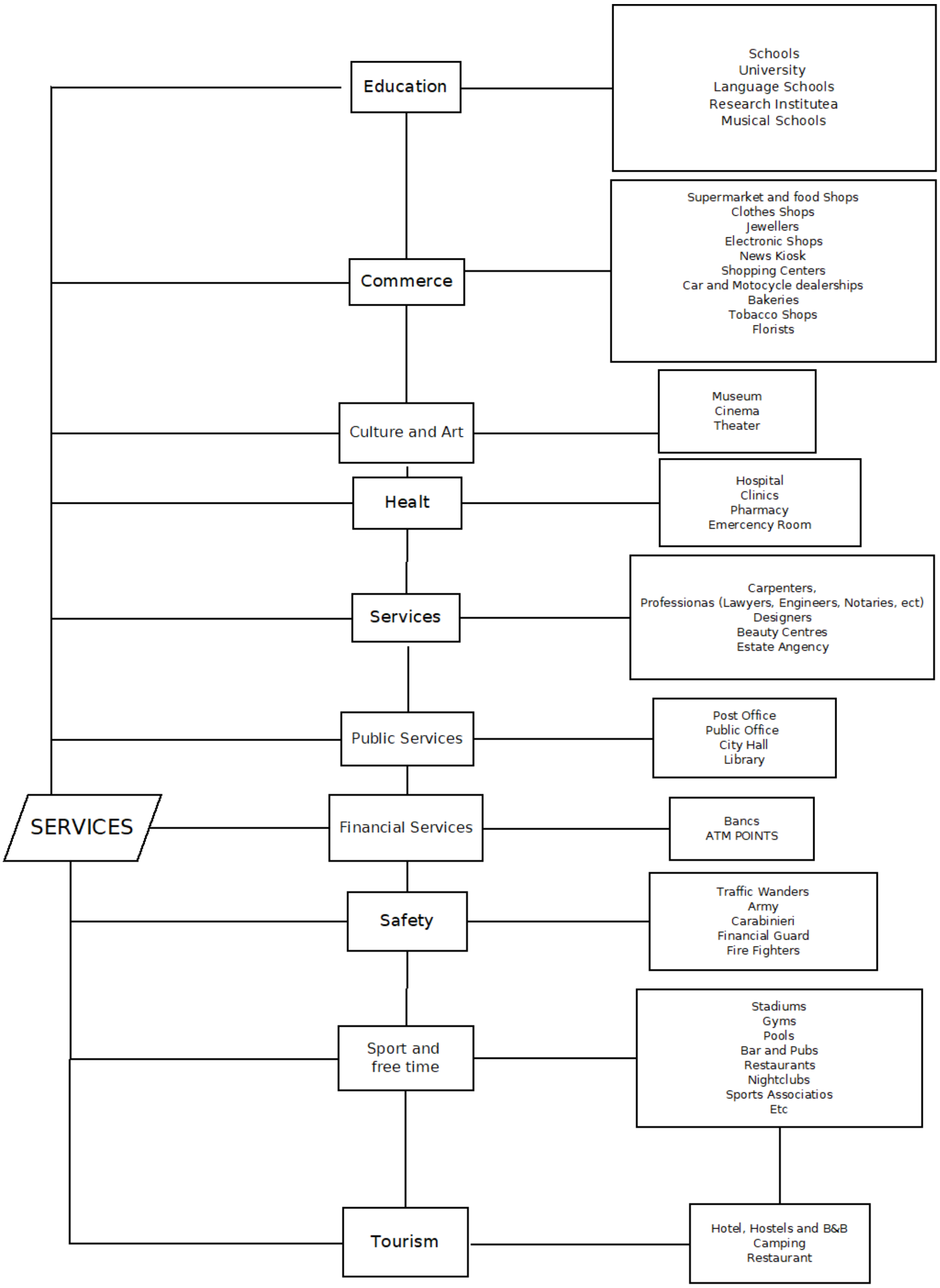


Figure 4. Main categories of services investigated.

The endowment index is an indicator that measures the level of availability of public or private services in a given geographical area. In essence, it provides a quantitative estimate of how easy it is for citizens in an area to access essential services, such as healthcare, education, public transportation, recreation, and more. The index is calculated on the basis of a series of variables, such as the resident population and the presence of services in each municipality.

The service endowment index is an indicator that makes it possible to evaluate the presence and accessibility of public and private services in a specific geographical area. To calculate the IDS, we started from the calculation of the resources available for each service, i.e., the number of services available in each municipality divided into categories. These resources were then compared to the resident population. In this way, an estimate of the quantity of resources available for each inhabitant of the area is obtained, i.e. the service endowment index.[97,104–106]. (See Appendix A2). The analysis on spatial accessibility, in the different centres of the SNAI classification, is mainly based on the estimation of spatial distances and travel times that a resident citizen must make in order to use the services in the area. This was made possible by using the site and the plug in "openrouteservice", which offers navigation services using free geographic data, and which allows isochrones to be mapped. Accessibility has been estimated in terms of the time distance from the urban centre to the main services in the municipal area. The services identified were reclassified into three main macro classes: upper secondary education, health care and mobility, choosing in the latter case the main connecting infrastructures such as airports, train stations and highway toll booths. ORS Tools provides access to most of the functions of openrouteservice.org, based on OpenStreetMap. The tool set includes routing, isochrones and matrix calculations, either interactive in the map canvas or from point files within the processing framework. Extensive attributes are set for output files, including duration, length and start/end locations. The analysis of the road distance was carried out through the use of the ORS Tools plugin (openrouteservice routing, isochrones and matrix calculations for QGIS), able to generate isochronous lines, i.e., the locus of points having the same spatial or temporal distance, with respect to a fixed point entered as input. The distance between the initial starting point and the arrival points is not linear but, by setting a value in meters or minutes in the plugin, it is calculated according to the possible real routes that can be travelled within the OpenStreetMap road network. In this study we have chosen to use a point belonging to the historic centre as a starting point, symbolically identifying it as the town hall. For the purposes of the study, it was deemed appropriate to set and select the option for choosing the fastest route. Starting from the information available in the dataset of the services, the elements of the vector files of the services have been reworked by associating the information relating to the distance range to which each element belongs.

2.2.2 Socio-economic and demographic trend in Basilicata Region

The inland areas, therefore, are defined as territorial areas that present conditions of peripherality, defined in terms of distance from the fundamental services of education, health and transport, and in which significant phenomena of shrinking human presence are recognised. These are manifested, in particular, in depopulation trends, an increase in the ratio of elderly people in relation to the resident population, a reduction in the number of employed people and in the level of local capital development. At the same time, the relevance of these inland areas, due both to their extension - equal to 60% of the entire surface area of the country, including 52% of the municipalities and 22% of the population as indicated in the framework of the National Strategy for Inland Areas (SNAI) - and to the significance of the environmental and cultural resources located there determines the centrality of governance and planning actions aimed at reversing depopulation trends, through measures to increase social inclusion, sustainable economic growth, health and quality of life, and building sustainable communities, consistent with the principles of the Sustainable Development Goals (SDGs) established by the United Nations. This paragraph studies the demographic trends of the Basilicata Region, the variables related to the demographic component are fundamental indicators for the evaluation of the critical conditions to which the mitigation and local development strategies must refer in order to define intervention priorities and scenarios of sustainable transformation of the territory. The objective of the study of demographic trends is to build cognitive frameworks of the trends of the local context useful to define and promote shared and participated strategies of mitigation of natural and anthropic risks related to land use. The study of the demographic trends relating to the Municipalities of the Basilicata Region was structured as follows:

- reconstruction of the resident population in the period 1981 – 2021;
- estimate of the population change, in absolute and percentage terms, in the periods 1981-2021 and estimation of the population change on an annual basis for the period 2011-2021;
- classification of the Municipalities of the Basilicata region into categories representing levels of demographic consistency, determined according to the resident population at the beginning of the time period considered;
- estimation of the distribution of the resident population among the identified categories and analysis of the population variation;
- evaluation of the Percentage of elderly resident population (age > 65 years), adult population (35> age < 65); youth population (19> age < 34) and child population (age < 18) on the total resident population, calculated in the years 1981, 2021.

The data are derived from the Database of the National Institute of Statistics (Istat) and from the indicators developed within the framework of the National Strategy for Internal Areas (SNAI)[103,107]. The considered area of analysis is the municipal context. This unit is identified in order to construct databases and to derive indicators that give an accurate, exhaustive and synthetic picture of the various trends and the consequent conditions of specificity, inequality and imbalance between the distinct areas of the Basilicata Region. The analysis focuses on the period 1981-2021, as the study of this time span makes it possible to discern the long-term demographic dynamics and, therefore, to grasp the effects of the settlement policy. The first aspect that appears when dealing with the demographic theme of Basilicata is that of the reduction of its population. In fact, according to ISTAT sources, Basilicata is among the Italian regions with a high rate of depopulation resulting from migration processes and territorial conditions of marginality. At this stage the research has focused on reconstructing the demographic structure of the resident population in the period 1981 - 2021 using ISTAT data as a reference. In the following paragraphs, the methods and techniques for analysing the data in relation to the purposes of the research are specified for each component. This study is based on tools for the basic analysis of census variables, identified in order to construct a methodology that is, on the one hand, useful to allow the comparison of distinct areas within the study area and, at the same time, transferable to other contexts. Population variation is quantified in percentage terms, with reference to different temporal dimensions. More precisely, the analysis determines the demographic dynamics in relation to the period 1981-2021, in relation to the periods between two consecutive census surveys (1981-1991, 1991-2001, 2001-2011, 2011-2021), and on an annual basis for the period 2011-2021. The demographic dynamics calculated for the municipalities of the Basilicata Region are compared with the population variations measured on a national, macro-area and regional scale. A further consideration concerns the definition of a set of categories to which the municipalities of the Basilicata Region are ascribed. These categories are defined according to the resident population in each municipality at the beginning of the period considered (table 2). In particular, category 1 includes municipalities whose population at the start of the reporting period exceeds 50,000 inhabitants. Category 2 includes municipalities whose population is between 10000 and 50000 inhabitants. Category 3 includes municipalities whose population is between 5000 and 10000 inhabitants. Category 4 includes municipalities whose population ranges between 2000 and 5000 inhabitants. Municipalities whose population ranges between 1000 and 2000 inhabitants make up Category 5 and, finally, Category 6 refers to municipalities with a resident population of less than 1000 inhabitants.

Table 2. Classification of municipality related to the number of inhabitants.

CLASS	N° INHABITANTS
1	> 50000
2	10000 - 50000
3	5000 - 10000
4	2000-5000
5	1000 - 2000
6	<1000

The cut-off values identifying the six categories are derived by combining the definitions of municipality types proposed by the Association Nazionale Municipalities Italian (ANCI) and ISTAT. More precisely, the threshold value of 1000 inhabitants define a demographic category comprising municipalities to which specific investments are addressed. The limit value of 5000 identifies smaller municipalities, according to the definition proposed by ANCI and SNAI. Finally, the limit values of 2000, 10000, and 50000 inhabitants are identified by ISTAT to define the Categories of Municipalities that constitute the unit of analysis of specific statistical indicators, relating to the macro-environments Culture and Communication and Economic Condition of Families and Inequalities.

Starting with the categories of municipalities, for the periods 1981-1991, 1991-2001, 2001-2011, and 2011-2021, the frequency, understood as the number of municipalities included, the cumulative resident population, and the calculated population change for each of the municipalities included was determined for each category. The purpose of this analysis is to describe the population dynamics of each category of municipality. The aim is to verify whether there is a relationship between the demographic dynamic, measured in a specific period, and the resident population at the beginning of the period. Lastly, for each category of municipality, defined as of 2021, the historical series of data on the resident population, recorded in the general censuses, was reconstructed for each year in the period 2011-2021. The aim is the restitution of the demographic trend that determined the frequency distribution of the municipalities according to the categories determined by the resident population.

The series concerning the natural balance, the internal migration balance and the foreign migration balance, the incidence of the cumulative balances was calculated for the period 2002-2021, for the period 2002-2011 and for the period 2011-2021. These variables were determined by dividing the cumulative balance for the reference period by the resident population at the beginning of the period. The analysis of the natural balance and migratory balances focuses on a more limited period of time, in order to construct a more precise interpretation of the demographic phenomena that contribute to determining the more general demographic dynamics, outlined by the change in resident population, and in particular to assess in the recent period, to what extent the natural balance, and the internal migratory balance affect depopulation phenomena and to what extent external migratory flows moderate this trend.

Concerning the historical series on the change in the incidence of the elderly population on the resident population, the temporal dimensions investigated include the periods between two consecutive census surveys (1981-1991, 1991-2001, 2001-2011, 2011-2019), the entire 1981–2019-time span, and the periods 2018-2019 and 2019-2020. The analysis focuses on the period 2018-2019 and the period 2019-2020, and identifies 2019 as the limit of the time series in order to capture the impact of the COVID-19 pandemic on the most vulnerable age group, i.e., people over 65. The analysis of the dynamics of the share of the elderly population is based on the definition of two types of indicators: a static indicator, aimed at describing the incidence of the elderly population at a specific point in time, measured as the ratio between the number of inhabitants over 65 and the total number of inhabitants; and a dynamic indicator, measuring the change in the incidence of the elderly population over a specific time period. These indicators are aimed at discerning and describing the trend towards a general increase in the proportion of the elderly population, which is particularly significant in inland areas, and at identifying the centres in which this trend becomes such as to jeopardise the endogenous capacity of a municipality to maintain an adequate demographic vitality. The analysis of this dynamic also becomes a criterion to be evaluated in determining new forms of basic services, aimed at these areas, particularly with regard to health and transport services.

2.3 Results and Discussions

2.3.3 The Stock of Services and Accessibility

The data collection phase resulted in the identification of approximately 19,000 activities and services throughout Basilicata, as shown below (table 3):

Table 3: Service and equipment classes in 2021.

TYPE OF SERVICE	NUMBER OF ACTIVITIES
Commerce	4697
Culture and Art	1574
Education	1137
Healt	1810
Services	4265
Financial Services	738
Public Services	437
Safety	540
Sport and Free Time	2061
Turism	1973

The final result was the preparation of the 'Service Charter of the Basilicata Region', which is useful for assessing the distribution of services throughout the region, so as to be able to define the equipment of each individual municipality (See Appendix- A1).
The map in the Figure 5 shows that there are few municipalities in the region that have a significant supply of services, in fact, in most cases, the supply of services is very low or almost none. The two provincial capitals and the municipalities of Policoro and Melfi are an exception. This index can be used to evaluate the quality of life in a given area and to identify any deficiencies or gaps in the services present, in order to plan interventions and improve the situation. Furthermore, it can be compared between different geographical

areas, making it possible to identify the differences in terms of accessibility to public and private services and to promote improvement interventions in those areas with a lower service endowment index.
The creation of this territorial dataset has made it possible to collect, analyse and organise in a synthetic form the territorial data relating to the stock of services present in the territory, which are useful for the planning and management of urban planning tools.
A large part of the regional territory is characterised by a spatial organisation based on minor centres which, in many cases, are able to provide limited accessibility to essential services. The characteristics of these minor centres consist in a significant distance from the main centres providing essential services (education, health and mobility). These inland areas represent a very variegated territory, the result of the dynamics of different territorial processes and anthropization processes that have occurred.

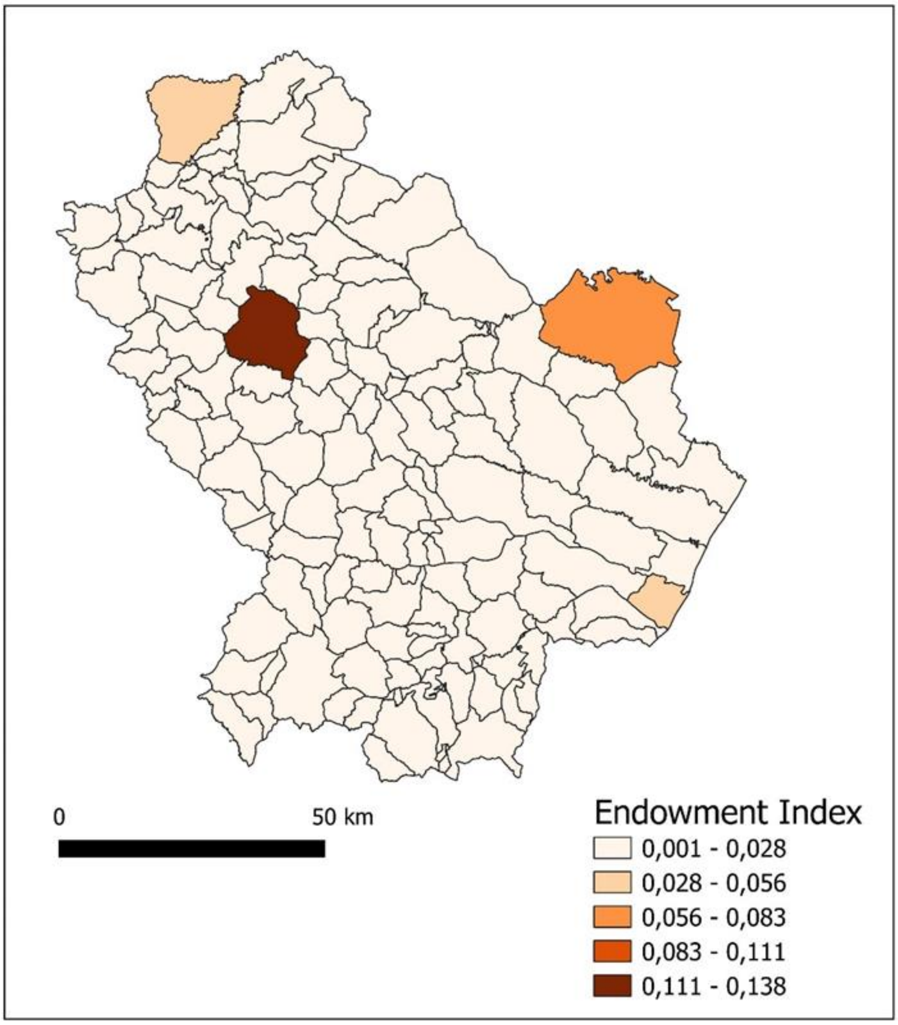


Figure 5. Endowment Index of Basilicata Region.

From a spatial point of view, the level of remoteness of territories with respect to the network of urban centres, home to a vast plurality of services, profoundly influences the quality of life of citizens and the level of social inclusion. In these, the presence of essential services can act as an attractor capable of generating discrete catchment areas. The centre of the offer of essential services is identified in that municipality capable of simultaneously providing all the schooling, at least one hospital and one railway station. This is where the concept of accessibility starts to come into play [108–110]. The concept of accessibility is widely used even though there are many definitions that can be attributed to it and which give it a changing and undefined outline. We can understand it as a right and an essential condition of living in cities and the territory [21,103,108,111,112].

All too often, however, this concept is only taken into account at the end of the planning and design stages, thus not responding to the real needs of those who live in the area. This is the result of a methodological approach that is objective and not centred on individual subjects; indeed, spatial planning focuses not on the individual and his or her needs-possibilities, but on following standard ideals that do not guarantee equitable liveability. It moves from an approach strictly related to the productive and economic sector to take root in that of services of social interest such as education, health and recreational areas. Among the variables that most influence the way accessibility is understood is the territorial context to which it refers. The latter can aggravate or bring out forms of social inequality in terms of equal opportunities and accessibility of services or, even more, isolate and marginalise certain urban contexts. Recent studies have highlighted the correlation between social exclusion and use of the city, showing monotonous and single-place combinations of city use [113–117]. This is the case in the Basilicata Region characterised by a serious development delay and a centuries-old infrastructure deficit, especially in rural and mountainous areas. The poor accessibility to essential services is also negatively affected by the infrastructural endowment of the Lucanian territory. The figure 6 shows the degree of infrastructure, what emerges is a region lacking in important infrastructure such as airports and high-speed railway stations.

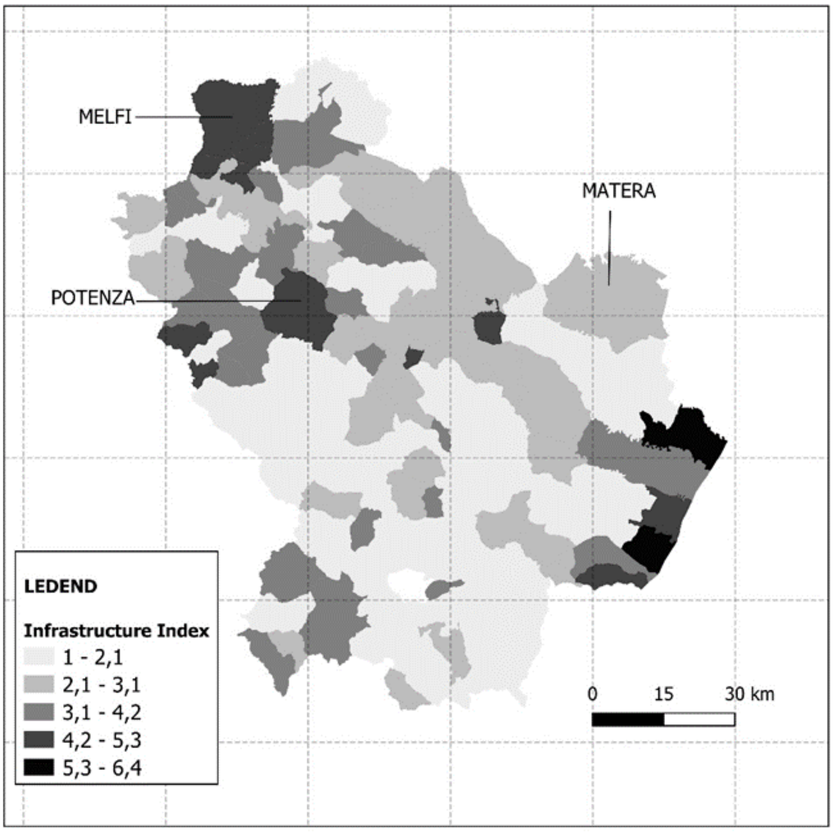


Figure 6. Infrastructure Index of Basilicata Region.

The main network of roads is represented by a few arterial roads that criss-cross the entire region and from which a system of secondary roads develops, whose function is to connect individual centres to higher-level roads, providing access to suburban roads and farmland. Analysing the network of infrastructures and services that can be used in the regional territory, an indispensable and fundamental component for full and active participation in social life, significant shortcomings are highlighted that specifically concern the railway and motorway networks. The regional railway network runs on a 365 km discontinuous line that divides the region into two sectors. The entire territory is also devoid of a motorway network and its tollbooths; the only points of entry to a fast road are in the municipalities of Lagonegro and Lauria, which are crossed by the Salerno-Reggio Calabria (Fig. 7).

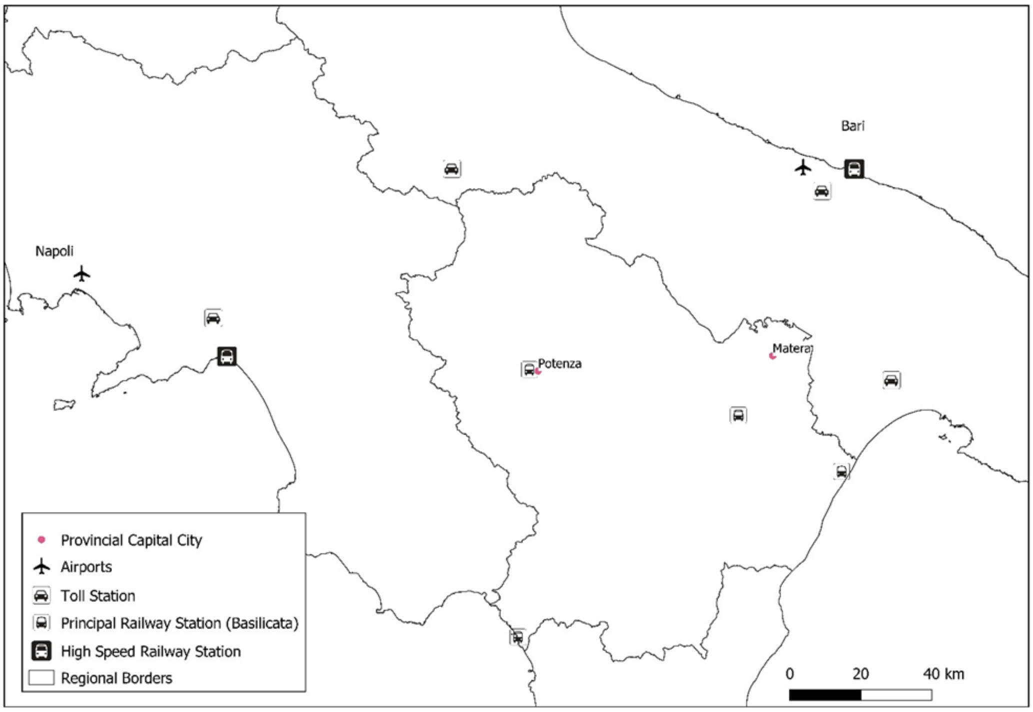


Figure 7. Transport system localization.

The estimation of time travelled to a particular service is aimed at highlighting areas lacking services, thus definable as peripheral and generating significant travel demand to central areas. For the calculation of accessibility, the municipal administrative headquarters was taken as the starting point, from which travel time from the urban centre of each municipality to the service considered closest has been calculated.

In GIS environment, the time distance travelled by car using the fastest route was taken as a parameter, creating isochrones every 10 minutes on the basis of route calculations, isochrones and matrices, interactive in the map area or from point files within the OpenStreetMap suite processing framework. The estimation of the kilometres travelled is intended to highlight the areas lacking services, which can therefore be defined as peripheral and generating a significant demand for travel to the central areas [118].

The SNAI (National Strategy for Inland Areas) [16] divides the Lucanian territory into four inland areas: Alto Bradano; Marmo Platano; Mercure Alto Sinni Val Sarmento and Montagna Materana, a territory comprising 119 municipalities out of 131. Figure 8 shows two maps: the map on the left shows SNAI's classification of 2020 with the location of the regional hospitals; figure two shows the accessibility of each individual municipality to the nearest hospital.

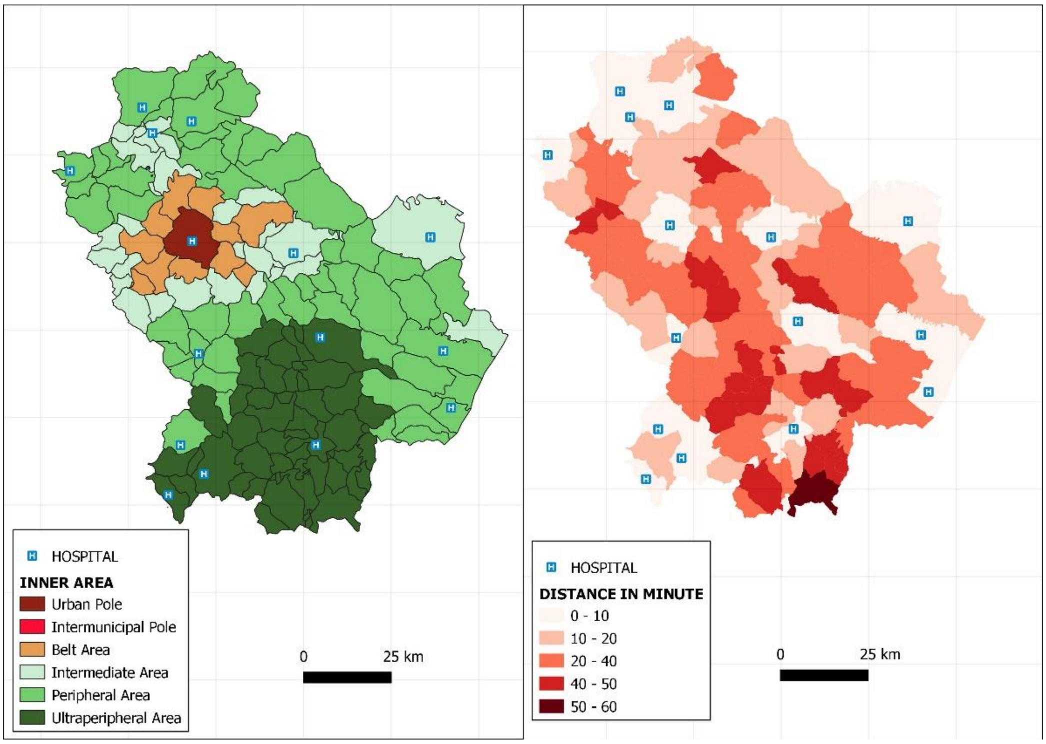


Figure 8. Map of the distance in terms of travel time from municipal centres to hospital medical centres.

It can be observed that the inland areas of the region are more distant from the hospitals, in fact on average it takes a citizen living there between 30 and 50 minutes to reach the nearest hospital.

Generally, from this analysis it has been found that the smaller centres provide services that only find an outlet in local demand as a result of limited economies of scale and are insufficient in infrastructures and services, even primary ones, while the larger centres accommodate a greater number of services diversified in terms of type, despite the lack of road infrastructures connecting them to the smaller centres.

In Basilicata, residential and productive settlements are not evenly distributed in space[119], but tend to cluster in centres, where the main productive activities and residential areas are clustered. The results of this research discussed so far are useful for interpreting the territory's peculiar characteristics, and in order to define a polycentric organisation scheme they must be integrated with an assessment of the levels of territorial accessibility. The work carried out has thus made it possible to highlight the gap between municipalities in the same region in terms of accessibility and provision of essential services, showing how this is one of the parameters affecting regional development. Improving the accessibility of these territories means, for example, bringing essential services back to the most isolated areas, enhancing the mobility offer and acting on local territorial capital. Although the improvement of infrastructure endowment is a difficult prospect to achieve, forms of territorial cooperation oriented towards the efficient organisation of the supply of the main public services should be undertaken on the basis of a strongly contextualised territorial organisation model.

2.3.4 Socio-Demographic Evolution in Basilicata Region

The analysis of demographic trends over the period 1981-2021 shows how, in the context of a modest increase in population, equal to 4%, in the national context, the macro-area of southern Italy shows a marked decrease in resident population (-40.4%). Trends in the regional context indicate, over the same period, a decrease in resident population of 11.6% (Potenza Province -15.24% and Matera Province - 5.22%). The resident population amounts to 539,999 inhabitants, distributed between the two provincial territories of Potenza (348,336 inhabitants) and Matera (191,663 inhabitants) for a total of 131 municipalities (ISTAT 2021), with 54 inhabitants per square kilometres. As regards the variation in population over the period 1981-2022, depopulation trends are particularly marked in the municipalities of San Paolo Albanese (-411 inhabitants, equal to a 65.10% contraction), Calvera (-516 inhabitants, equal to a 59.40% contraction), San Mauro Forte (-1749 inhabitants, -57.60%). Marsicovetere (+2167 inhabitants, equal to an increase of 64.2%), Policoro (+5615 inhabitants, +46.2%), Pignola (+2775 inhabitants, +69.3%), Tito (+2301 inhabitants, +47.6%) are in contrast. The two provincial capitals show opposite demographic trends: Potenza shows a slight demographic decrease (-208, - 0.3%), while Matera (+8766, +17.2%) shows an increase in demographic variation (Fig 9).

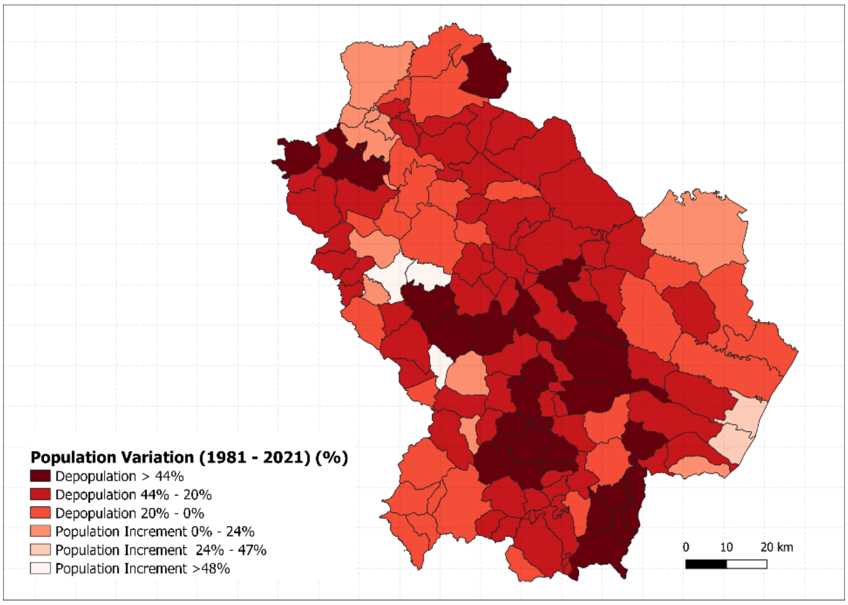


Figure 9. Depopulation Index.

Referring to distinct categories of municipalities, it can be seen that in Category 6 municipalities, with a resident population of less than 1,000 inhabitants as of 01/01/2021, the phenomenon of depopulation over the period 1981-2021 is extensive and significant. The municipalities of Carbone, San Paolo Albanese, San Chirico Raparo, Armento and Calvera, in which the highest demographic decrease reported for the entire Region of Basilicata is found, are included in this category. Similarly, for municipalities with a resident population between 1,000 and 2,000 inhabitants (Class 5), there is a constant and significant drop in the resident population, which is most evident in the municipalities of San Mauro Forte (-1749 inhabitants, -57.5%), Terranova di Pollino (-993 inhabitants, -49%), and San Giorgio Lucano (-947 inhabitants, -46.9%). In the Municipality of Sarconi alone, there was an increase in resident population of 18 (+216 inhabitants).

On the contrary, less uniform trends are to be found among the municipalities of Category 4, where there was a significant demographic contraction, most marked in the municipalities of Marsico Nuovo (-2185 inhabitants, - 63.9%), Stigliano (-3577 inhabitants, -50.7%), and Irsina (-2032 inhabitants, -60.9%). The data for the municipalities of Baragiano, Francavilla in Sinni, Rapolla, Satriano di Lucania, Atella and Viggiano emerges, where the population has remained stationary or increased slightly. The heterogeneity of demographic trends is, however, even more marked in the case of municipalities with a population between 5000 and 10000 inhabitants. Finally, in the two provincial capital municipalities, there is a negative trend in Potenza (- 211 inhabitants, -0.35%) and a positive one in Matera (+8766 inhabitants, +17. 2%). With reference to the period between 2011 and 2021, there is a general contraction of the resident population, particularly evident in the municipalities of San Paolo Albanese (-97 inhabitants, equal to a demographic decrease of 30%), Oliveto Lucano (-126 inhabitants, -25.2%), San Mauro Forte (-410 inhabitants, -23.8%), Carbone (-160 inhabitants, -22.5%), San Costantino Albanese (-173 inhabitants, -21.7%). A slight demographic increase can be seen in the municipalities of Marsicovetere, where a population increase of 176 inhabitants (+ 3.3%), Sarconi (+49 inhabitants, + 3.6%), Viggiano (+150 inhabitants, + 4.8%), Scanzano Jonico (+528 inhabitants, + 7.4%). More significant is the figure 14 for Policoro, with 1809 new residents, an increase of 11.3%. In the Capital Municipalities, there is a modest decrease in the resident population in Potenza (-1636 inhabitants, -2.4%), and a stationary condition in Matera (-19 inhabitants, -0%). During the period 1981-2021, there was a significant increase in the number of municipalities in category 6, i.e., with a population of less than 1,000 inhabitants. This category comprised only 10 municipalities in 1981, the number of which increased to 14 in 1991, to 20 in 2001, to 24 in 2011 and to 32 in 2021, thus showing a constant negative demographic dynamic in smaller municipalities. In general, an increase of 12.9% of municipalities with a population of between 1,000 and 2,000 inhabitants is noted over the period under consideration. These trends are followed by a consistent decline in the number of municipalities with a population between 2000 and 50000 inhabitants. Class 1 includes only the municipalities of Potenza and Matera since 1981, thus showing an almost unchanged trend (Fig. 10) (See Appendix A1).

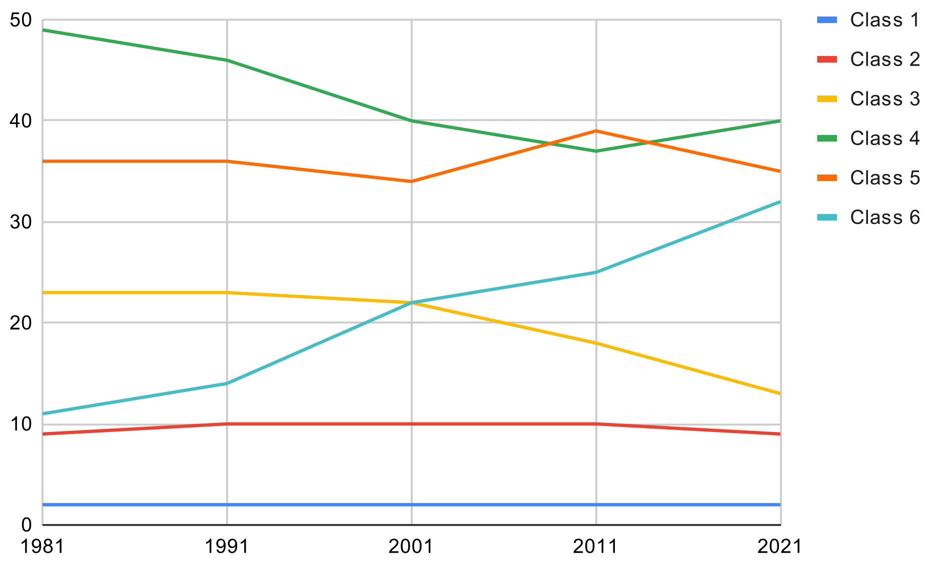


Figure 10. Trend of population classes in the period 1981 - 2021.

It can be seen that the population residing in class 6 municipalities (table), i.e., with a population of less than 1,000 inhabitants, increased from 8554 inhabitants in 1981, to 21881 inhabitants in 2021. As a result, in 2021, 4% of the population of the Basilicata Region resides in municipalities with a population of less than 1,000 inhabitants. In 2021, therefore, about 13% of the regional population is distributed among municipalities with a population between 1000 and 2000 inhabitants. In the case of classes 4 and 5, there is a decrease in the cumulative resident population in both classes.

Table 4. Distribution of resident population divided into classes, years 1981 and 2021.

Class	***1981***	***2021***
6	8554	21881
5	50004	50026
4	170446	137231
3	148467	87035
2	119573	123743
1	116110	125214

Whereas in 1981 the resident population in the Basilicata region was mainly concentrated in municipalities with a population between 2000 and 5000 inhabitants (27.8%) followed by municipalities with a population of over 5000 inhabitants (24.2%), in 2021 a significant increase in the population of municipalities with a population between 1000 and 2000 inhabitants (classes 6 and 5) and in capital municipalities (23%) can be observed. The last demographic consideration concerns the percentage development of the resident population divided into the four categories: elderly, adult, young and child population. By comparing the percentages of the population divided into these 4 macro-categories in the two years taken into consideration (1981 and 2021), it was possible to identify a large and significant increase in percentage terms of the resident elderly population (Fig. 11). (See Appendix A1).

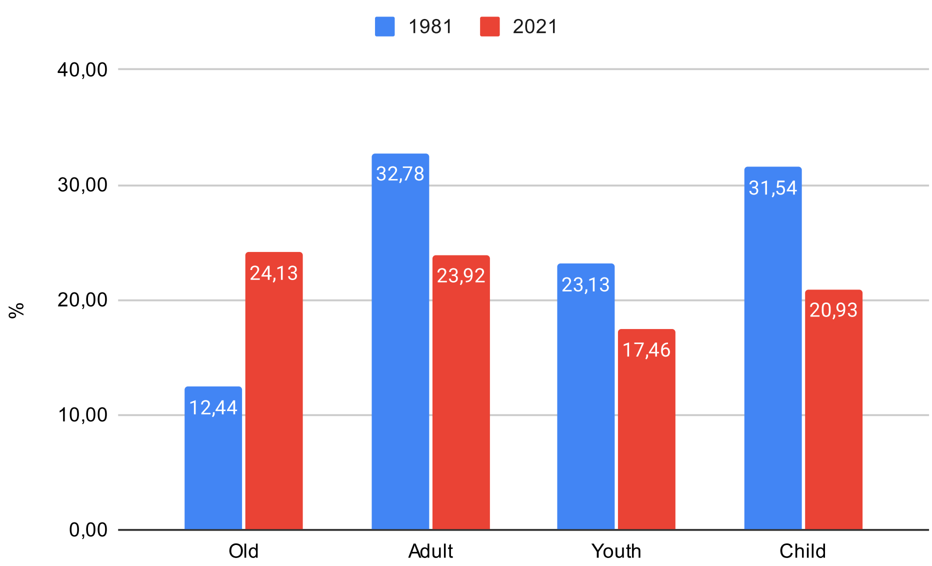


Figure 11. Regional resident population in percentage terms, divided into macro-categories (elderly, adult, young and child population) in the two periods considered.

The graph shows an increase in the resident elderly population in 2021 compared to 1981 of almost double in terms of percentage value, while the other categories analysed show a significant decrease. This incidence, in 2021, is 23.5 per cent in the national context, 22.0 per cent with reference to the Mezzogiorno macro area, and 24.1 per cent with reference to the regional context (Fig. 11).
Most municipalities have values above 30 per cent of resident elderly population, a value identified as the demographic no-return point, i.e., a limit value that identifies a condition whereby a municipality loses the endogenous capacity to maintain an adequate demographic vitality.
Through the data provided by the Basilicata Chamber of Commerce, it was also possible to investigate the trends in the economic activities registered and active in the 131 municipalities over the 2002 - 2021 period. The figure 12 shows the percentage change in economic activities on a municipal basis, out of 130 municipalities, 120 show a negative trend synonymous with a decrease in enterprises over the period considered, only 11 municipalities show the opposite trend, a growth in enterprises in the municipal area.

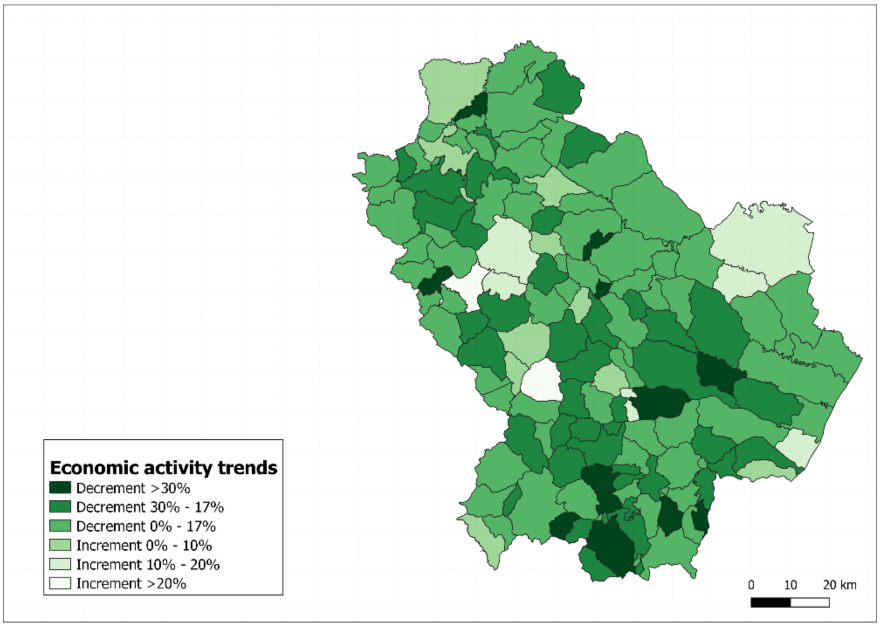


Figure 12. Spatial distribution of the variation of Economic Activities in the period 2002 - 2022.

2.4 Conclusions

The work carried out illustrates the distinction that exists between the different centres in Basilicata, showing how the endowment and location of essential services, considered as a fundamental parameter for the study, is an index of the marginality and fragility of these territories. The low population density, the decrease in economic activity, and the fragmentation of the peripheral areas limit the possibility of a reconfiguration of the service system that meets the requirement of proximity, and that also favours the use of alternative forms of mobility. In conclusion, the analysis of demographic trends, reveal the peculiar phenomena of peripheral and ultra-peripheral municipalities: the demographic contraction and the increase in the share of population over 65 years old, such as to determine, the loss of endogenous ability to maintain adequate demographic vitality. The demographic decline, which is mainly observed in the peripheral and ultra-peripheral areas, seems to accompany the economic decline; in fact, even the only regional hub registers a loss of population. Thus, both population contraction and aging are likely to be influenced by the rate of migration than by natural population growth, despite the communities' efforts to attract young people.

Basilicata is characterised by obvious structural gaps between municipalities: those located in the hinterland of the two regional capitals, which enjoy the presence of services and facilities, are in a more favourable position than those in the hinterland, which are difficult to connect due to a poor road network that is often rutted or interrupted by landslides and landslips and sometimes lack basic services. These gaps can be considered as a form of insularity effect, which shows a gap in connections and accessibility and therefore needs extraordinary instruments to support development territorial development. The research shown in this chapter essentially provides a case study of the application of statistical and geo-statistical tools to map the marginalisation effects of insularity in inland areas and then relate them to the dynamics of LULCC in the following chapters. Constant negative demographic trends and reduced opportunities for access to primary and secondary public services are indeed the factors contributing to a weak territorial profile. However, the extensive academic debate and institutional policy proposals have not yet led to an adequate clarification of how the planning and development process of inland areas can be effectively implemented. The report prepared by Barca (2009)[84,87] calls on all governmental institutions, from the national to the local level, to focus on inland areas and to direct their policies towards sustainable development strategies.

Making the most of inner area village and towns is essential for sustainable development of the region. However, the actions to be take are complex. In fact, the widespread distance form City, the lack of adequate infrastructure, the absence of basic services, the absences of concrete employment opportunities, incentivizing the population, especially younger people, to prefer metropolitan life. Therefore, actions capable of capturing social, economic and environmental aspects are needed [120]. Nevertheless, it is possible to outline guide-lines and good practices for the sustainable planning of inner areas.

Chapter 3: Application of Remote Sensing for Land Use/Land Cover Change Analysis: Land Take Assessment

Land use is one of the factors determining Land Cover Change (LCC) and represents the conversion of natural to artificial land cover. This chapter describes the activities to monitor land use and to analyse development trends in test areas of the Basilicata region. This section presents some analytical applications to investigate the time series of land consumption at municipal scale, to discuss the relationship between urban expansion and demographic trends, to quantify land consumption at temporal scale. Land transformations involving increased soil sealing and, more generally, transitions from natural and semi-natural soils to artificial soils have been investigated. These changes in land use and land cover have, fragmented the territory, moving from a natural and artificial landscape often characterized by sprawl and sprinkling [15,94,119] direct consequence of uncontrolled and unregulated land take. In many cases, land take is associated with an increase in urbanised areas that are not accompanied by adequate housing demand and affects fragile land areas that are not suitable for transformation, such as hydrogeological risk areas. Remote sensing is the main technique for extracting land use and land cover (LULC) data. In this chapter, a new methodology is proposed to classify Landsat (TM - OLI) and SENTINEL 2 data to automatically detect land cover information and identify soil sealing to perform a multi-temporal analysis. Furthermore, within the defined model, it is essential to use the spatial information layers of the geotopographic database (GTDB) for the detailed definition of the territory. All steps of the classification process were developed using the Support Vector Machine (SVM) supervised classification algorithm, change detection analysis, integrating geographic information system (GIS), remote sensing data and adopting free and open-source software and data. The application of the proposed method enabled the rapid extraction of detailed land-use maps with an overall accuracy of over 90 per cent, reducing processing costs and time. Through a spatial-temporal analysis, the land consumption due to the creation of new buildings, infrastructure and renewable energy facilities and more generally all land cover classes were estimated. The results show an increase of sealed soils not only due to traditional urban and rural sprawl caused by the construction of new buildings, but, especially in the last decade, by the unregulated installation of renewable energy plants on the territory with the consequent construction of additional road infrastructure in a spatial context of high landscape value and generally negative demographic rates. This chapter is organized as follows: the first part is dedicated to an overview of land take and a focus on Basilicata. The second part on the methodological framework describes an initial methodology applied to the study of historical trends in the estimation of land take from urbanisation, the second methodological part concerns the case study of the Melfi area where a focus on land take from renewable energy sources was carried out.

3.1 Land Take Overview

Land Take can be defined as the increase of artificial areas over time (EEA, 2021). Land take is the growth of areas with artificial land cover (soil sealing), not necessarily urban, but also industrial. It is associated with soil loss, defined as the change from non-artificial to artificial land cover. In literature, the change of soil from natural to artificial cover is referred to in many ways, such as land take, soil consumption, soil sealing, impermeable soil, etc [16,17,121,122].

Land take is thus defined as the change from non-artificial land cover (non-consumed soil) to artificial land cover (consumed soil), with the distinction between permanent land consumption (due to permanent artificial land cover) and reversible land consumption (due to reversible artificial land cover) [25]. The European Union has adopted the Thematic Strategy for Soil Protection [123,124], which recognizes soil sealing as one of the main threats to soil health and promotes the prevention of soil sealing through the use of sustainable land-use planning techniques, reduction of urban pressure on soils, promotion of sustainable construction techniques, and citizen awareness of the importance of soil protection. Land take is monitored under the name of Land Take and Soil Sealing at the European scale, by the European Environmental Agency, in its report it states the long-term changes over the period 2000–2018 show that the area of artificial surfaces in Europe has changed the most, with an increase of 7.1% [125]. Whereas 'land take' refers to areas taken for purely artificial uses involving total soil sealing, 'land consumption' refers to the consumption of land cover, including areas consumed for new expansion (sealing), for intensive land use due to agriculture, forestry and other economic activities, as well as other intensive uses such as pastures [59,60]. The characteristics and impacts of land take are well known in the scientific literature [91,126,127] . In the European Union (EU), the greatest part of the population lives in cities, towns and suburbs and further urbanisation is expected. It is predicted that by 2030 there will be 3 per cent of the land area occupied. In Europe, the rate of occupied land is one of the highest on the globe, the increase of artificial surfaces for new expansions often causes the compromise or disruption of important soil ecological functions, such as biomass supply, soil biodiversity and soil carbon pool or water infiltration potential. All these factors contribute to the negative impacts of climate change, decreasing the potential for carbon storage and sequestration or increasing surface runoff during floods. Land cover with impermeable materials (soil sealing) is probably the most impactful use that can be made of the soil resource, as it results in the total loss or permanent degradation of its biological functions. Knowing the changes in land use and land cover, from natural to artificial, is important to understand the interactions between human activities with the environment. Within the European framework, several policies are aimed at land protection and degradation reduction, although none of them has a binding legislative function on the planning policies of the different Member States. The European Commission has legislated on soil protection with the EU's 7th Environmental Action Programme to 2020 (7th EAP)) setting the target of having zero net soil consumption by 2050 [128] while the UN's Agenda for Sustainable Development has established, through its Sustainable Development Goals (SDGs), two indicators to track land take issues such as land degradation and urban growth. This can be achieved by aligning the increase in land take with actual population growth by 2030. In recent years, bills on soil monitoring and protection have followed one another without ever completing the discussion and approval process, postponed, sometimes depreciated in their basic principles, and completely covered by modification. According to ISPRA, the rate of soil consumption in Italy has been steadily increasing since 2012 and is moving us even further away from the goals of zero net soil consumption, showing a worrying inversion of the trend. The data confirm that we are continuing to increase the level of artificialisation and soil sealing, causing the loss, often irreversible, of natural and agricultural areas. These areas have been replaced by new buildings, infrastructures, commercial, logistical, productive and service settlements and other artificially covered areas inside and outside existing urban areas. Urban areas are of key importance in the analysis of evolution dynamics and in the study of land consumption. In fact, urbanisation processes are among the main causes of the increase in soil and habitat degradation and the increase in the degree of fragmentation of natural areas, with consequences on the state of land cover, ecosystems, the hydrological cycle and in general on the capacity of territories to respond positively to climate change risks. In recent decades, the evolution of urban areas has been characterised by a gradual acceleration and significant evolution leading to a new era of urban processes. Urban areas are larger and show a trend towards expansion. Today, cities are home to almost half of the world's population and this share is expected to reach 55 per cent by 2050. Urbanisation is occurring with increasing intensity on the fringes of the established city and in agricultural and natural settings with high ecological value. The trend of consolidated urban expansion has been accompanied by new forms of urban sprawl that are discontinuous, heterogeneous and fragmented, generating dispersed areas that cannot be properly defined in terms of either urban or rural areas, and difficulties in delimiting them [15]. Demographic trends are crucial in the process of urban expansion of a territory. Urban areas have expanded mainly at the detriment of agricultural land and, in recent decades, urban sprawl has not matched population growth [129,130], in fact, in many low-density and continuously depopulating urban contexts, urban expansion is accompanied by a negative demographic trend [119]. The National Environmental Protection System (SNPA) monitors soil consumption and ISPRA publishes an annual study on the state of the art of soil consumption in Italy. Urban transformations in recent years have changed the relationship between urban centres and rural areas with an increase in land fragmentation[93,131]. The principal processes related to land take include settlement dispersion such as urban sprawl [132] and urban sprinkling [133]. These processes, in fact, lead to an increased infrastructure of the territory with the consequent exploitation of agricultural or natural areas and an increase in the running costs of technological and transport networks, proving to be environmentally, socially and economically unsustainable. In several territorial contexts, such as the Basilicata Region, urban sprawl is strongly present, resulting in extensive land sealing [134,135]. These trends have been driven by weaknesses, or the total absence, of measures and policies to limit land take, increasingly promoting the occupation of vacant land away from urban centres rather than reconstruction or redevelopment within established urban areas [136]. For many years in Italy, the regional regulatory framework has been evolving on the specific issue of soil consumption and through regulatory instruments aimed at encouraging urban regeneration, all in the absence of a national-level reference. The result is a rather heterogeneous and overall, poorly effective landscape that includes provisions. There are 21 observatories in the country to date, including, for example, Valle D'Aosta, Piedmont, Campania and Lombardy.

3.1.1 Land Take Assesment in Basilicata Region

To date, Basilicata still has no regional law regulating land take and has not yet set up a regional observatory. The weak and confusing regulatory framework has contributed to the spread of soil sealing processes, such as the unrestrained installation of wind farms, resulting in an increasing fragmentation of the territory with associated soil degradation developments. The creation of a regional observatory would support public bodies in defining policies, strategies and actions aimed at containing the phenomenon and would also implement measures to limit, prevent, monitor and mitigate it. The National System of Environmental Protection (SNPA) monitors land take and the Superior Institute for the Protection and Environmental Research (ISPRA) every year elaborates a study of the state of the art of land take in Italy.
According to the ISPRA, in 2022 in Italy artificial cover has been estimated at 69 km^2, an average of 9 hectares per day, of which the total sealed areas amount to 25 km^2[25]. An increase that shows a clear acceleration with respect to the reduction trend of recent years and makes Italy lose 2.2 square metres of soil every second. In Basilicata in 2021, the soil consumed amounts to approximately 317 km^2, of which 225 km^2 in the province of Potenza and 91.95 km^2 in the province of Matera. per capita soil consumption amounts to approximately 582 m^2/inhabitants[25].

Numerous experiences have been carried out in defining criteria to identify the spatial dimension of urban areas, with reference to the Italian context but also on a European and global scale. The different methodologies differ first of all in the approach used, in some cases referring to a characterisation based on the observation of the presence and density of the built-up area alone (as in the case of Copernicus data), while in other cases the information on land use and land cover is integrated with demographic data or with economic information with reference to the OMI mapping of the Italian Revenue Agency.

Nowadays, remotely sensed data with high spatial and spectral resolution, along with GIS software tools, have become increasingly available and used to quantify and monitor land use and land cover change from a local to a global and urban scale [24,31]. Remote sensing data provides detailed information and an overview of landscape features and changes in urban and rural areas. Land cover mapping and assessment is one of the main areas of application of remote sensing data [32,137]. This issue has been addressed in numerous studies using different applications, multispectral data and classification methods [27,138,139].

Appropriate classification techniques are essential to derive reliable information from satellite data effectively. The careful choice of the classification method influences the results of the land use/cover mapping [140,141]. Several classification methods have been developed for satellite image processing in recent years. A general overview of such methods includes both non supervised classification algorithms (i.e., K-means algorithms, Isodata, etc.) and traditional supervised classification algorithms (i.e., maximum likelihood) and machine learning algorithms such as support vector machines (SVM), k-Nearest Neighbors (kNN), decision trees (DT), and random forest (RF) [142,143]. Haydary et al. [144–146] used Landsat images applying several classification algorithms (kNN, SVM and Artificial Neural Network) to compare the accuracy of results obtained using different classifiers and sampling methods heterogeneity of images, distribution of classes in space [68]. This chapter concerns a practical study on land take time series, carried out through remote sensing data by the Landsat Mission, aiming to provide accurate information for selected sample area in Basilicata Region from 1994 to 2014. The choice of analyzing land take starting from 2014 and then continuing backward in time is mainly related to updating the cartography present on the regional geo-topographic database. The information layers of the GTDB relating to urban/impermeable areas represent the ancillary reference data of our work, with which to compare, using map algebra, the map obtained from the classification process. Landsat images were classified using an automatic classifier [80,147]. All process steps have been developed integrating Geographical Information System (GIS) and remote sensing and adopting free and open-source software QGIS. This aim of this part of thesis regard to create and use an expeditious methodology for classifying multitemporal Landsat imagery, using the semi-automatic classification algorithm in a GIS environment for mapping land use. The method developed has the potential of SVM based on machine learning theory to produce a synthetic map of land take provides valuable and detailed information to improve the accuracy of land cover mapping in complex landscapes and environments such as urban peri-urban areas.

3.2 Material and Methods

3.2.1 Land Take Historical Trend Identification

3.2.1.1 Study Area

The morphology of the Basilicata Region is prevalently mountainous and hilly, with a single wider plain in the Metaponto area (Ionian coast) and four valleys that lift the main rivers from the south towards the northern part of the region. Urban centers are mainly located in the highest parts of the region for historically defensive reasons. They are generally delimited by large uninhabited areas and scattered houses or small civil or industrial agglomerations. Thirty per cent of the territory is affected by areas subject to environmental constraints; this fact further highlights the need for a prudent and more sustainable use of the natural territory. Basilicata is among the Italian regions with a high depopulation rate; according to the National Institute of Statistics (ISTAT), the region's resident population will decrease from about 600.000 in 2000 to about 547.500 in 2021. The municipalities with the highest land consumption based on surface area are Potenza (10.7%), Melfi (8.6%) and Policoro (8.4%). In terms of absolute values of soil consumed in 2020, the municipalities with the highest values are Matera (21850 m^2), Potenza (18690 m^2) Melfi (17590 m^2). According to the information processed by ISPRA, the historical trend of soil consumption in the municipalities with the highest values was analyzed. The municipal areas investigated are Potenza and Matera and the municipalities of Pignola, Melfi, Policoro and Scanzano Jonico (Fig.13).

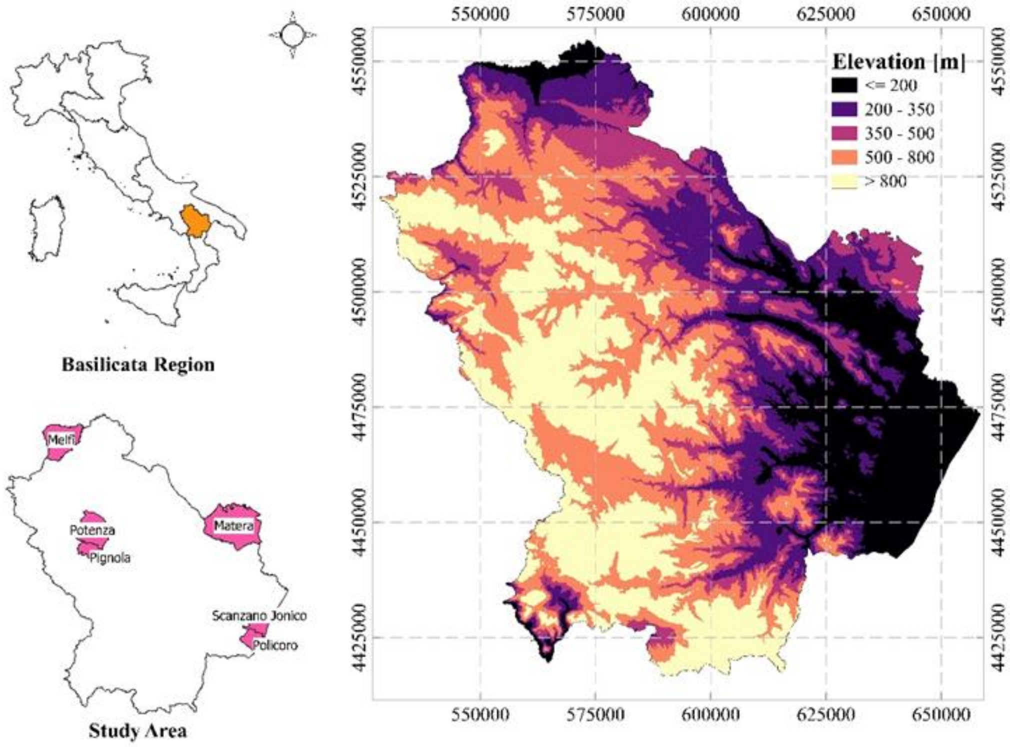


Figure 13. Location map of study areas.

Potenza is the main town located in the central-western part of the territory. The municipal area has an extension of about 175 km^2; the morphology is mainly mountainous. The capital city, with about 65.000 inhabitants, is the political and administrative center of the region. Despite being the fulcrum of the administrative and commercial life of the region, it too suffers, like the whole region, from depopulation; the resident population has decreased by about 3 thousand units in the last seven years. Over the years, urban expansion has taken place in a disorderly and uncontrolled way towards peripheral areas combined with a decline in population density. Pignola is a small municipality (approximately 56 km^2 of territorial extension) of about 7. 000 inhabitants, close to Potenza. It is one of the municipalities with the most significant interaction with the city as the territorial development of the two municipalities is often shared.
Matera, the other provincial capital, is located in the eastern part of the region, on the border with the Puglia region. As invested with the role of European Capital of Culture 2019, it is interesting to evaluate an increase in tourist flows and a potential increase in accommodation facilities and infrastructures in order to outline a trend of land take. The city is one of the few urban centres in the region to show a constant growth in resident population (in 2021, about 60.000 inhabitants). The morphology of the city of Matera is purely hilly, featuring the karstic gorge carved into the limestone by the Gravina stream and the presence of evident superficial karstic forms; it is one of the largest municipalities in the region (388 km^2).
Policoro (which is the third most populous municipality in the Region of Basilicata with about 18.000 inhabitants) and Scanzano Jonico (about 7.600 inhabitants) are located in the Ionian area of Basilicata in the fertile Metapontum plain; their territorial extension is about 67 km^2 and 71 km^2. The coastal area, characterised by strong tourist pressure, especially in the summer season with the opening of bathing establishments, is one of the most relevant areas for analysing changes in land use. Both municipalities, in fact, have significant tourist flows in the summer period, with a consequent increase in land consumption related to the construction of tourist infrastructures. The resident population has shown a positive trend in recent years, probably due to the increase in commercial activities related to the strong tourist presence. The municipality of Melfi (about 204 km^2) is located in the northern part of the region, on the border with the Puglia region. The city is another critical urban centre of great interest due to the territorial evolution linked to the construction of the Stellantis automobile industrial district, whose production began in 1994. It is characterised by a settlement structure based on two main components: the historic city surrounded by post-World War II residential expansion and a vast industrial area where the most important Stellantis production plant in Italy is located. A series of supporting activities have developed around the factory, leading to a significant increase in land consumption in recent decades. The rest of the municipal territory is characterised by a solid agricultural vocation and widespread areas of high natural and environmental value, already fragmented by three railway lines and a high-speed road. The resident population, after a slight increase in the decades 1990-2000, has experienced a negative trend in recent years with a small decrease in inhabitants.

3.2.1.2 Data Set and Pre-processing Image

The use of multispectral and multitemporal satellite imagery with medium and high spatial resolution is highly appropriate for land-use assessment and monitoring. Landsat 4 - 5 TM and Landsat 8 OLI images, for the years 1994 - 2004 - 2014, were used to classify LULC classes and to derive urban land use. The historical Landsat dataset (years 1994, 2004 and 2014) was downloaded from the United States Geological Survey (USGS); images were selected based on cloud cover conditions. The scan line error of the Landsat ETM+

sensors affected data availability in the 2000s. Orthophotos produced from aerial images were made available by the national geoportal of the Ministry of the Environment and the Military Geographic Institute (IGMI). These images were used as a dataset for the definition of classification training areas and accuracy assessment. The regional geo-topographic database (GTDB) of the Basilicata Region's Regional Spatial Data Infrastructure (RSDI) represents auxiliary data used for the implementation of urban areas. These data sources are open and generally provide basic information; this approach allows the replicability of the study in other territorial contexts. The processing and analysis of the collected data were carried out with the QGIS software. The satellite images used in this research come from Landsat 4-5 and Landsat 8 missions-based cloud-free data. The images chosen concern the month of May in the years 1994 - 2004 – 2014. The downloaded remote sensing images were provided as L2 level data, were clipped with the mask of the municipal boundaries of each test area, and then a check was made to realign any saturated pixels. The reference system used is UTM projection (zone 33 N). Landsat data provide thirty-year time series data, helpful in achieving an accurate temporal analysis. Landsat-4 and Landsat-5 Missions equipment a multi-spectral scanner and a Thematic Mapper, with spatial resolution at 30 meters, while the Landsat-8 has an OLI sensor and a thermal sensor, the first with a resolution of 30 meters, the second at 100 meters. The bands used for this study are summarized in the following table (table 5).

Table 5. Landsat 4-5 and Landsat 8 bands used.

Landsat 4 – 5 TM	**Landsat 8 OLI**
Band1- Blue (0.45-0.52μm)	Band2- Blue (0.450-0.51μm)
Band2 – Green (0.50-0.60μm)	Band3 – Green (0.53-0.59μm)
Band3 – Red (0.63-0.69μm)	Band4 – Red (0.64-0.67μm)
Band4 – Near Infrared (NIR) (0.76-0.90 μm)	Band5 - Near Infrared (NIR) (0.85-0.88μm)
Band5 – Shortwave Infrared (SWIR) (1.55-1.75 μm)	Band6 – Shortwave Infrared (SWIR) (1.57-1.65μm)
Band6 – Mid – Infrared (MIR) (2.08-2.35 μm)	Band10 – Thermal Infrared (TIR) (10.6-11.19μm)

The images for each year are then prepared by layer stacking the relevant bands of Landsat images and further cropped to the study areas for image classification using Semi-automatic Classification Plugin (SCP). The satellite images classification process allows identifying pixels with similar spectral responses and grouping them into categories representing the classes recognized on the soil. The techniques of classification can be divided into supervised and non-supervised. The non-supervised classification does not require the a-priori knowledge of the elements to be discriminated. Still, it is based only on the reflectance of the image pixels. In contrast, supervised classification implies the role of the operator who chose an a-priori number of test areas ("training areas") representative of the "regions of interest." Input spectra can be obtained from Region of Interest (ROIs) carefully identified with the help of GIS techniques; from technical or thematic cartography of the investigation area in the same reference system and superimposed on the image. Support vector machines (SVM) is a supervised automatic algorithm based on machine learning theory for data analysis [38]. The DZETSAKA plug-in is a powerful classification plugin for QGIS software that supports several classification algorithms (e.g., Random Forest, kNN) and SVM [148,149]. The SVM classifier has been selected for the land cover classification of Landsat time-series data. This algorithm has proven to be a potent tool to handle a segmented raster input or a standard image SVM can map the original data input into a higher-dimensional feature space. The algorithm finds the optimal hyperplanes: subspace capable of identifying distinct classes with minimum classification errors. For this purpose, the training sample is selected at the class distribution margins in a n-dimensional space. It is possible to use SVM to achieve high classification accuracy using a small number of training areas. In literature, several previous studies showed that SVM could generalize unseen data with a small training dataset [81,143,145,150]. Therefore, using the SVM algorithm allows to manage of high-dimensional data with a limited training area set. A detailed description of the SVM algorithm can be found in Burges [81]. Many aspects allow evaluating the classification result of a satellite image, e.g., the visualization of the map output, the query of the data on the GIS desktop, and the use of accuracy algorithms. The analytical procedure adopted in this work is oriented to discriminate the change detection of land take based on differences in territorial patches at different dates. The overall methodology of the study is illustrated in Figure 14.

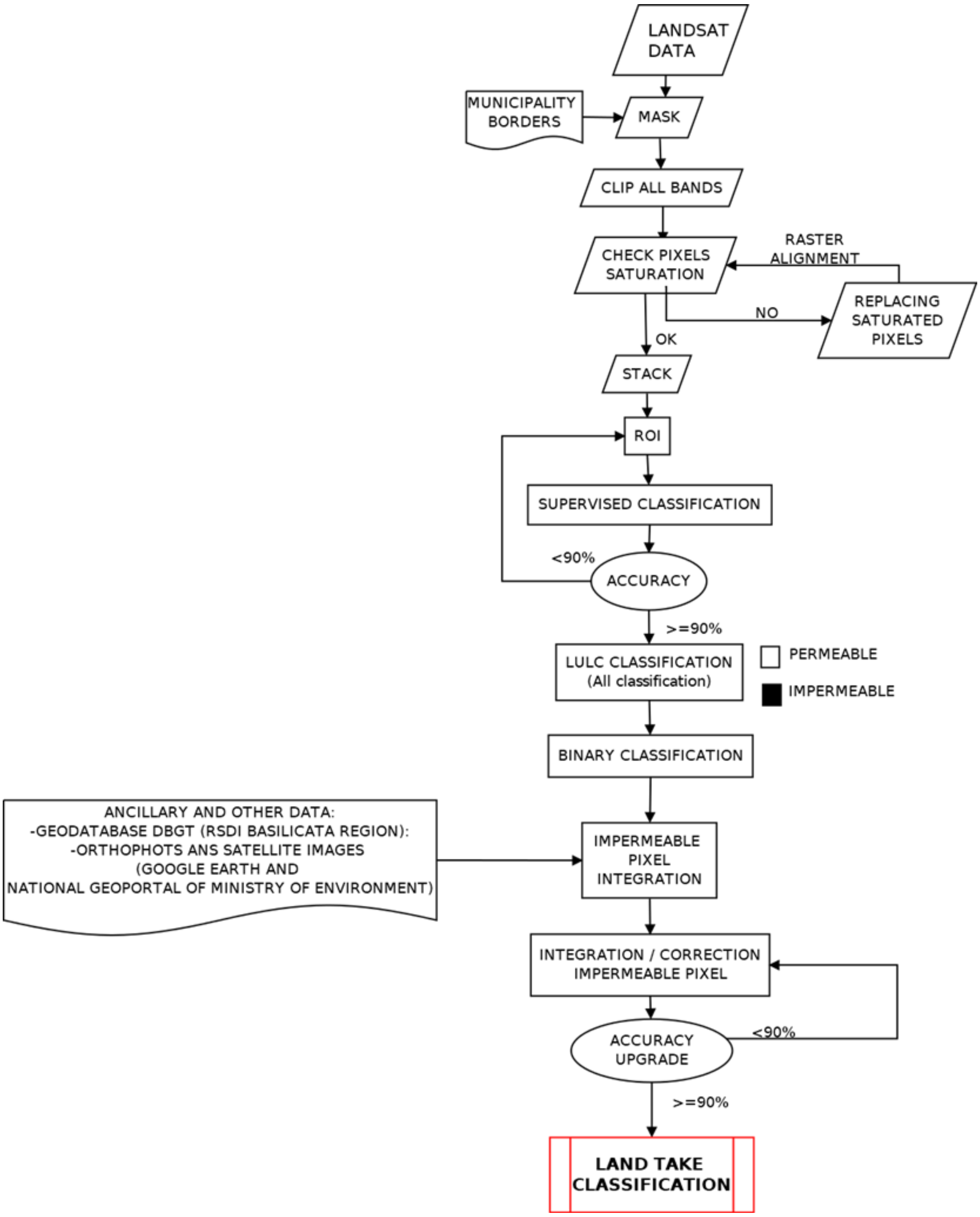


Figure 14. Flowchart of classification methodology.

The Landsat images were classified using an SVM algorithm to derive land use and land cover maps of 1994, 2004, and 2014. The training areas mainly include four typical classes: built-up (including roads, buildings, quarry, dump and artificial areas), vegetation (including cultivated areas, forest, etc.), bare soils, and water. To facilitate the identification of the ROIs, the use of ancillary data from the GTDB (Geo-Topographic Database) of the Basilicata Region and orthophotos were used. GTDB is composed of different classes of information layers in shapefile format. Informative layers related to traffic (roads, railways, cycle paths, etc.), buildings, and artificial areas (buildings, quarries, support works, landfills, etc.) have been adopted in this study. All the elements present in these informative layers have been merged in a single vector layer and then converted into a binary raster with a spatial resolution of 30x30 meters, whose pixels represent the artificial areas. The analytical approach is characterized by a backward process starting from the 2014 data (available in Basilicata Region GTDB and considered the most accurate datasets on urbanized features) and comparing it with previous information ranging from 2004 and 1994.

3.3 Results and Discussions

3.3.1 LULCC and Land Take Classification

Applying a supervised classification with the integration of auxiliary data (orthophotos, ground truth data), the land cover map is obtained and subsequently used as input for the estimation of land take in the test areas. The land cover map is finalized to obtain four classes: Built-up, Vegetation, Bare soil and Water (Fig. 21; table 6).

Table 6. Class definition for training areas

MC_ID	Definition	Description
1	Urban	Built-up, Streets, Industrial buildings
2	Vegetation	Forest, Cultivated Areas, Grassland
3	Bare Soil	Rocks
4	Water	Lake, river

The ROIs were defined by identifying these four macro-categories called Macro-classes /Identifier (MC_ID) associated with them (Table 2). The geographical areas under consideration are particularly large; therefore, it was necessary to define a large number of homogeneously distributed ROI on the entire image to obtain a better response in terms of classification. Once the classification was obtained, to assess the accuracy of the classification, the "Accuracy" tool of the SCP plug-in was used in a GIS environment. In the SCP plug-in, several statistics are calculated: overall accuracy, user's accuracy, producer's accuracy, and Kappa hat coefficient. In particular, these statistics are calculated according to the area-based error matrix, where each pixel represents the estimated area proportion of each class. This allows for evaluating the user's accuracy and producer's accuracy, the unbiased area of classes according to reference data, and the standard error of area estimates. The confusion matrix confirms the results' reliability with overall accuracy values greater than 92% and K coefficient just below 0.93 (Table 3). Accuracy indicates the number of pixels correctly classified according to the classes corresponding to the soil. The accuracy matrix is generally composed of overall accuracy, user accuracy, producer accuracy, and Kappa coefficient. Overall Accuracy indicates the number of correctly classified pixels divided by the total number of pixels analysed. User's Accuracy is the ratio between correctly classified pixels in the considered class and the total number of pixels assigned to that class. The user accuracy indicates the probability that a pixel assigned to a given class corresponds to that class.

Table 6. Example of accuracy statistics for the pixel-based classification algorithm of Matera LULC Classification (2014).

Overall Accuracy (%)	Kappa Hat Coefficient	Classes	User Accuracy (%)	Producer Accuracy (%)
94.28%	0.9281	Class 1 (Built – up)	89.213	92.989
		Class2 (Vegetation)	94.237	95.660
		Class 3 (Bare Soil)	93.434	91.735
		Class 4 (Water)	100	99.759

Producer's Accuracy is the ratio between the number of pixels correctly classified in the considered class and the total number of reference pixels in that class. The Kappa coefficient provides a parameter that considers that the correct part of the classification is due to chance or compares the error generated by the classification obtained with that of a classification performed in a completely random manner. The Kappa coefficient has a value between 0 and 1; the more significant the agreement between real data and classified data, the closer the value of the coefficient will be to the value 1 [149,151,152].

Image classification has been performed with an overall accuracy of approximately 90% in 1994 and 2004 and > 92% in 2014. In the literature, an overall classification accuracy of 85 per cent is generally considered acceptable for scientific use [35]. The accuracy of image classification depends on the classification methodology, the quality of the data, the spatial resolution of the satellite images and the purpose of the study. The urban landscape of the six areas studied is more heterogeneous and our methodology fulfils our purpose and is suitable for the 30-metre spatial resolution of the Landsat images. Overall, the Landsat OLI data performed better than the Landsat ETM+ data and performed satisfactorily in land cover classification in this study.

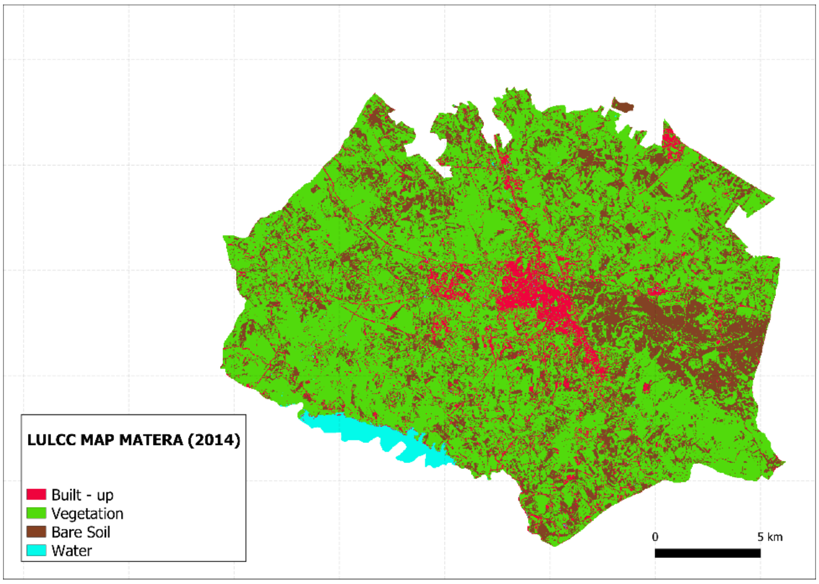


Figure 15. Landsat 8 OLI image with ROIs and LULCC map 2014 obtained with the SVM (Support Vector Machine) algorithm (Example of classification referred to Matera Municipality).

The LULC images include four classes: agricultural land, built-up land, vegetation, bare soil and water bodies. The area of each land use class is shown in Fig. 15, based on the SVM algorithm. After that, the 2014 land cover map thus classified was analysed and compared with ancillary data, orthophotos, etc. The GTDB of the Basilicata Region (dated 2014) includes multiple information layers (urban areas, buildings, roads and other anthropic objects) in vector format, which represent important ancillary data used to validate the class of built-up area in the maps obtained. The GTDB vector layers related to urban/impermeable areas are rasterised into a 0-1 binary map (1 impermeable soil, 0 rest of land) (Fig. 16). In order to compare the resulting binary map with the LULC map obtained from the identification of the training areas, both maps must have the same spatial resolution; for this reason, the rasterised map of the GTDB vector layers was assigned the same spatial resolution as the LULC map of 30 metres.

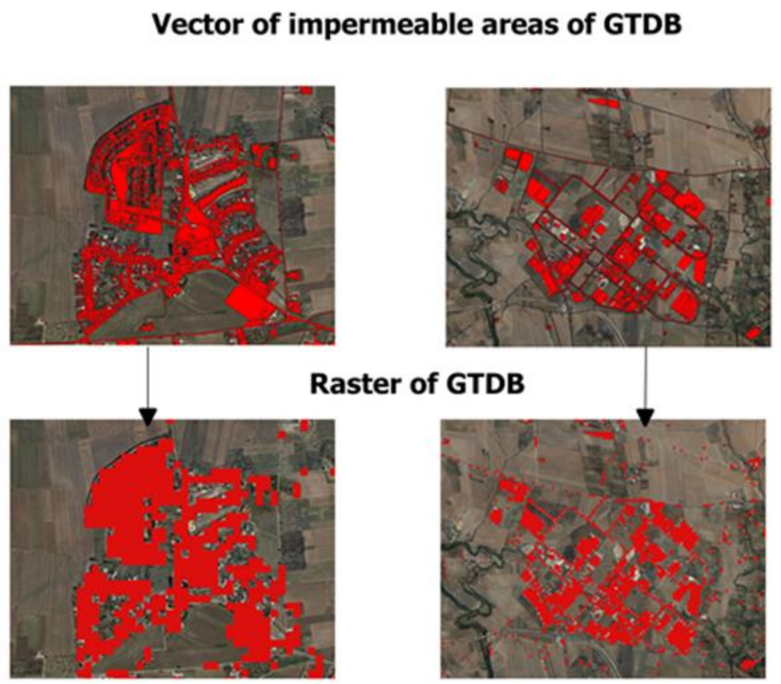


Figure 16. Example of rasterization process of GTDB vector layers relating to urbanized areas (Built Up Areas).

This map is critical for identifying and removing, using map algebra, all class 1 pixels erroneously classified by the SVM. In this way, the 2014 map represents the land consumption footprint that delimits the area within which to develop analyses for previous years. The classification system used by ISPRA and SNPA provides for a division of land take into two categories: permanent and reversible land take. Irreversible classes are connected with soil sealing processes, such as the construction of new buildings, roads, airports, etc. The approach adopted assumes that the sealed soil will not turn into permeable soil over the years. This concept is not always true, as this can happen in some rare cases. Starting from this concept, we proceeded backwards from 2014 by analyzing 2004 and 1994, comparing this information with previous cartography and orthophotos. This comparison with the orthophotos, available as Web Map Service (WMS) on the National Geoportal of the Ministry of the Environment, allowed us to construct the spatial time series analysis based on the aero photogrammetric surveys. The built-up areas extracted from the LULCC 2014 layer (Fig.17) are used as an impermeable base map, which was used as a comparison and reference in the analyses performed for 1994 and 2004 for Landsat.

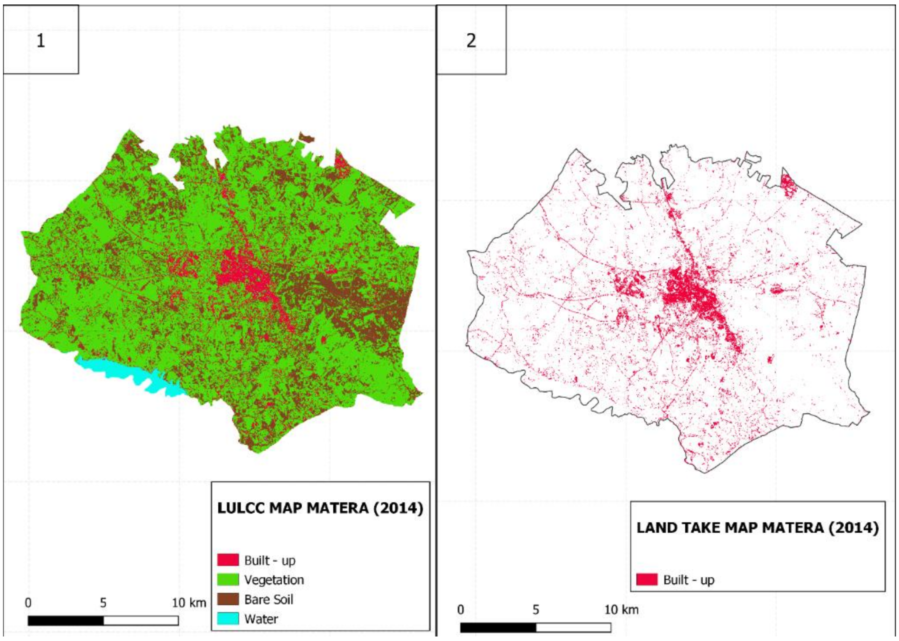


Figure 17. Correspondence between the LULCC map showing all the classes identified in 2014 in the Municipality of Matera (1) and the binary map of waterproof areas (Built Up) (2).

The results show that the increase of impermeable areas (built-up areas) has occurred predominantly in areas away from urban centres, especially near industrial areas and rural areas.

In the six municipalities described above, the historical development of land take due to the growth of impermeable (built-up/urbanised) areas was analysed. Analysing and comparing the binary land take maps obtained in the three different reference years (1994 - 2004 - 2014) showed a progressive intensification process of urbanised areas. The results show that the analysed municipalities have undergone a clear spatial transformation over the two decades considered, characterised by a steady increase in land take. The graph in Figure 18 represents the increasing growth rate of all analysed built-up municipalities. The most significant amount of land take occurred between 2004 and 2014 in all analysed municipalities, suggesting that both socio-economic and natural characteristics drive the urbanisation of these areas.

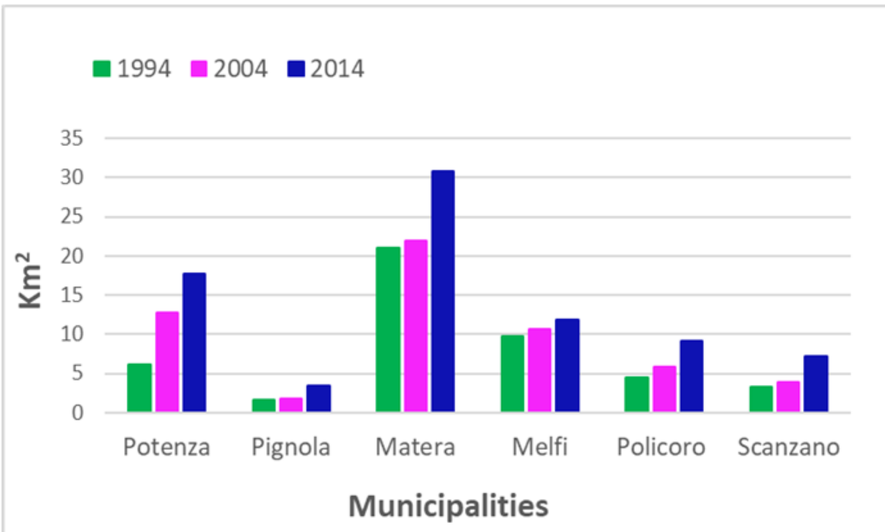


Figure 18. Observed built-up growth in square kilometers in the studies area from 1994 to 2014.

The towns of Potenza, Pignola and Melfi show slow growth in land take. Potenza and Pignola show a significant urban sprawl, characterized by disordered urban expansion. In particular, in the 20-year period analysed, land take in the capital city involved the development of commercial and residential areas near the historic centre. It is also significant to note the development and construction of new infrastructure and roads. In the area of the municipality of Pignola, the significant increase in land take occurred mainly with the construction of residential structures along the main provincial road connecting the town with the capital and surrounding municipalities. Land take in the Melfi municipality area is closely linked to industrial and urban expansion; as Figure 9 shows, the areas with the most significant increase of impermeable soil are to be found in the industrial area of the Stellantis plant and its allied industries and in the urban area where growth of the city has occurred. In addition, several roads connecting the urban centre with the peripheral and industrial areas have been built and extended.

The municipalities of Policoro and Scanzano Jonico, like Potenza and Pignola, have a solid territorial and socio-economic relationship; they have a consistent settlement spread throughout the municipal territory, but land take follows the structure of the territorial viability. The growth of land take in the two municipalities on the Ionian coast could be linked to the increase in tourist flows in the area in recent decades. Moreover, in this case, most of the impermeable soil is located near the settlements that have developed near the main road connecting the area with the neighbouring regions (Apulia and Calabria). The area of the two municipalities is characterised by a strong anthropic tourism pressure along the coasts, which has occurred in recent years as a result of the construction of tourist infrastructures; this has led to a fundamental waterproofing of the entire Ionian coast. The area in question is also intensively cultivated with various crops ranging from vegetables to the cultivation of fine fruits; over the years, there has been a progressive construction of greenhouses and roads that have contributed to an increase in land take in agricultural and rural areas.

Matera displays an evident urban dispersion similar to the case of Policoro and Scanzano Jonico: new buildings are mainly located along the main roads. The construction of new buildings has been disorganised, both near the urban centre and in the suburbs. Moreover, in the case of Matera, an essential percentage of the increase in waterproof soil is linked to the presence of infrastructure. Matera was the European Capital of Culture in 2019. Consequently, in previous years, many services and infrastructures have been built throughout the municipality, increasing the sealed soil occurring.

The examination of the maps shows the pixels that have changed in recent decades, highlighting an expansion of the urban area into areas that once belonged to open land. This just confirms that the territory of the analysed municipalities and their neighbourhoods have undergone substantial changes in recent decades.

3.3.2 Discussions

This methodology presents an innovative supervised classification approach to detect land use and land cover change from natural to impervious areas.

The classification results for Landsat TM and Landsat OLI, presented in this paper, with SVM show an accuracy of more than 92%. The land use and land cover maps obtained from the classification were validated with an overall accuracy of more than 92% and a kappa coefficient of more than 0.90 (Tables 6) and represent the evolution of land occupation in the areas considered. The results of this study are in agreement with those of previous research [24,36,37,140,143,153,154]. The SVM algorithm keeps the spatial attributes of these landscapes, such as fragmentation, and is the most appropriate algorithm in the classification study of land cover analysis of an urban environment. Ghayour et al [138] used and evaluated different algorithms such as Support Vector Machine (SVM), Artificial Neural Network (ANN), Maximum Likelihood Classification (MLC), Minimum Distance (MD) and compared them to generate a LULC map using Landsat 8 satellite data. They assessed that the SVM classifier produced a land cover analysis that retained the spatial characteristics of these landscapes, such as fragmentation, and is most appropriate for the study of land cover in urban environments. The SVM classifier produced the highest overall accuracy of 94%, performing better than the other methods. Agapiou [36] for his study on the city of Lanarca (Cyprus) used the CORONA satellite image and performed a land cover classification using the SVM. He selected five main land cover classes: land, water, vegetation and urban areas. The results show a classification accuracy > 85, with a kappa coefficient of 0.91. In another study, Adam et al [154] used two machine learning algorithms, SVM and Random Forest, to create a LULC map of a region on the East African coast using high-resolution RapidEye imagery. Using the training data, they classified the region with an overall SVM accuracy of 91.80%. Jia et al [155] classified the land cover of Beijing by comparing Landsat 7 and Landsat 8 images and using the supervised MLC and SVM algorithms. The SVM algorithm, with an overall accuracy of 91.03% and a Kappa coefficient of 0.89, is more accurate than the MLC algorithm. Therefore, the SVM algorithm performs better than other algorithms applied in other studies because it requires fewer training areas, reducing the possibility of classification errors. The overall accuracy values of each classification are always above 92%. The process of classification of satellite images can produce errors. These classification errors are mainly due to the detection of water (lake, reservoir) or bare ground (rocky outcrops with perennial absence of vegetation cover). In contrast, omission errors correspond to some mixed urban and vegetation patterns, such as residential subdivisions, where vegetation is particularly dense or even to the different types of vegetation present. These limitations are mainly due to the spatial and spectral resolution of the Landsat OLI and TM sensors. Both have a spatial resolution of 30 m, each pixel thus having an area of 900 m^2. Furthermore, both sensors are multispectral and not hyperspectral, which leads to limitations in the detection of certain spectral signatures. In Fig 19, the observed changes are mainly identified as blocks of pixels in urban areas representing urban growth.

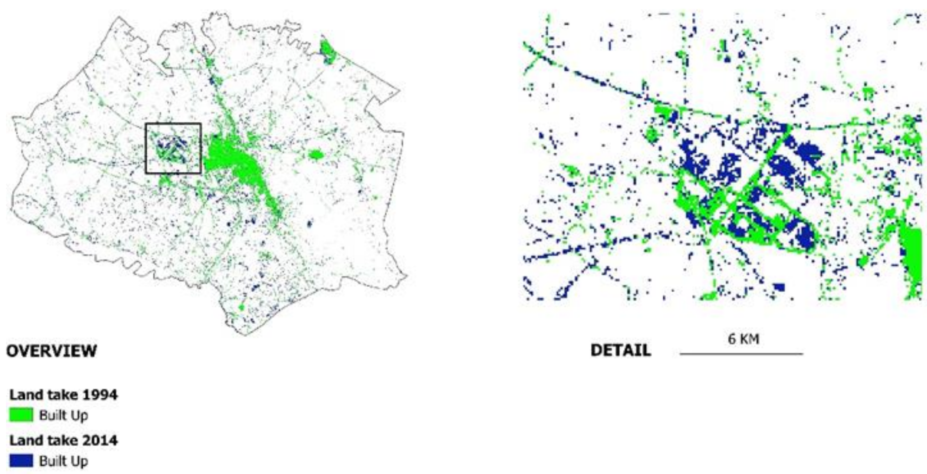


Figure 19. Change Detection (1994 to 2014) of Land Take in Matera. Overview of the entire area and a zoom of black squared area.

The change detection analysis showed an increase in impermeable areas and a decrease in other natural areas from 1994 to 2014. Although the land take process is generally non-reversible, rare cases of reversibility can be recognized. Therefore, the model is suitable to detect such areas; an example of this reverse transformation process was identified, from impermeable land (housing and roads) in 1994 to permeable land in 2014, following a landslide event (Figs. 20 – 21).

Figure 20. In reverse transformation: from impermeable soil to permeable. In red, in 1994 and 2004, it is possible to see the urban agglomerate, which was destroyed in 2013, due to a landslide (Bosco Piccolo street - Potenza Municipality).

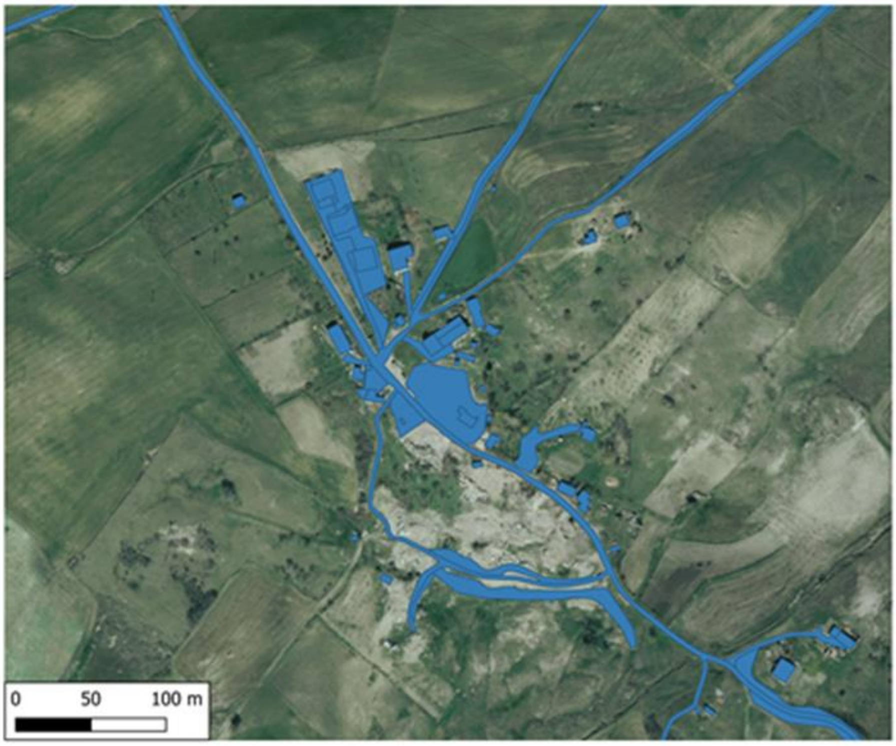


Figure 21. Detail of the urban agglomeration (Via Bosco Piccolo - Municipality of Potenza) destroyed by the 2013 landslide. In blue the information layers of the GTDB of the Basilicata region regarding the waterproof areas.

In this research, both TM and OLI images were acquired in the same month to have a low margin of error in classification. The month of May, in fact, at these latitudes represents the period of the year when the vegetation is at its maximum vegetative development. So, using the Landsat OLI images, the methodology presented here provided the most accurate spatial shape and conformity of the classes, regardless of the input classification settings. The algorithm achieved better accuracy for Landsat OLI images for the same classes and using the same training and validation data. In contrast, Landsat TM image classification maps were less accurate and required more ROIs. Some confusion between the classes also existed in OLI results,

but not as much as in the case of TM. At the same time, the separation of bare soil and impermeable areas (artificial vs. natural) was performed with greater precision.
It should be highlighted that the aim of the work is not to monitor the changes in land cover in the area but to identify the waterproofed areas in the years analyzed. In conclusion, by analyzing medium resolution imagery provided by Landsat TM and OLI, using advanced methods like the SVM and change detection analyses, it is possible to result in highly accurate classification maps.
The layers of the impermeable areas present in the dataset used in this work are updated to 2014 and no future updates are expected, this represents a limitation for the study of the historical evolution of land take in Basilicata, as this dataset constitutes the fundamental reference data of the impermeable areas in the classification process.

3.4 Land Take and Renewable Energy Sources: The Case of Melfi

In recent years, spatial transformations related to land take have been associated, especially in Basilicata, with the installations of renewable energy sources (RES). After the global challenges on climate change and international agreements on the reduction of CO_2 emissions and in line with the European policies aimed at increasing energy production from renewable sources, European states have promoted and encouraged the use and installation of photovoltaic panels and wind turbines. Renewable energy sources (RES) are an important element in the list of options adopted to address global climate change issues and the increasing demand for energy, directing land development toward a low-carbon economy and principles of sustainability [98,102,156]. The installation of renewable energy sources, from the point of view of environmental sustainability, helps to contribute to the decrease in the use of fossil energy sources, but introduces a new class of land take that has hitherto been ignored, in disagreement with the European Commission's goal of zero land take by 2050. In fact, RES installations can be considered as a real new component of land settlement, and if the resulting land take is analysed, it becomes clear how the uncontrolled development of RES installation represents a critical aspect for effective and sustainable land use planning. The installation and operation of RES represents a significant land transformation, producing effects on different land components: land use change, land take, fragmentation of natural habitats[157], noise, etc. The new territorial transformations due to RES plants are a consequence of the development policies of the energy sector, Basilicata and specifically the municipality of Melfi, for its low population density and its territorial characteristics represents a useful case to analyse the land take related to RES. The hypothesis underlying this paragraph is that in the last decade, as highlighted in several studies [158,159] in the area under investigation, there has been a reversal in the amount of land taken for the construction of new residential, industrial and infrastructure buildings, which has given way to new forms of land take due to the installation of renewable energy sources. In recent years, wind energy has established itself as an economically and technically more profitable source and as a renewable source [160]. According to the GSE 2020-2022 report, the Basilicata region has the highest number of wind turbines, a supremacy that does not respect the energy output of the installed wind turbines. In fact, by comparing the number of wind turbines and the total installed power, Basilicata deviates from the national average by 1.01 MW/pale (Basilicata average 1.01 MW/pale). We wanted to investigate how much the installation of numerous renewable energy plants (and related road infrastructure) affected the land take in the period 2010, 2014 and 2018. The 2010 - 2018 chronological section is significant for analysing the land take from renewable sources, especially wind power, because the first decade of the new millennium is indicative of the period in which the installation of these wind power plants began, both in the municipality of Melfi and in the entire region of Basilicata, where they have grown disproportionately in number.

3.4.1 Methodology

This part of the research aims to develop a methodology capable of providing land cover and land cover change products for operational purposes due to the installation of renewable energy sources using Sentinel 2 and Landsat data. The study is in continuity with the analyses in the previous section on monitoring land take on a time scale. As in the previous analyses, the SVM classification algorithm with the integration of ancillary data was used to obtain a detailed land cover map (orthophotos, GTDB data, GSE data), this map subsequently used as input for the estimation of soil consumption in the test area.

The RES farm datasets were first constructed using data from the GSE website. The resulting vector file was subsequently edited and integrated through photointerpretation and integration of data available on the GTDB. Through comparison with orthophotos at different time intervals, the RES dataset was divided into three time periods: RES existing before 2010, RES existing in 2014 and installed between 2010 and 2014, and RES existing in 2018 and installed between 2014 and 2018. Based on the PIEAR classification, wind turbine data were grouped into three classes: small, medium, and large wind turbines.

Based on the SNPA classification reference, the binary land take map obtained was classified as impermeable soil and unconsumed soil. The supervised classification process is an iterative process that ends with the choice of the output map after a check of the photo-interpretation with orthophotos and data from the same period and the evaluation of the accuracy matrix (Fig. 22).

After obtaining a binary land take map, a check was made with the SNPA map, classifying the impermeable soil (consumed soil) into two subclasses: reversible consumed soil and irreversible/permanent consumed soil. Considering that the land take map called bu_2017_utm33N by SNPA has a spatial detail that is not very high in some Italian territorial contexts, such as the one of Melfi, the final part of the map elaboration process involved several photo-interpretation phases through the use of updated orthophotos. Particular importance in the classification process was given to the identification and classification of land take by RES (Eolic pad and street). From this, the pixels associated with RES were analysed in detail for the years 2010, 2014 and 2018.

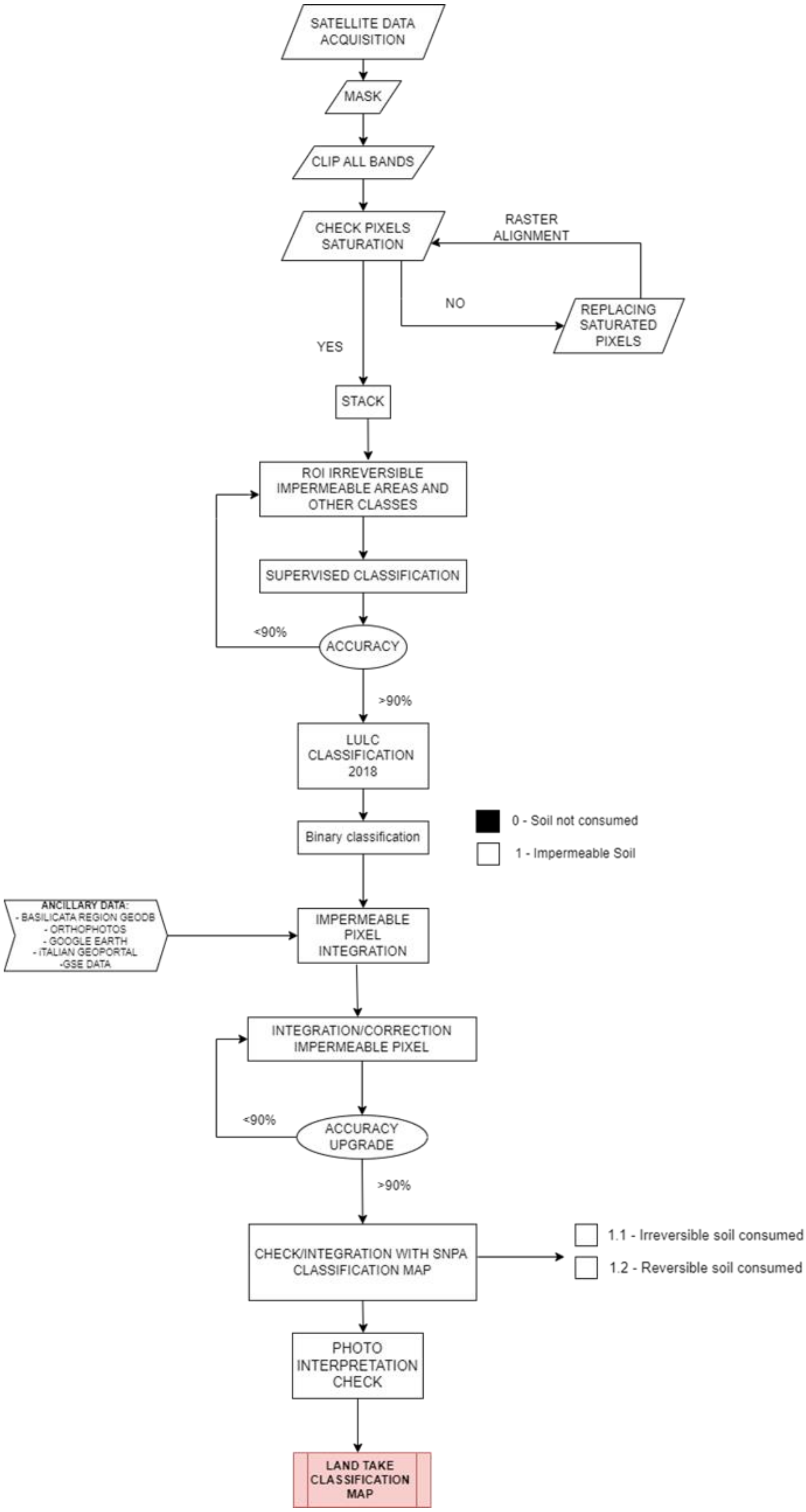


Figure 22. Flowchart of classification methodology.

3.4.2 Results and Discussions

The land cover map obtained presents indications of all land cover classes in the Melfi area (Fig. 23). From this, the pixels associated with renewable energies were analysed in detail for the years 2018, 2014 and 2010.

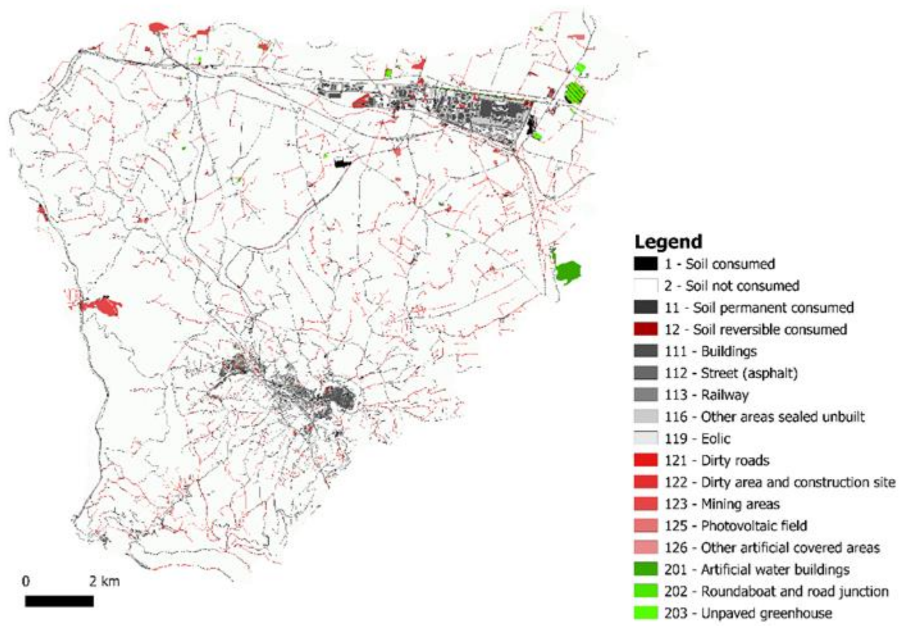


Figure 23. Land Cover Map of Melfi (2018).

In fact, a comparison with the SNPA map showed that, in the years considered by the study, the land cover classification type related to wind energy, which was assigned code 119, was not present. The table 7 summarises the main types of reversibly and permanently consumed land identified by the classification process and the related SNPA coding, with the addition of the new land take class due to wind energy.

Table 7. Land take classes used in Land Cover Map classification according SNPA CODE Classification.

LAND TAKE CLASSES	**TYPE OF SEALED SURFACE**	**SNPA CODE**
Equipped soil area (116, 122)	Other area sealed	116, 122
Road element (112, 121)	Paved /Unpaved	112, 121
Street (116)	Street	116
Buildings (111)	Buildings	111
Railway Network (113)	Railway	113
Photovoltaic field (125)	Photovoltaic field area	125
Eoilc (119)	**Eolic park**	**-**

The class of land take of wind power was reclassified by dividing the relevant street from the wind turbine pad; the table summarises in terms of km^2 the land take for each land take macro class: urban, Eolic pad, eolic street and photovoltaic. Subsequently, through the GSE database and photo interpretation, the area occupied by the wind turbines was reclassified according to the power of the turbines, in order to better discriminate the land take associated with each individual plant.

Table 8. Land take due to RES installation and new Urban settlements.

Land Cover Class	CODE	2010 km^2	2014 km^2	2018 km^2
Urban	1	14,74	14,84	14,97
Eolic Pad	119	0,0048	0,036	0,35
Eolic Street	121	0,0059	0,056	0,19
Photovoltaic	125	0,035	0,167	0,165

Examining land take due to urbanization and renewable energy, it is evident that in the former the trend is steadily increasing, while in the latter there has been a sharp increase since 2014 due to the development of small and large wind farms as economic policies have promoted the installation of wind turbines (Fig. 24).

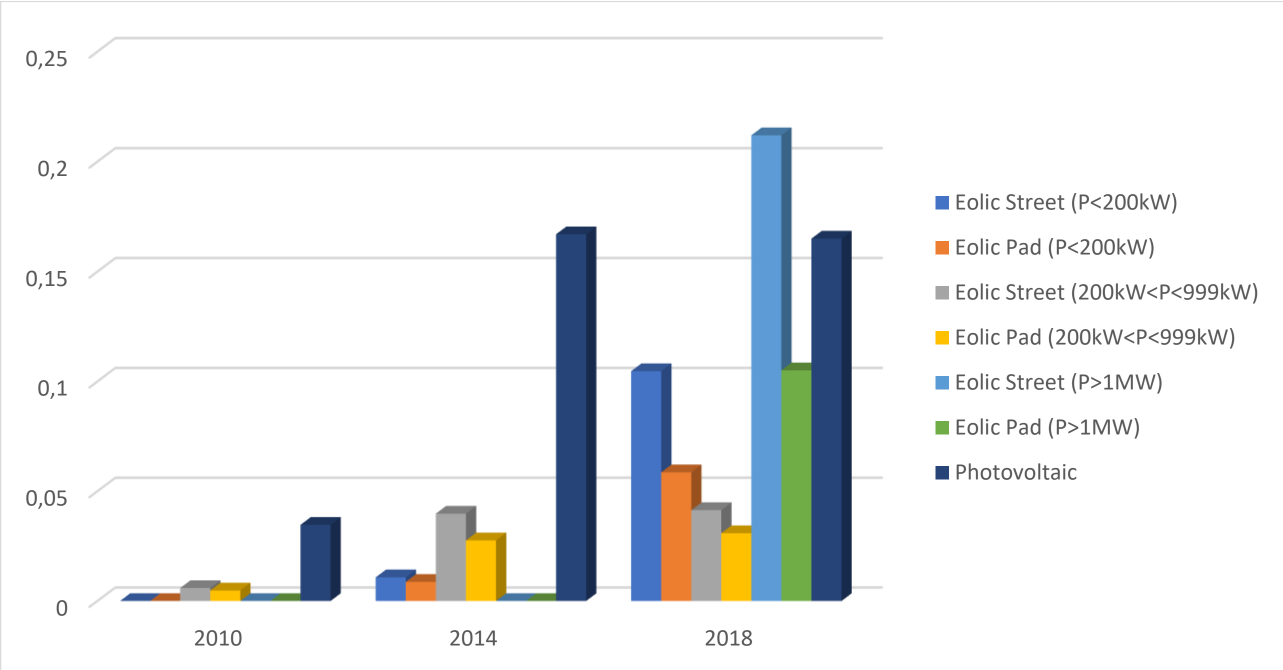


Figure 24. Land take historical trend due to the implementation RES.

The development of RES technologies has thus resulted in a deep transformation of the territory. The implementation of energy and climate policies requires new multi-level governance models, in which local authorities play a key role in managing energy and environmental issues [159].

3.5 Conclusions

Nowadays, land use and land cover maps and the use of the information they contain are fundamental to spatial planning. The use of satellite imagery and appropriate classification algorithms, such as SVM, is the most appropriate strategy to create land use maps at detailed scales. Satellite data have proven to be useful to develop an accurate diachronic analysis of land take and impermeable soils. The integration of remote sensing and spatial data allows a detailed monitoring of anthropogenic land transformations.
The methodology presented here made it possible to obtain summary maps useful for analysing land use changes and interpreting the evolution of urbanised areas (in terms of growth) and natural and semi-natural areas (generally decreasing in extent). The use of satellite imagery and remote sensing techniques in a GIS environment made it possible to define spatial parameters through a supervised classification to discriminate urban areas from other land use classes. The methodology adopted highlights a possible way of verifying land use using free data and software. The great advantage is that this methodology can greatly improve planning processes at any scale. The information obtained in this work for the analysis of built-up development paints a fragmented picture of the study area. Although applied to urban areas, the methodology can be used in any other land cover classification topic.
Moreover, a quantitative analysis of land take due to the uncontrolled installation of RES is proposed in this chapter. The unordered spatial distribution of installations is a demonstration of the current urban planning weakness, where planning instruments are not able to keep up to date with rapidly changing anthropization categories. A fundamental assumption is to consider wind farms as a new component of spatial settlement whose effects in terms of land occupation are comparable to traditional settlement categories. Today, new energy transition policies on the national territory are needed to plan new clean energy installations in a sustainable way, as incentives for renewable energy production without any planning strategy led to an increase in land take.
The critical point is that renewable energy sources (wind and photovoltaics) imply intensive land use and the relationship with land take and spatial dimension of installations is a key aspect to be taken into account for management It should therefore be noted that the issue of land use and occupation and its relationship with the spatial dimension of renewable energy sources is an essential sustainability criterion for the management of renewable energy and the proper implementation of these technologies, regardless of their nature and size. Indeed, sectoral policies produce rapid changes in the anthropization categories to which traditional planning tools and urban laws are no longer able to respond because they are obsolete and unsuitable to support decision-making towards an effective and sustainable development scenario. Limiting soil sealing and stopping land take means stopping the conversion of natural or semi-natural land into artificial land. National and regional policies have the task of limiting, or better still stopping, uncontrolled urban sprawl[161]. Producing an extremely detailed analysis through the perspective of spatial planning is a fundamental step to plan renewable energy in rural areas and prevent impacts on occupation and land use. The debate on the renewable energy production model shows the need to control the implementation process of these technologies so as to avoid conflicts with land use/occupation in rural areas.
The exploitation of renewable energy sources clearly represents a new form of competition for land, resulting in pressure on all territories from the need for urbanization while at the same time preserving forest areas, natural resources and land with agricultural characteristics. The implementation of renewable energy renewable energy sources therefore require the formulation of a new rural land zoning that is compatible with landscape protection, biodiversity conservation and is fully integrated within the municipal planning and management. Population density plays a central role in describing urbanization processes and spatial

dynamics. Analysing the population density in the three years considered, it is clear that the trend is increasing in all the municipalities analysed, only in the city of Potenza it is decreasing (Fig. 25).

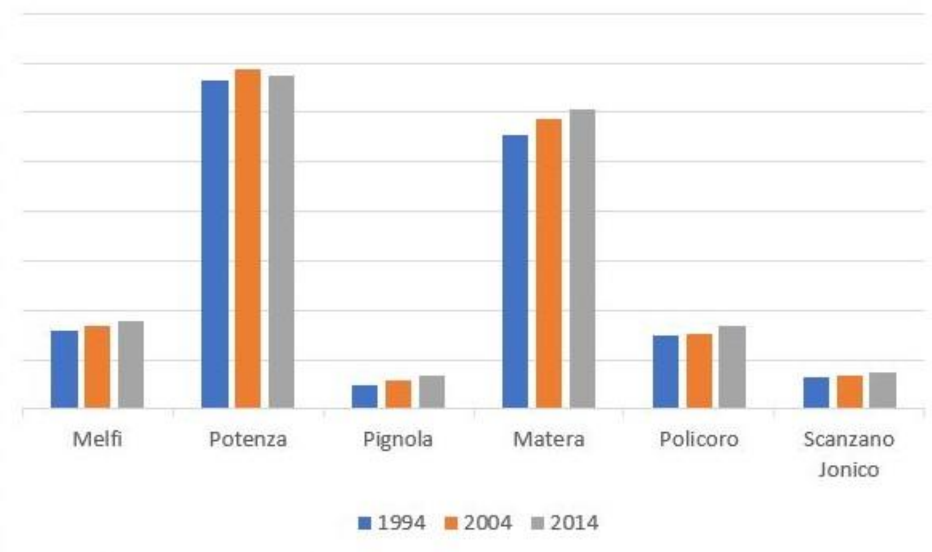


Figure 25. Population trend (1994- 2014).

In order to analyse the evolution of land take it is interesting to relate it to population density, in the table 9 we compare the absolute values of land take obtained with the per capita land take, it is interesting to note a rapid growth from 2004 to 2014.

Table 9. Comparison of land use and population density.

	Land Take 1994 (km^2)	Land Take/Inhabitant 1994 (m^2)	Land Take 2004 (km^2)	Land Take/Inhabitant 2004 (m^2)	Land Take 2014	Land Take/Inhabitant 2014 (m^2)
Matera	20,99	378,42	21,96	377,94	30,79	509,49
Melfi	9,77	612,81	10,59	648,38	11,88	698,29
Potenza	11,75	176,91	12,83	187,38	17,73	269,44
Pignola	1,58	319,32	1,71	303,95	3,53	514,65
Policoro	4,5	301,49	5,89	387,58	9,21	548,05
Scanzano Jonico	3,21	503,37	3,83	562,16	7,14	971,96

Comparing the change in land take between 2014 and 2004 with the change in population we note that the municipality of Potenza shows a decoupling of values, population decreases while land take increases (Tab.10).

Table 10. Comparison between land take variation and population variation.

	Land Take variation (2014 – 1994)	Population Variation (2014 – 1994)
Matera	0,318	0,090
Melfi	0,178	0,067
Potenza	0,337	-0,009
Pignola	0,552	0,386
Policoro	0,511	0,126
Scanzano Jonico	0,550	0,152

The analysis of land take, taking into account changes over the historical reference period, with the structural dependency index allows us to verify the relationship with a variable of economic and social relevance[109,117,162]. The dependency ratio represents the ratio of the population of non-working age (0-14 years old and 65 years old and over) to the population of working age (15-64 age), multiplied by 100, indirectly providing a measure of the sustainability of a population structure. The denominator represents the segment of the population that is expected to support the segment indicated in the numerator. This ratio expresses the theoretical social and economic burden of the population of working age: values above 50 per cent indicate a situation of generational imbalance.
The relationship between land take and the dependency ratio is useful for analysing how land use changes based on the distribution of the working population (Table 11).

Table 11. Comparison between dependence Index e land take in hectares.

	Dependence Index (See Appendix A2)	Land Take (ha)
Matera	51,19	3079
Melfi	46,44	1188
Potenza	50,19	1173
Pignola	40,93	353
Policoro	43,22	921
Scanzano Jonico	43,48	714

In the overall balance there is a growth in urbanization. Furthermore, land take is provided by differences in development on a spatial basis which at different geographical scales give rise to different migration flows. These flows create in the places of destination a housing demand that consumes land leading to a redistribution of land take, which is not compensated by any land gain in the places of origin due to the irreversible decrease in the value of housing and land that are often abandoned. It is the different way of thinking about city-countryside relations that drives large segments of the population to abandon the congestion of the urban centre and move to peri-urban locations. Moreover, these housing choices are favoured by the increasingly intensive use of the car and the presence of a transport system strongly unbalanced towards the road and motorway network. Contributing to land take and increased housing demand is an increasingly individualistic living culture oriented towards independent living solutions. Equally harmful in terms of land take is the exploitation of coastal areas for tourism. The building of holiday homes, hotels and residences in these areas, which are often endowed with great landscape and environmental value, is a driver of land take that takes on particularly dramatic connotations, where it is only partially contained by the protection of landscape plans. This trend is mainly affected by the propensity to buy second homes in places with a high degree of naturalness. In addition to the above-mentioned reasons, there are others linked to political-legislative and governance issues and gaps[109].

Finally, from a technical-methodological point of view, satellite data have proved useful for modifying an accurate diachronic analysis of land take and impermeable soils. The integration of remote sensing and spatial data allows a detailed monitoring of anthropogenic land transformations. The methodology presented here made it possible to obtain summary maps useful for analysing land use changes and interpreting the evolution of urbanised areas (in terms of growth) and natural and semi-natural areas (generally decreasing in extent). The use of satellite imagery (Landsat TM 4-5, Landsat OLI 8 and Sentinel 2) and remote sensing techniques in a GIS environment made it possible to define spatial parameters through a supervised classification to discriminate urban areas from other land-use classes.

This work confirmed that the SVM algorithm and the methodology presented here are the appropriate LCC classification tool. By analysing and comparing different years, the process of urban intensification and the increase in urbanised areas was observed.

The methodology adopted highlights a possible way of verifying land occupation using free data and software. The great advantage is that this methodology can greatly improve planning processes at any scale. The information obtained in this work for analysing building development paints a fragmented picture of the study area. Although applied to urban areas, the methodology can be used in any other land cover classification topic.

Chapter 4: Land Cover Change and Abandoned Agricultural Land in Basilicata Region

Land is a non-renewable limited resource characterised by a potentially very high rate of degradation and, at the same time, extremely slow regeneration processes. According to the ISPRA report [25], the national territory is undergoing a progressive degradation process as a result of artificialisation processes caused by an alteration of soil conditions due to the reduction or loss of productivity linked to the expansion dynamics of urban areas, infrastructures and industrial areas. Also, part of this process is the phenomenon of land degradation, which causes the progressive and irreversible shrinkage of natural and agricultural areas, often in favour of urbanised ones, with various environmental, economic and social impacts. One of the main negative impacts is the reduction of permeable surfaces, with effects on climate and hydrogeological structures, the contraction of the productive potential of agriculture, the reduction of biodiversity and the ecological functionality of the soil[163].

Land degradation is one of the most negatively impacting ecological problems; in fact, it is found in the literature that due to the process of soil degradation, agricultural land becomes unproductive due to the loss of its capacity to produce crops and biomass. The causes are manifold but, especially in the inland areas of the Mediterranean regions, certain dynamics linked to agriculture have particularly influenced the degradation process. Specifically, agricultural overexploitation with unsustainable practices and land abandonment are leading to alterations at the ecological level that require contextual analyses to assess the medium- and long-term effects. In fact, some agricultural practices, which are geared towards over-exploitation of soils, excessive mechanised tillage and the use of chemicals, are leading to a reduction in soil quality and subsequent degradation (erosion caused by water and wind, compaction, a decrease in soil organic carbon and soil biodiversity; salinisation, sodification and soil contamination by heavy metals and pesticides, or by excess nitrates and phosphates). The other phenomenon, i.e., the abandonment of agricultural activities and more generally of the land, is at the attention of the scientific community as it can produce environmental and landscape impacts, as well as socio-economic impacts [41,164,165].

The effects are highly variable in relation to territorial contexts and thus according to climatic, ecological, biological, soil and topographical differences. The causes and extent of the abandonment of agricultural activities also differ from region to region. In fact, in the marginal inland areas of southern Italy, there has been a constant and exponential abandonment since the 1970s and 1980s, which is causing a change in the ecological and soil balances of the territory. In these areas, following an increase in cereal cultivation favoured by the Agrarian Reforms for the Southern Italy and an increase in mechanisation, there has been an increase in the agricultural surface used even in marginal areas with little vocation for cereal cultivation. In the following decades, with the changes in socio-economic conditions, the crises in the agricultural sector that made cereal growing economically unfavourable for many areas, and some agrarian reforms linked to the Common Agricultural Policy (in particular the 'set-aside'[166,167]), there was a steady abandonment of agricultural activity[168,169]. These territories, give origin to different landscapes in relation to climatic conditions, age of abandonment, management before and after abandonment, and disturbances triggered afterwards. All the factors indicated condition vegetation successions and soil properties, often producing discordant ecosystems and landscapes. That said, the link between abandonment, soil erosion, and land degradation needs in-depth methodological and technical investigation as the factors, dynamics, and correlations are highly varied and, often, discordant. Obviously, overuse and abandonment may have, in some particular land contexts, a close connection. In fact, some areas may be abandoned precisely because of problems following the agricultural overexploitation that occurred in the past. These causes of degradation may also be compounded by overgrazing, deforestation of certain types of environments, fires, and urbanization processes. There are many methods used to study and assess soil degradation. The most common are the application of spatial analysis through GIS, remote sensing and direct measurements on soils through sampling and laboratory surveys. In comparison with field analysis methods, the remote sensing technique is more flexible because it allows in a short time, to observe large areas using a range of spectral indices. Remote sensing data is a great help in supporting the planner to be able to study the phenomenon and monitor it. Land degradation can be addressed with the use of remote sensing and other spatial data. The basic information to refer to is that of vegetation cover, rainfall, surface runoff and soil erosion. In addition, useful models can be established to define areas susceptible to degradation.

Basilicata is particularly affected by the risk of land degradation; among these is the phenomenon of soil erosion with the development of typical morphological forms (gullies). An assessment of land degradation at a regional scale is of fundamental importance to identify the characterisation of the soil surface, its variations over time and the identification of the area's most susceptible to degradation. A useful tool for studying the response of vegetation to climate change is the analysis of time series from satellite images. In many studies, multi-time series are used to highlight positive and/or negative vegetation anomalies. In this work, the analyses conducted involve the application of remote sensing techniques and spatial analysis to estimate land take related to land degradation phenomena and land use change dynamics for impact assessment and vulnerability estimation. In order to highlight and relate the phenomenon of land degradation to land cover over time, it was decided to exploit an established methodology, namely the RUSLE (Revised Universal Soil Loss Equation) model. Initially adopted to calculate and monitor the erosion of small agricultural areas, with the development of new calculation algorithms, it is now also used to investigate very large areas. The study area concerns a territorial context of the Basilicata Region that is particularly vulnerable to the phenomenon, due to the combination of anthropic and natural factors. The work was divided into several phases. The first phase concerned the bibliographic study and theoretical aspects of land degradation, land abandonment and soil erosion. Then the different spatial and satellite datasets were analysed and the various possibilities of integration and processing (after a careful study of the state of the art concerning the integration between GIS tools and Remote Sensing techniques). Finally, the RUSLE model was applied to the area under investigation along with spatial analysis techniques in order to assess land use changes in the area under consideration. Change detection and spatial autocorrelation techniques were also used in the work to characterise "aggregated" areas based on RUSLE values. The different methodologies used (qualitative and quantitative) contribute to the definition of the relationships between erosion, abandonment and land cover.

4.1 Land degradation, land abandonment and soil erosion: overview

Land degradation involves all processes of alteration of soil conditions due to the alteration of soil conditions, reduction or loss of biological and/or economic productivity. In general terms, it is a complex process triggered by a combination of combined phenomena such as aridity, soil erosion, land morphology and orography, vegetation cover, anthropogenic factors and climate[170–173]. One of the processes of land degradation is soil erosion, due particularly, but not exclusively, to the intensity of rainfall. When short, intense rainfall occurs on land without vegetation cover, runoff removes the surface layer richer in organic matter from the soil. Arid, semi-arid and sub-humid areas that are exposed are generally at risk of short but intense rainfall, which instead of mitigating the effects of low rainfall, causes erosion. Slope orientation and land slope are also an important vulnerability factor in the climatic and geomorphological context, in particular for water-stressed areas. The slope reduces the absorption capacity but at the same time contributes to an increase in surface runoff. For example, southern hillsides, being exposed to a greater flow of solar radiation, have microclimatic conditions that are averse to the regeneration of more stable vegetation with a higher degree of cover (due to the absence of moisture) and thus promote erosion situations. In 2015, the UN Sustainable Development Agenda defined the Sustainable Development Goals (SDGs) and among the goals to be achieved by 2030 (target 15.3) is Land Degradation Neutral Word, as a target to be achieved to safeguard the essential functions of soils and ecosystem services [25,92]. In 2017, the United Nations Convention to Combat Desertification (UNCCD) adopted the strategic framework 2018 - 2020 based on SDGs target 15.3 aimed at achieving degradation neutrality by 2030 (Land Degradation Neutrality)[174–176].

Climate change and the dynamics of land use and land cover change play a significant role in land degradation processes, since soil deterioration, loss of natural vegetation, anthropogenic pressure and unsustainable land management are responsible for large-scale land degradation, not only in semi-natural areas but also in agricultural and peri-urban areas [164,177]. Since World War II, land use change (LUC) has undergone rapid changes due to the acceleration of processes such as land abandonment, agricultural intensification, and uncontrolled expansion of urban areas. Agriculture is the dominant land use type on the Earth, currently covering about 40 percent of the Earth's land area, and abandonment in agriculture is one of the most important land use change processes in Europe [178]. In general, the request for land for food purposes is increasing globally, at the same time the process of agricultural abandonment has shown an increasing trend since the 1950s. Although the process of agricultural abandonment seems at variance with the increase in agricultural production, it is often closely related to the intensification of land uses for agricultural purposes and stems from several physical, environmental, social and economic factors in an increasingly globalized agricultural economy [178]. Although the current extent of abandonment is unknown, European agricultural statistics and land cover maps show a clear decrease in agricultural areas in recent decades, especially for extensive and small-scale farming systems, and modelling studies predict significant levels of agricultural abandonment in Europe in the coming decades[179,180]. Agricultural land abandonment is defined as the cessation of agricultural management for more than two to five years. The land is first colonized by annual plant species and grasses, which after three or four years pass to perennial grasses and shrubs, five years after the abandonment, almost 30% of the trees sprout. Many authors who have studied the issue of agricultural abandonment in Europe have shown that agricultural abandonment occurs primarily in less productive areas, remote and mountainous regions, and areas with soil erosion or climatic conditions unsuitable for agriculture [181–183]. Secondary causes of agricultural abandonment include rural depopulation and region-specific factors related to land ownership and tax regimes [184–186]. An example of agricultural abandonment is the abandonment of agricultural areas around cities related to urban sprawl, which is often driven by rising land prices and farm fragmentation [187,188]. Agricultural policies also play an important role, as abandonment often occurs in areas where land productivity does not provide adequate income to farmers. In Southern Europe, low land productivity combined with small farm sizes, often consisting of dispersed agricultural parcels, has led to very low agricultural profitability, resulting in the abandonment of farming. Policy measures designed specifically for mountain areas have been established mainly to provide compensation for the disadvantages and low agricultural productivity of mountain areas.

Indeed, the EU's Common Agricultural Policy (CAP) recognizes the natural disadvantages of these areas and their association with depopulation and land abandonment through structural support for "less-favoured areas" (Regulation 950/97). 56 percent of the EU's utilized agricultural area (UAA) falls within the delimitation of less-favoured areas, much of which is classified as mountainous area. Much of this mountainous area is designated as Objective 1. The French, Austrian and Italian memoranda on mountain agriculture and forestry submitted to the EU Agriculture Council reflect continuing concern about the economic and social pressures facing mountain agriculture. However, despite the efforts of compensation policies, agricultural incomes in mountainous areas remain much lower than those in the lowlands, to the detriment of the resulting environmental impacts and agricultural decline [189]. Even with the support of subsidies such as support and agri-environmental payments, which are part of the rural development pillar of the Common Agricultural Policy (CAP), agriculture in these areas is often not competitive. Activities implemented to reduce support for agriculture and to decouple support from production within the CAP were therefore much debated within the EU, as member states feared that this could lead to several risks, including the abandonment of agricultural areas resulting in increased degradation [190]. Agricultural abandonment can have positive and negative impacts, although the consequences differ depending on location and scale [191]. Soil erosion is an example of the several impacts of abandoning agriculture. Agricultural activities and the abandonment of agriculture are both predisposing factors for soil erosion and land degradation. Other factors influencing erosion and sedimentation rates are lithology, topography and climate [182,192]. Intensification and extensification of land use (for agricultural purposes) are the main contributors to the abrupt changes in LULCC and are also determined by local and global socioeconomic[193]. Drought, loss of soil organic matter, soil erosion, overexploitation of groundwater and soils, and salinisation of agricultural fields are some examples of consequences of LULCC that can potentially lead to land degradation. The degradation rate of land depends on the deterioration rate of land cover, aggravated by land use management and climatic conditions. Vegetation cover, land use type and distribution, and land use management are the main factors influencing the rate of land erosion [173]. The causes of agricultural abandonment can be environmental, socioeconomic, political, and improper land management and maintenance. Negative environmental factors such as poor soil qualities, altitude, and a highly seasonal climate can reduce the suitability of land for agriculture. In addition, from a socio-economic perspective, low farm profitability and stability are considered as drivers of abandonment. After abandoned, soils can evolve in two ways: toward degradation and toward rinaturalization. Agricultural abandonment can lead to soil erosion when adequate management after abandonment is absent, especially when environmental conditions hinder the restoration of natural vegetation, e.g., due to degraded soils [182]. The CAP has influenced erosion processes and rates because of the set-aside policy. This requires farmers to keep their set-aside fields as fallow sown with non-food crops, or as unseeded fallow land with continuous ploughing to avoid plant colonization, if they want to receive if they want to receive subsidies [194]. Agriculture has modified the natural environment in many ways over the past centuries.

Agricultural abandonment can be defined in different ways depending on the type of research approach used (administrative, ecological, social, landscape and environmental) and there are different ways to study it[195]. For example, some studies use a qualitative definition of abandoned land (describing the condition of the land), while others use a quantitative definition considering years without cultivation or grazing [195]. In all cases, agricultural land is considered abandoned when it no longer has agricultural functions. This type of analysis also requires the definition of agricultural land, which is always characterised by a dynamic change in land use and land cover over the centuries. The Food and Agriculture Organisation of the United Nations defines agricultural land as land use and land cover represented by arable land, permanent crops, permanent grassland and permanent pasture. Arable land is associated with the cultivation of occasional crops and occasional meadows for mowing and grazing. Vineyards and orchards, or shrub plantations, belong to the land use type of permanent crops. Permanent meadows and pastures are grasslands used for mowing and grazing that are not part of the crop rotation system. As stated above, the abandonment of agricultural land is, therefore, one of the most significant land use changes, which has always attracted scientific and political attention due to its impacts and drivers. Indeed, 11% of agricultural land in the EU is expected to be at high risk of abandonment by 2030[112,196]. As mentioned above, the Common Agricultural Policy (CAP) has further accelerated the dual process of agricultural intensification and farmland abandonment. This context has prompted scientific research to improve large-scale examinations of farmland abandonment in the EU [4-6], including forecasting and modelling for the near future [77,188,197]. Earth observation (EO) data and elaborate remote sensing methods, using data from various satellite platforms (Modis, Landsat, Sentinel), have been a crucial and continuously developing aspect of this type of research analysis[198,199]. Mapping agricultural land abandonment patterns and timing accurately is important for understanding its spatial determinants and environmental and socioeconomic consequences.

4.2 Material and Methods

The use of satellite data and GIS tools can provide useful data for the estimation of land degradation, land abandonment and soil erosion and for mapping and monitoring areas subject to degradation.
These methos are based mainly on the use of indices obtained by combining of the different spectral bands, which emphasize and detect any change in the vegetation status. The integration of soil erosion models (RUSLE model) with GIS and remote sensing are effective tools for mapping and quantifying areas and rates of soil erosion for the development of better conservation and monitoring plans for the land. In addition, the use of spatially explicit geostatistical surveys allows a more accurate quantitative analysis of the various results obtained. In order for a more fluent understanding of the methodologies, techniques and analyses performed, the following below are listed and briefly described the different parts of the work:

- Calculation of the RUSLE (Revised Universal Soil Loss Equation) for the estimate of the monthly erosion (of the months from October 2019 to September 2020) and of the total annual erosion of the period from October 2019 to September 2020;
- General statistical investigation between land cover classes and RUSLE values on a monthly and annual basis;
- Clustering of the RUSLE, through Getis & Ord. autocorrelation algorithm, in order to highlight areas that show continuous erosion month after month;
- Time-series investigation of NDVI for the period 1990-2020 in order to establish a database on transitional land-cover dynamics;
- Susceptibility to land degradation of areas classified as arable land and areas with post-crop vegetation based on deviations from average RUSLE values and mapping of areas of vegetation degradation, relative to arable land, through statistical correlation with vegetation factor C.

4.2.1 Dataset

This phase of the research was based on the integration of remote sensing techniques and Geographic Information Systems (GIS) with open and freely available technologies and datasets. The methodologies identified are based on the use of Sentinel and Landsat satellite data to which other various data sources, map bases and orthophotos have been associated. Both are very useful for the construction of land characterisation models, for risk assessment and for the susceptibility of soils to erosion. A valuable contribution to the study and monitoring of the areas under study is given, for example, by the Sentinel products of the Copernicus Mission as they provide high resolution multispectral optical images using spatial resolution ranging from 10 m to 60 m. The Sentinel 2 satellite images were downloaded from the THEIA site, which re-processes the data by aggregating atmospherically corrected TOA bands using the MAYA (Multi-sensor Atmospheric Correction and Cloud Screening) algorithm. In particular, FRE (Flat Reflectance) bands were used, which in addition to being atmospherically corrected, also have the suppression of reflectance variations due to slope. For images with cloud cover, the algorithm calculates relative masks with two resolutions at 10m and 20m. In our case, the CLM (Cloud Mask) band at 20m was used. The other reference satellite data is Landsat, which is used to calculate the NDVI (Normalized Difference Vegetation Index) time series. Landsat images represent a basic point for the historical analysis of terrestrial phenomena, in fact the database has remote sensing images from 1972 to the present day, a maximum spatial resolution of 30m and up to 11 spectral bands. Land cover classification was based on the Corine Land Cover 2018 (CLC) dataset and, for spatial and statistical analyses, the 2013 Nature Map at a scale of 1:50,000 in a format freely available from the ISPRA repository in the form of a shapefile. In addition, for the estimation of the RUSLE model parameters, in addition to Sentinel satellite data and weather data, the 'European Soil Map' and the Basilicata Soil Map were used.

4.2.2 Territorial Framework

The analyses and processing were carried out in an area of approximately 1554 km^2 within the Basilicata Region, including the municipalities of Tricarico, Ginestra, Irsina, Acerenza, Cancellara, Albano di Lucania, Forenza, Maschito, Oppido Lucano, San Chirico Nuovo, Grassano, Palazzo San Gervasio, Tolve, Genzano di Lucania, Venosa, Pietragalla and Banzi. The area is characterised by a typical Mediterranean climate, with a pronounced two-seasonal regime with hot, dry summers and cold, wet winters. Natural hazards and anthropic activities make this area an interesting context for study because the combination of anthropic activities and natural hazards contribute to the establishment of degradation phenomena. The remote sensing data used for the first part of this work are part of ESA's Copernicus Mission. Specifically, the data used is Sentinel 2, the spatial coverage provided by the satellite swatch determined the extent of the study area (Fig. 26).

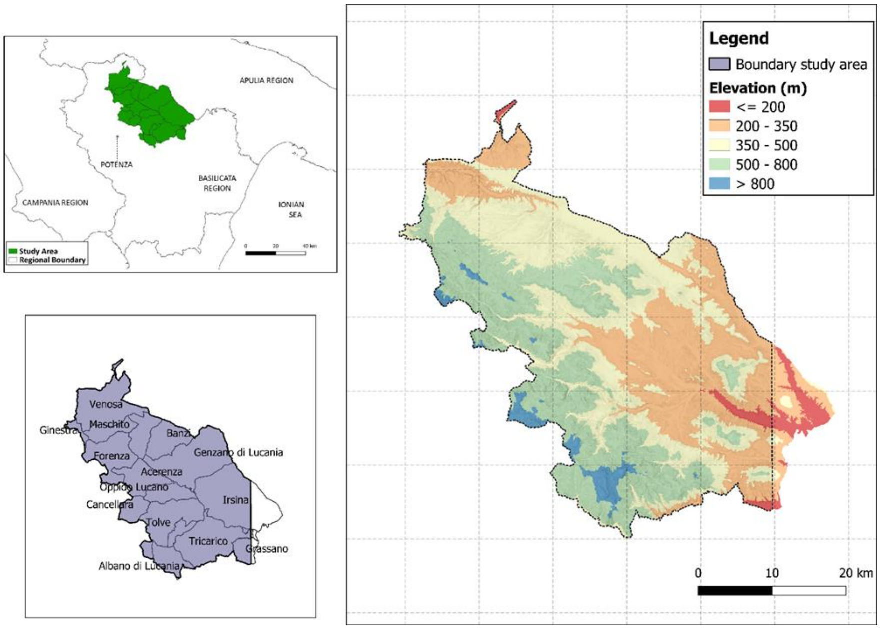


Figure 26. Overall outline of the study area with detail (bottom left) on the part actually considered in the methodology.

The overall study area is interested by landslide phenomena of different nature, which differ according to the lithology of the outcropping soil. The IFFI Project (Inventory of Landslide Phenomena in Italy), carried out by ISPRA and the Autonomous Regions and Provinces, provides a detailed picture of the distribution of landslide phenomena on the Italian territory. The landslides surveyed by the IFFI Project, whose last update for the Basilicata region was in 2014, number 858 in the study area, distributed as in the Fig. 27.

From the analysis of the land cover data with respect to the overall study area of all the Municipalities (Table 12 and Fig. 28), it can be seen that the area is mainly occupied by agricultural areas of different types. In fact, considering arable land, heterogeneous agricultural areas, permanent crops (vineyards, olive groves, orchards and wood arboriculture) and stable meadows, agricultural activity affects just over 80% of the entire study area. On the other hand, natural areas (wooded, shrubby and grassy areas) occupy almost 18%. The study area can ideally be divided into two zones: the western part, corresponding to the zones with a more complex and diversified morphology, is the most heterogeneous from the point of view of land cover. In fact, it is also the portion in which there are more natural areas of different types and in which it is possible to find the typical characteristics of an agroforestry territory. The remaining part, on the other hand, in the light of different morphological and geological characteristics, is represented almost exclusively by arable land and the natural areas are linked to a few areas and to the watershed areas. For this analysis, reference was made to the Corine Land Cover at level II (2018).

Table 12. Land cover based on the Corine Land Cover I Level expressed in hectares (ha) and percentage (%) with respect to the overall study area.

Corine Land Cover 2018	**Km^2**	**%**
Agricultural Areas	1266,186	81,45
Artificial Areas	12,44	0,8
Forest and Seminatural Areas	271,4	17,46
Water Bodies	3,772	0,24
Wetlands	0,799	0,5
TOT	1554,597	100

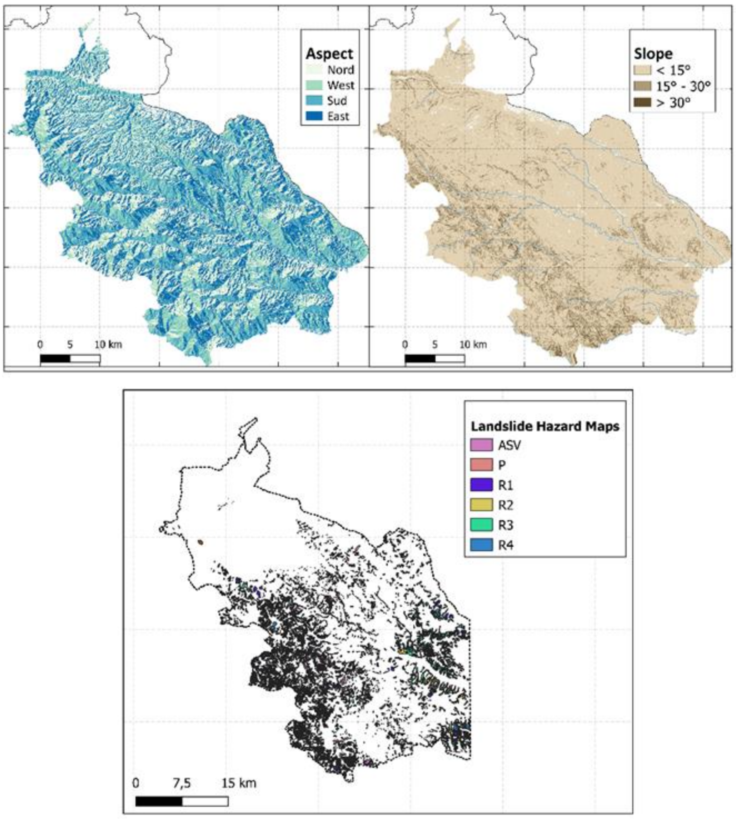


Figure 27. Geomorphological framework of the study area. Above: slope and aspect of the study area from the Digital Terrain Model. Bottom: landslide areas detected by the IFFI Project.

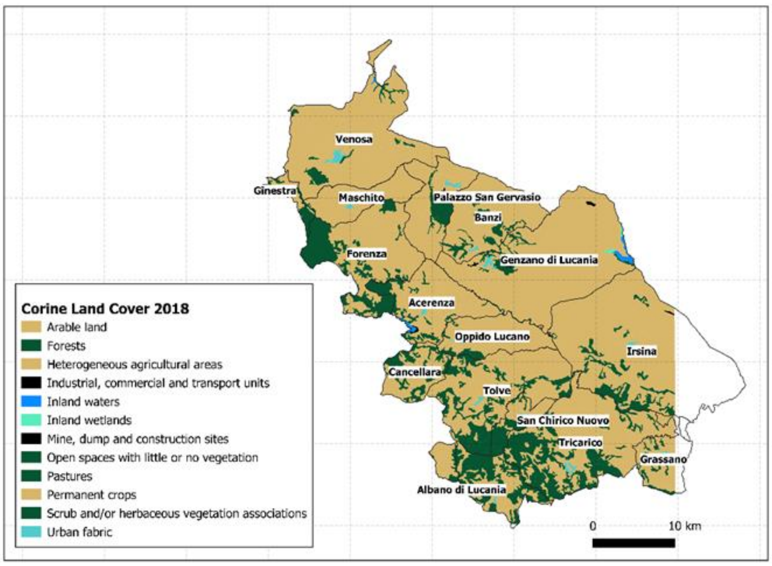


Figure 28. Land cover map based on the Corine Land Cover II level of 2018. Source: CLC2018 Copernicus Land Monitoring Service data processing.

For a more complete and detailed analysis of the characteristics of the study area, the Nature Map (Fig. 29, Table 13) (2013) and the relative tabulation of the surfaces in ha and percentage with respect to the overall study area are also reported. Given the greater level of detail and accuracy, the Nature Map represents the reference dataset for all subsequent spatial and statistical analyses.

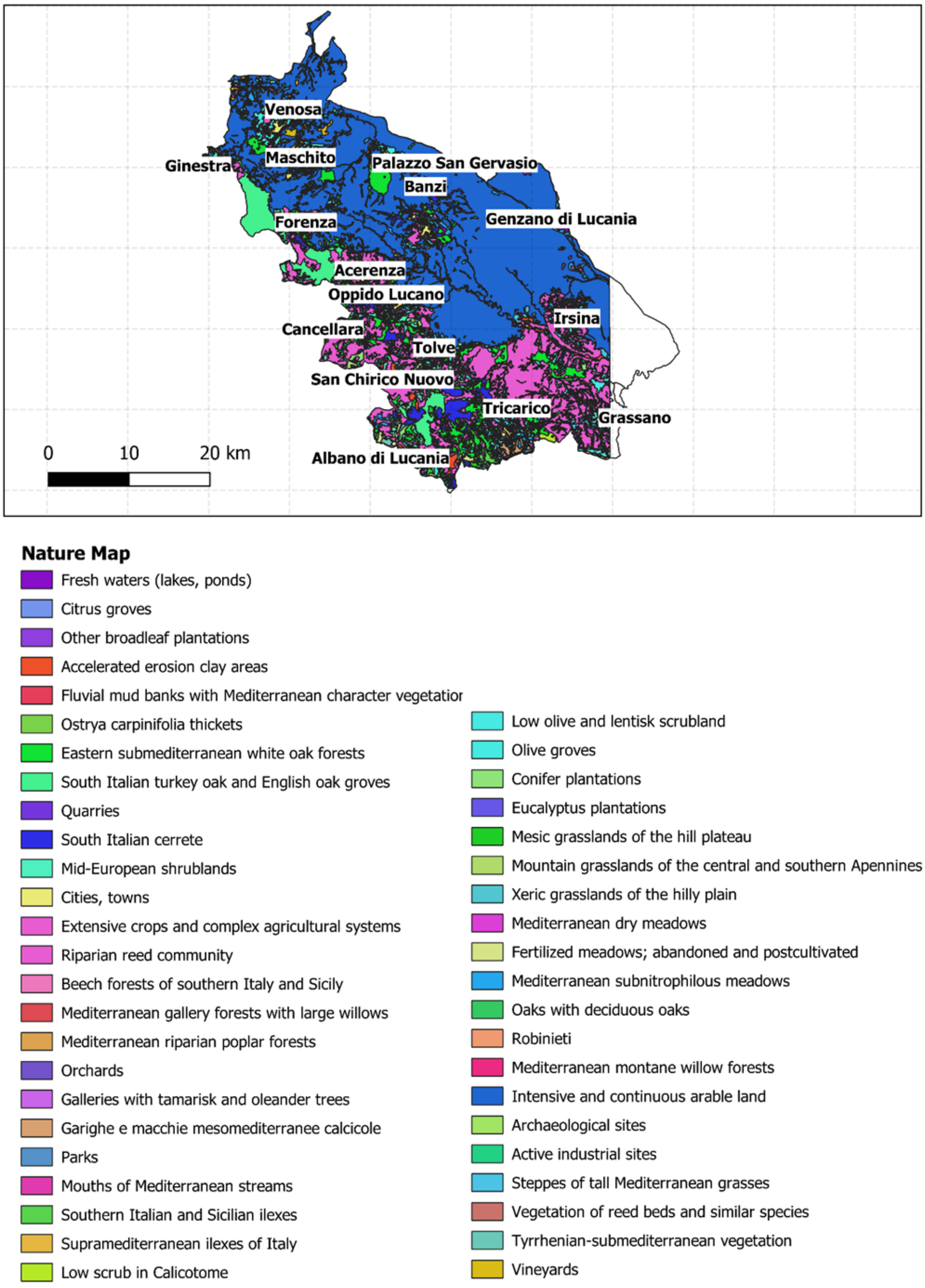


Figure 29. Land cover map based on Nature Map.

Table 13. Land cover based on the Nature Map expressed in hectares (ha) and percentage (%) with respect to the overall study area.

Nature Map 2014	Hectares	%
Mediterranean riparian poplar forests	1903,02	1,22
Archaeological sites	12,29	0,01
Tyrrhenian-submediterranean vegetation	3660,23	2,35
Steppes of tall Mediterranean grasses	1922,04	1,24
Other broadleaf plantations	283,18	0,18
Fluvial mud banks with vegetation	3,4	0
Xeric grasslands of the hilly plain	285	0,17
Lowland and Mediterranean montane hillside willow forests	144,42	0,09
Extensive crops and complex agricultural systems	30611,59	19,69
Quarries	112,81	0,07
Orchards	100,97	0,06
Low scrub in Calicotome	163,63	0,11
Olive groves	6643,4	4,27
Parks	12,63	0,01
Fertilized and grazed meadows; also abandoned and vegetation	499,44	0,32
Middle European shrublands	707,5	0,46
South Italian cerrete	3950,23	2,54
Eastern submediterranean white oak forests	9848,93	6,34
Ostrya carpinifolia thickets	10,94	0,01
South Italian turkey oak and English oak groves	5284,43	3,4
Mediterranean gallery forests with large willows	604,25	0,39
Southern Italian and Sicilian ilexes	349,32	0,22
Galleries with tamarisk and oleander trees	116,16	0,07
Intensive and continuous arable land	71592,59	46,05
Low olive and lentisk scrubland	2004,79	1,29
Beech forests of southern Italy and Sicily	0,34	0
Robinieti	19,34	0,01
Mesic grasslands of the hilly plain	1185,35	0,76
Vegetation of reed beds and similar species	283,42	0,18
Conifer plantations	1791,12	1,15
Mountain grasslands of the central and southern Apennines	89,3	0,06
Beds of Mediterranean streams	332,19	0,21
Oaks with deciduous oaks	21,23	0,01
Garrigue and mesomediterranean calcicolous scrubland	316,82	0,2
Cities, towns	1089,53	0,7
Active industrial sites	180,35	0,12
Supramediterranean ilexes of Italy	30,94	0,2
Subnitrophilous Mediterranean meadows	5761,27	3,71
Citrus groves	1,58	0
Accelerated erosion clay areas	1504,8	0,97
Mediterranean dry meadows	380,55	0,24
Vineyards	1223,23	0,79

Reeded riparian communities	86,91	0,06
Eucalyptus plantations	18,29	0,01
Fresh waters (lakes, ponds)	342,19	0,22
TOT	**155485,94**	**100**

Even from this mapping, it can be seen that agricultural areas cover most of the territory. In particular, just over 65% is represented by arable land including the classes "Intensive and continuous arable land" (in a higher percentage) and "Extensive type crops and complex agricultural systems". The difference between the two classes refers to the structural and ecological characteristics. In fact, in continuity with what was expressed previously", the class of extensive crops refers to those highly fragmented cereal systems with small strips of hedges, woods, stable meadows, etc., characteristic of morphologically more heterogeneous areas. In fact, it is possible to identify them in the eastern and southern part of the study area. In particular, the southern area is the one with the smallest surface affected by arable land and a significant variability in terms of land cover. Forest areas, on the other hand, are mostly present in four areas at higher altitudes. For details on natural vegetation areas deriving from abandonment of agricultural activity, please refer to the specific paragraph.

The areas of naturalistic interest for which two Natura2000 sites have been identified 2 are: "Bosco Cupolicchio" (between the municipalities of Tolve, Albano di Lucania and San Chirico Nuovo) and "Valle Basento Grassano Scalo" which affects the municipality of the same name. Furthermore, a limited area is affected by the “Lago Rendina” site in the Municipality of Venosa. Finally, as far as the landscape aspects are concerned, several landscape assets of regional importance and recognized at national level fall within the area. In particular, one of these assets is worth mentioning because a transformation of the territory due to processes of soil consumption, agricultural abandonment and land degradation can compromise its peculiarities. The asset subject to protection is represented by the entire municipal area of Irsina (Cod. BP136_024) which was subjected to protection with the DM 07 March 2011 (GU n 68 of 24 March 2011) for related reasons: <<... presents one of the most homogeneous and unaltered aspects of the agricultural landscape of Basilicata, characterized by the wide and uninterrupted expanse of wheat fields which, from the Bradano plain, cover the surrounding rolling hills without interruption.

4.2.3 Rusle Model Processing

The first part of work involved implementation methodologies useful for estimating and mapping areas with high erosion rates. Soil erosion was estimated using the RUSLE (Revised Universal Soil Loss Equation) [200], developed from the previous USLE model [201] by resampling all necessary parameters to the spatial resolution of Sentinel 2A (10 m). The estimate of annual soil loss according to the RUSLE model is a function of five variables related to rainfall regime, soil characteristics, soil topography, crop cover and management, and the conservation cultural practices, according to the following formula:

$$A = R * K * LS * C * P$$

Where is it: A = annual soil loss (Mg - ha -1 - year -1); R = precipitation erosion factor (MJ - mm - ha -1 - h -1 - year -1); K = soil erodibility factor (Mg - h - MJ -1 - mm -1); LS = slope length and slope factor (dimensionless); C = crop and cover management factor (dimensionless); P = crop or erosion control factor (dimensionless). The RUSLE is based on five variables related to rainfall patterns, soil properties, topography, crop cover and management, and conservation tillage practices. The result is an estimate of the amount of soil lost due to surface erosion and stream (canal) erosion.

The reference period goes from October 2019 to September 2020. Among the various climatic factors that characterize a territory, rainfall has the greatest erosive impact. The precipitation erosivity factor R is an average index that measures the kinetic energy and intensity of precipitation to describe the effect of erosion, two parameters that have a significant influence on erosive processes. From the online database of the Functional Centre of the Basilicata Region, the cumulative monthly rainfall data of 6 meteorological stations were downloaded, namely Venosa, Albano di Lucania, Palazzo San Gervasio, Oppido Lucano, Grassano and Irsina.

The R-factor equation is based on the rainfall intensity developed for the Basilicata region in the work of Capolongo [202]; in which only daily rainfall contributions with values greater than 10 are added up.

$$R = 0.1087 * \left[daily\ cumulate\ rainfall^{\,(1.86)} \right]$$

After having obtained the punctual values of R for all the months of the period considered for each rain gauge, the data were spatialized and using interpolation tools, thus obtaining a probable erosivity factor R for the entire study area.

The soil erodibility factor K is the rate of soil loss per unit of the rainfall erosion index (t ha h ha − 1 MJ − 1 mm − 1) as defined by newfoundland. The factor K is the long-term average response of soil and soil profile to the erosive power of storms. In particular, it represents the detachment and transport of part of the soil components due to the impact of rain and surface flow. It takes into account specific characteristics of the soil components, from abrasive effects due to transport and localized deposition of soil parts depending on the topography, as well as rainwater infiltrations in the soil profile.

$$K = \left[\frac{2.1 * 10^{-4} * (12 - M) * [(Si + fS) * (100 - C)]^{1.14} + 3.25 * (A - 2) + 2.5 * (P - 3)}{100} \right]$$

M represents the organic matter expressed as a percentage (%) present in the soil, Si is the percentage of silt from 0.002 - 0.05 mm, fS the content of very fine sand with diameter 0.05 - 0.1 mm, and C the percentage of clay with diameter <0.002 mm. The K values thus obtained, were multiplied by the factor 0.1313 in order to be expressed in the unit of the International System. For the definition of the factor on the area of investigation the parameters were derived from the Pedological Map of the Basilicata Region and from the Basilicata Region soils database.

The L and S factors represent the effect of topography on soil erosion rate. Slope length (L) in RUSLE is defined as the distance from the point where surface flow begins, to the point where storage occurs or runoff waters are channelized [203]. Soil loss increases if the slope length increases as a result of downward runoff accumulation. Slope (S) describes how erosion increases with slope angle. Soil erosion increases with slope angle due to the increasing velocity and erosivity of runoff [204]. The formula proposed by Mitasova [205]

was used to calculate the topographic LS-factor relative to a point r. The LS product factor is dimensionless and it was assumed to be constant over the entire period of observation.
The C-factor is dimensionless and is calculated to consider the impacts of vegetation cover on erosion. There are several approaches to calculation in the literature as C can vary depending on the different parameters being considered. C depends on many sub-factors such as cover given by plants, soil moisture, leaf residue, which vary continuously throughout the year, so there is a need to be able to estimate an indicator to calculate both spatial and temporal vegetation status. For this purpose, the index of SAVI closely related to the NDVI index, which is less sensitive on sparsely vegetated or bare soils, by applying the following formula:

$$SAVI\colon \frac{[(NIR - RED) * (1 - L)]}{(NIR + RED + L)}$$

The equation defined by Kuo [206] was used to calculate C factor:

$$C = -a * SAVI + 1$$

Where a value is land cover management factor and is assumed as a value of 1.18. Factor C will have values between 0 and 1; where 0 indicates complete coverage vegetation cover, 1 indicates no vegetation cover or bare soil. Therefore, a value of C close to zero is indicative of soil not exposed to erosion, while high values of C is indicative of soil exposed to erosion.
Therefore, Sentinel 2 satellite images pre-processed by MUSCATE were used to calculate the C-factor. In consideration of the monthly and annual RUSLE calculation, one image was processed for each month. In the case of cloudy images, the C value of the previous and next month was averaged for missing pixels. The last factor (P) considers the effects of agricultural practices carried out to mitigate the erosion effect of rainfall. The P factor is dimensionless and values range from 0 (presence of agricultural practices for erosion mitigation) to 1 (absence of agricultural practices for erosion mitigation).
The P factor was derived from a dataset freely available online at the ESDAC website [207]. All parameters calculated were resampled to spatial resolution of Sentinel- 2A (10 m) and summed to get the actual value of RUSLE expressed in Mg * ha −1 * year −1. The RUSLE values were calculated for the following months: October, November, and December 2019 and March, April, May, June, July, August, and September 2020. For the monthly RUSLEs a specific model has been implemented by Graphical Modeler of QGIS to realize a batch processing in order to calculate the different parameters in a semi-automated way. Finally, the monthly values were summarized to have an annual RUSLE value. The months of January and February 2020 were not included in the calculation of RUSLE because cloudless satellite imagery is not available for C factor estimation. The integration of satellite imagery and geostatistical analysis is a very innovative approach for analyses and mapping that rely on factors known to be influenced by the spatial component. In the study of statistical variables representative of phenomena or processes acting at the land scale, the issue of spatial autocorrelation is key to assessing whether a particularly intense phenomenon in a specific area, implies the presence of the same in contiguous areas as well. Monthly and annual soil erosion maps, obtained from the application of the Model RUSLE, spatial autocorrelation indices were applied. The concept of spatial autocorrelation is one of the most important in the field of spatial statistics. It derives from the first law of geography introduced by Tobler in 1970 [208], “everything is related to everything else, but near things are more related than distant things.” Autocorrelation indicators measure whether and how much a dataset is autocorrelated across the study region. In the presence of positive spatial autocorrelation, similar values of the variable result in spatially clustered, while in the presence of negative spatial autocorrelation, spatially

clustered different values of the variable; the absence of spatial autocorrelation indicates a random distribution of values in space. After applying several indices to the monthly RUSLE values, the choice fell on using the Gi local autocorrelation index proposed by Getis and Ord [209,210]. Getis and Ord's algorithm is a local indicator of spatial autocorrelation; local indicators allow us to identify clustered pixels, measuring how homogeneous the features within the area are. In particular, a high value of the index means a positive correlation for high-intensity values, while a low value of the index means a positive correlation for low intensity values. In applying autocorrelation methods, it is important to define the nature of the events investigated and the geometric relationships involved. In image processing, the spatial event is associated with a pixel, and spatial autocorrelation statistics are usually calculated by considering the geographic coordinates of its centroid[211]. Intensity, on the other hand, should be chosen by strictly considering the empirical nature of the case study. The conceptualization of geometric relationships in the case of image processing is very simple because the distance between events is always equal or is a multiple of the pixel size. The application of spatial autocorrelation statistics to remote sensing images allows us to obtain a new raster that contains in each pixel a number expressing how much it is autocorrelated to another pixel.

4.2.4 Spatial Analysis Between Land Cover and Rusle

With the aim of evaluating and investigating regarding the relationships between agricultural transition phenomena and land degradation, several methodologies are proposed, based on existing datasets or on purpose-built classifications. One of the methodologies was based on preliminary mapping of areas susceptible to land degradation, which took into account the land cover classes of greatest interest (arable land and areas with post-crop vegetation) and the differences in erosion values in the months of greatest interest and the areas with the greatest "accumulation" of erosion in the year of analysis. For a preliminary statistical investigation between erosion and land cover, we evaluated how the RUSLE values (monthly and annual) vary for each land cover class. For the purpose of proper spatial analysis, the monthly RUSLE rasters (October 2019 through September 2020) and the annual RUSLE raster were re-processed by assigning each pixel a value equal to the average to the mean of the values resulting in a 3x3 cell. For land cover data and related changes, first the open datasets of Corine Land Cover 2018 and Nature Map 2013 from ISPRA were analysed. Considered the maps' characteristics, scale, classification techniques, the characteristics of the information contained and the level of accuracy, it was decided (after visual comparisons through photointerpretation) to use the Nature Map. This, although dated 2013, was produced using methodologies that ensured the production of a very accurate and reliable dataset. Considering that the objective of this section is to carry out a focus on land degradation processes for some specific land cover classes, a preliminary investigation was carried out on the classes related to arable land and areas with post-crop vegetation with respect to monthly and annual values of RUSLE. The classes " Arable crops " were derived from the aggregation of the classes: "82.1 Intensive and continuous arable crops" and "82.3 Extensive type crops and complex agricultural systems." In the former case, these are the arable crops (corn, soybeans, autumn-winter cereals, sunflowers, garden-crops) in which mechanized activities, vast and regular agricultural areas prevail. While the second includes traditional agricultural areas with arable systems occupied especially by low-impact autumn-winter cereals. These environments are highly fragmented, degraded and/or subject to land degradation. The class " post-crop vegetation " is the result of the aggregation of several Nature Map classes that present areas that were once cultivated and are now abandoned and/or characterized by the presence of post-crop vegetation. Specifically, the difference maps between the March 2020 RUSLE map and the average RUSLE value calculated for the whole class in the same month were considered for arable land; while for areas with post-crop vegetation: same type of data but with reference to November 2019. The months indicated were chosen based on the analyses on the basic statistical parameters from which those with the highest average values were extrapolated. A normalization of the values was carried out according to a continuous range from 0 to 1 and considering only the positive ones as they are the most appreciable for erosion purposes. This step made it possible to transform the data in an analytically useful way to make comparisons between variables at different scales. The resulting normalization rasters were multiplied by the permanent erosion raster obtained from the clasterization process, which, being a discrete binary 0-1 raster, allowed only areas with permanent erosion to be included.

4.2.5 Spatial investigations on historical series for the identification of abandoned arable land and areas susceptible to degradation

A first step in analysing land degradation is to highlight which spatial and phenomenological aspects are closely related to this phenomenon. One of the most important indicators in defining the phenomenon is certainly the change in land cover followed by the loss of productivity. Soil and land degradation is a complex phenomenon caused by multiple factors that limit or inhibit productive, regulatory and utilitarian functions as well as the ecosystem services that a natural soil can provide. The United Nations Convention to Combat Desertification (UNCCD) has drafted a methodology aimed at qualitative assessment using an approach that involves the combined use of the following sub-indicators:

- Land Cover Changes;
- Productivity Loss:
- Fragmentation;
- Loss of ecosystem services.

Productivity loss is estimated through the use of the normalized difference vegetation index (NDVI). normalized difference (NDVI). The NDVI index is an indicator that provides the health status of the crop based on the reflectance of the leaves. It is known as the most accurate indicator of ground-level biomass, as it reflects greenness density and photosynthetic activity [212–216].

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

The NDVI vegetation index takes into account the ratios of leaf reflectance at various wavelengths and gives us the health status of the crop. The higher the index, the more the crop is in an optimal state. Values can be around at in a range from -1 to +1. The index has been widely employed in multi-temporal approaches [217–219] because a single image of the date is not always sufficient to differentiate crops solely on the basis of their signature's spectral signatures. Vegetation dynamics can be defined on multiple time scales. In the short term, different crops have season-driven phonologies that typically follow annual cycles. Between years, phenological markers may respond differently; these changes are influenced by short-term climatic fluctuations (e.g., temperature, precipitation) and/or anthropogenic forcings (e.g., extraction groundwater, urbanization, abandonment) [219].

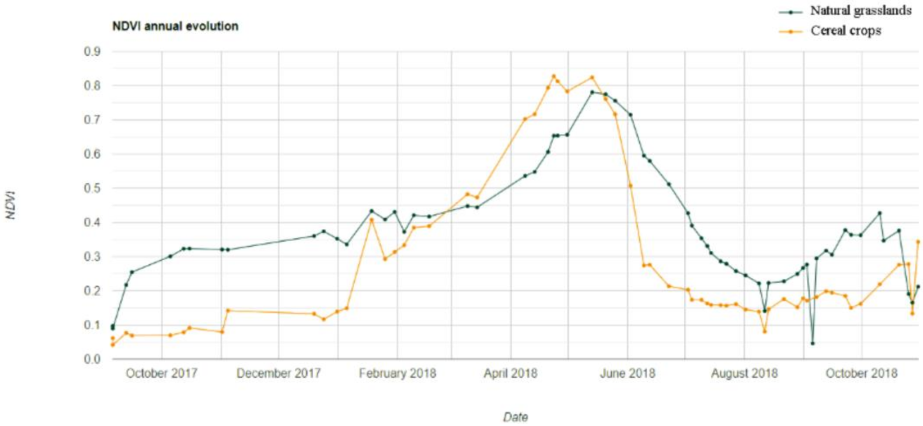


Figure 30. Example of a phenological curve calculated on a historical NDVI series from October 2017 to October 2018 for an agricultural area with cereal crops and a natural grassland (abandoned agricultural area). For this example, the time series was calculated in the Google Earth Engine platform based on Sentinel-2 L2A images.

In addition, the use of more than one year of data gives the opportunity to include information on interannual phenological changes [220]. However, the full potential of long-term NDVI time series is often hampered by poor quality data caused by instrumentation problems, weather conditions (e.g., clouds and haze), and soil conditions. These problems tend to create data gaps and make phenological markers difficult to identify. The applied methodology involved the use of LANDSAT 4/5 TM and LANDSAT 8 OLI satellite images available from 1990 to 2020. Precisely, the useful images (devoid of clouds and distortions) used in this analysis are: 1990, 1992, 1993, 1994, 1999, 2000, 2001, 2004, 2005, 2009, 2011, 2014, 2017, 2019, 2020). To create a realistic phenological curve, it was assumed that arable crops have an annual cyclicity, where we find a maximum of NDVI values in the spring periods (March and April) and a minimum in the fall months (October and November) (Fig. 30). No atmospheric correction was performed because, in this case, it does not significantly improve classification accuracy When multi-seasonal image dates are grouped into a single composite (layer stack) and classified according to NDVI values. In the absence of snow, the NDVI of the land surface rarely drops to zero, as woody vegetation and soil maintain positive NDVI throughout the year. Negative and zero values are typically caused by cloud contamination, water bodies or missing data. After calculating the NDVI difference (spring -autumn) for each year, the next step was to discriminate the images for each individual year, through change detection analysis, the NDVI difference values of the probable arable crop areas (equal to NDVI values greater than 0.5) from all other values. Cover density maps were elaborated according to the following formula:

$$dNDVI = NDVI_{max} - NDVI_{min}$$

where NDVImax and NDVImin represent the maximum and minimum NDVI value for each arable land signature. After calculating the NDVI difference for each year (spring - autumn), the next step was to discriminate the images related to each single year, through change detection analysis, the values the difference of NDVI of probable arable land areas (equal to NDVI values greater than 0.5) from all other values. A binary raster was thus obtained, conventionally assigning value 1 to the pixels of likely arable land areas and 0 to all other areas. Then through raster and vector analysis operations, the historical series of the results obtained was analysed, quantifying in terms of km the areas that have not undergone any change in agricultural land use (areas always cultivated with arable crops and areas not cultivated with arable crops) and above all, those that show an agricultural transition, moving from arable farming to another type of agricultural land use and/or abandonment. The objective of this type of analysis was to be able to identify areas that underwent a probable change in agricultural land use and/or abandonment during the period analysed. The results obtained were subsequently cross-referenced with the classes of the Nature Map (2013) divided into agricultural and non-agricultural areas. The data obtained by overlaying the obtained rasters with Nature Map agricultural area maps were then divided into three decades (1990 - 2000; 2000 - 2010 and 2010 - 2020). This made it possible to identify which Nature Map agricultural classes have undergone agricultural land use change and/or abandonment. Subsequently, these data were compared with the values for the soil erosion map obtained from the RUSLE analysis with the aim of relating and studying how agricultural abandonment or land use change may have affected current soil erosion over time. The same was done for the areas identified as continuously cultivated during the 30-year period under consideration. To study the phenomenon of large-scale soil erosion in even greater detail, an additional methodology referring specifically to agricultural areas was chosen to be implemented. This is based on the factors that make up the RUSLE; in particular, on the correlation existing between some of these and the overall erosion index so as to identify areas more exposed to the effects of degradation. In order to analyze the phenomenon of erosion in agricultural areas (arable land in particular), reference was made to factor C, which in RUSLE is the one that assesses the weight of management of areas in agricultural use on the erosion factor (A). Land covered with vegetation is definitely more protected from erosion because the leaf area present interposes a physical barrier to the impact of rainfall and the sliding effect of debris downstream. Identify cultivated agricultural areas where the erosion phenomenon is high, especially during periods of vegetation growth, implies that that area shows obvious problems caused by poor vegetation growth. Therefore, isolating the factor C, compared to the other factors and linking it to A during periods of maximum vegetation activity, it is possible to obtain degraded areas as they show a high erosion rate despite the fact that the soil is covered by vegetation. The month of March was chosen to be analyzed because it is the period when arable crop growth is considerable and the soil is largely covered by vegetation. In order to show how the C factor affects the A factor compared to the other parameters, it was chosen to set in a range consisting of 3 classes each, the slope factor (for the morphological part) and the R factor for erosivity given by rainfall. It is possible to construct a table of combinations based on the class of each factor as shown in the following figure (Fig. 31).

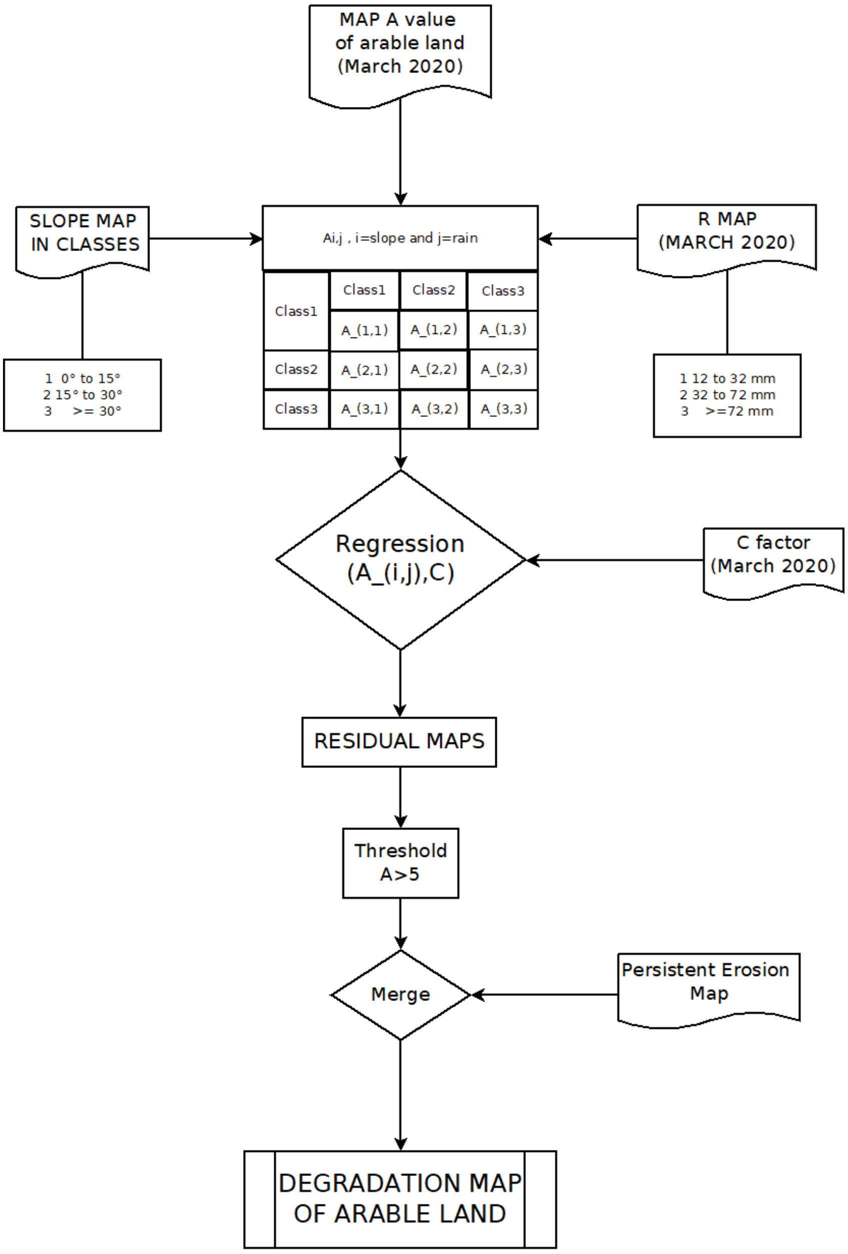


Figure 31. Flow Chart for the elaboration of a degradation map of Arable land.

For each combination of the slope classes and the R factor of erosion given by rainfall, the value of A was selected only for the arable land obtained from the Nature Map, thus obtaining 9 distinct layers in the ranges of slope and erosivity R referred to March 2020. Since the objective is to look for the correlation between the erosivity of RUSLE A (dependent variable) and the factor C (independent variable), it was chosen to compare them through the tool of analysis of linear regression by which the map of residuals for each regr[A_(i,j),C] pair. The residual maps A_res(i,j) quantifies pixel by pixel the error Ɛ calculated on the difference between the value of estimated A and actual A. The direct proportionality Y=AX+B+Ɛ is given by the points closest to the regression line and thus the points at which the value of residuals Ɛ is small in absolute value. In order to select the values of A where the error can be considered minimal, a threshold

Ɛ=|YReal-Y Estimate|<2 was defined around the regression line in order to highlight all points that fall therein and to identify areas instead of only recurring to points that lie right on the line. The pixels thus obtained will be characterized by very obvious direct proportionality because they are close to the line as opposed to the more distant pixels, which instead do not give proportionality and consequently are not of interest for the purpose of analysis. Defined the areas where the vegetation factor weighs more on the value of A, all other things being equal, in order to define those showing a high erosion value, a threshold was placed on each layer A_res(i,j) excluding all pixels with values less than or equal to 5 Mg/ha^-1*year^-1. The result represents those areas that despite being covered by vegetation have a high erosion factor, areas where erosion could or already is causing low productivity and destined for abandonment. The nine A_res(i,j) maps were combined successively to compose a single map of areas of degradation.

4.3 Results and Discussions

4.3.1 Persistent Erosion Map

The processing of the RUSLE model, as previously illustrated, goes through the creation of intermediate rasters representing different processes that may influence, to varying degrees, the overall erosion of soils. For a more accurate analysis, it may be useful to evaluate the individual factors individually so as to examine how each one influences and weighs on the final value of the RUSLE. One of the most important factors is that related to R, the rainfall erosivity.
The histogram in Figure 32 highlights that the highest average values of the R factor during the October 2019 - September 2020 observation period, occurred during the month of November and followed by March 2020 and July 2020.

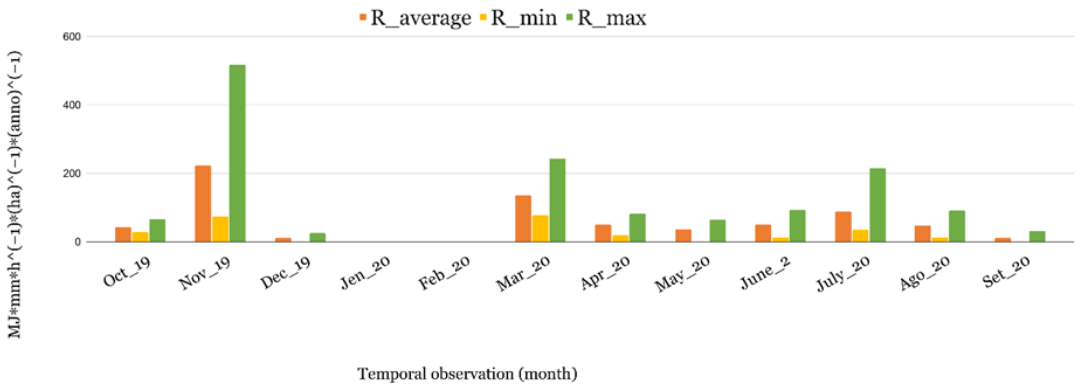


Figure 32. Histogram of the trend in R values during the months of analysis (October 2019 to September 2020).

Figure 33 shows the trend of the average C-factor with respect to the study area during the time span of one year (See Appendix). Being a factor related to vegetation cover, it can be seen that the highest values occur in the two summer months in consideration of the fact that the study area being mostly covered by crops and therefore very little vegetation cover during that period. October and November, also present high values. In this case, the overall value still higher than average takes into account the absence of vegetation cover in forest areas.

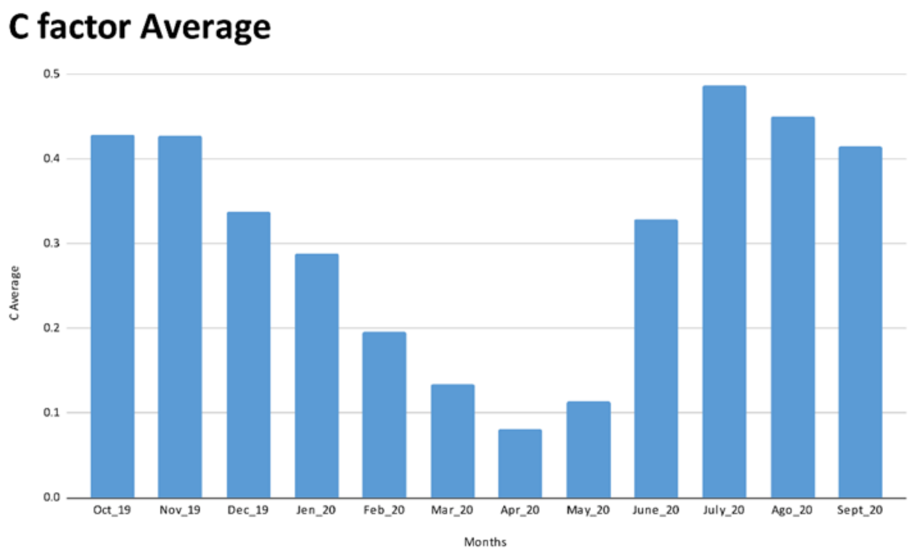


Figure 33. Histogram of the C values trend during the months of analysis (from October 2019 to September 2020).

The calculation of monthly RUSLEs and, subsequently, of annual RUSLE (Fig. 34), made it possible to create rasters in which each pixel expresses the amount of soil potentially eroded expressed in Mg-ha -1 -year -1.

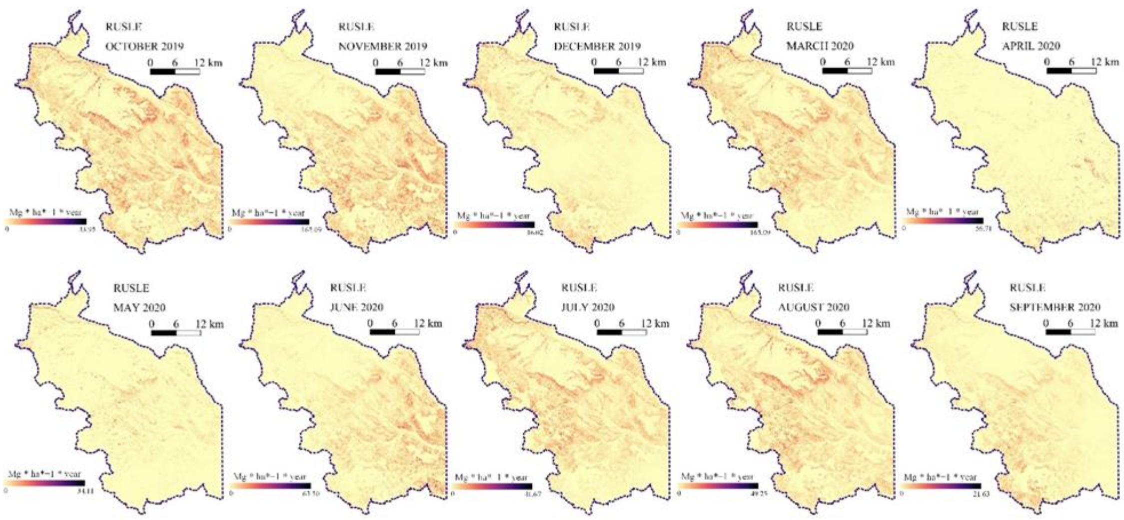


Figure 34.Maps of monthly and annual RUSLEs expressed in Mg-ha -1 -year -1.

Statistical interpretation of the index allows values to be grouped on the basis of a hot spot (pixel values above the mean) or cold spot (values below the mean [210]. The index was applied individually to each month highlighting only pixels with positive autocorrelation and then subsequently cumulated into a final raster. This allowed the development of a map highlighting areas with persistent erosion rate based on clusters of hot spots (Fig. 35).

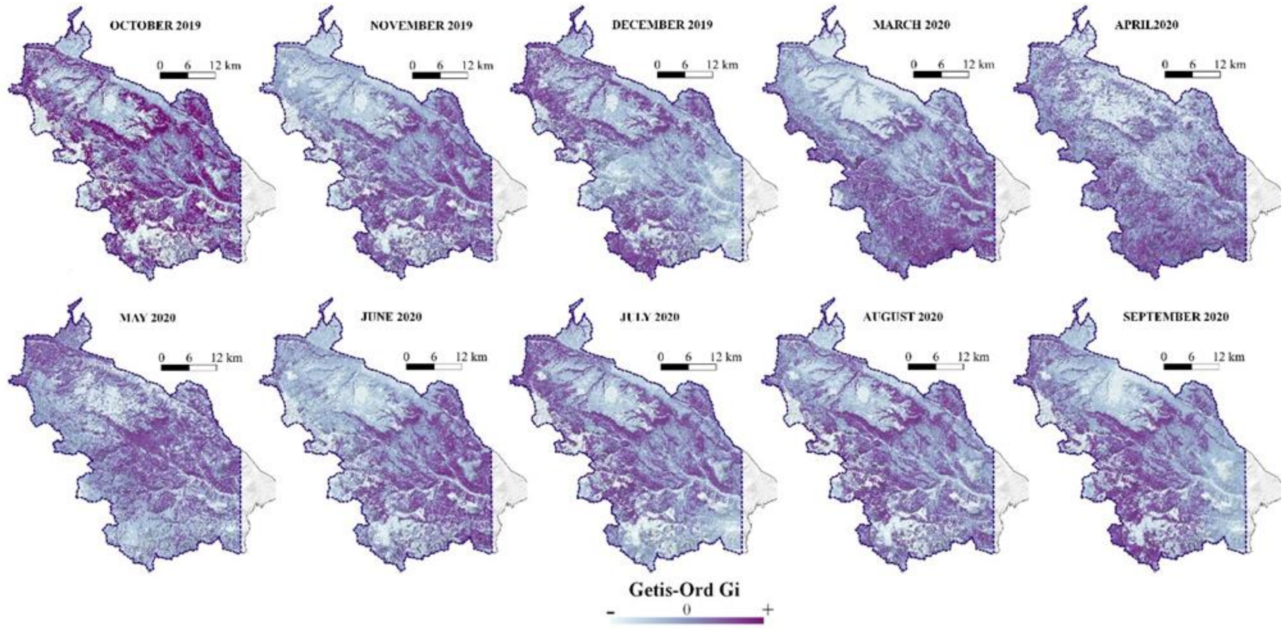


Figure 35. Intermediate layers of Getis-Ord Gi applied to monthly RUSLEs. Values express positive or negative autocorrelation.

4.3.2 Results of Spatial Analysis Between Land Cover and Rusle

The purpose of this part of the thesis work was to relate erosion data to land cover in order to assess how this process may influence degradation phenomena and the relationship between agricultural abandonment. At first, the average monthly RUSLE values were compared with the Nature Map principal classes in the study area so as to have an overall view of the erosion level.

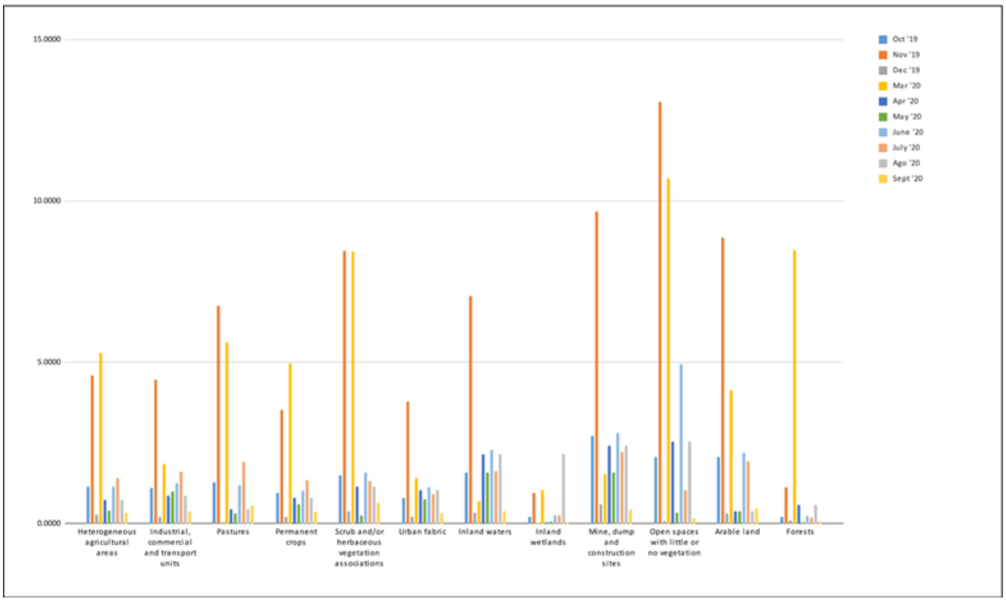


Figure 36. Histograms on the relationship between the average values of the monthly A [expressed in Mg ha −1 year −1] with respect to some classes of greater interest in the Nature Maps.

The level of detail of the classes makes it possible to discriminate more accurately the relationships that may exist between erosion and land cover. Primarily, it allows us to identify, for the classes of interest, the months that contribute most to soil erosion. It is evident from the Figure 36 that the months that most have high average values are November 2019 and March 2020. Overall, the class with the highest average annual value is that of clayey areas with high erosion (Badlands). Next, the highest average values are recorded for all those areas in which vegetation types (herbaceous and shrubby) typical of post-crop processes resulting from the abandonment of arable land are present. These areas are included in the classes characterized by species and ecological successions typical of areas where agricultural activities (cereal cultivation and/or grazing) have been interrupted for quite some time and with some temporal continuity. The classes related to crop abandonment; all show mean values higher than the overall annual value. Areas covered with forest species, too, can present erosion problems in particular contexts (e.g., overgrazing in steeply sloping areas, reckless cutting in the past, and fires).

Considering the aggregate classes of Arable Crops and Post-Crop Vegetation the actual study area is affected by slightly more than 9% (table 14, Fig. 47) by areas with post-crop vegetation which, affect the west and southwest portions, areas with morphological, soil and socio -economic characteristics different and less profitable for a certain type of agriculture.

Table 14. Area of abandoned agricultural areas and arable land in hectares and % of the actual study area.

	Hectares (ha)	Percentage (%)
Agricultural Abandoned Area	13294.87	9.04
Arable Land	96156.83	65.36
Effective Study Area	147107.71	

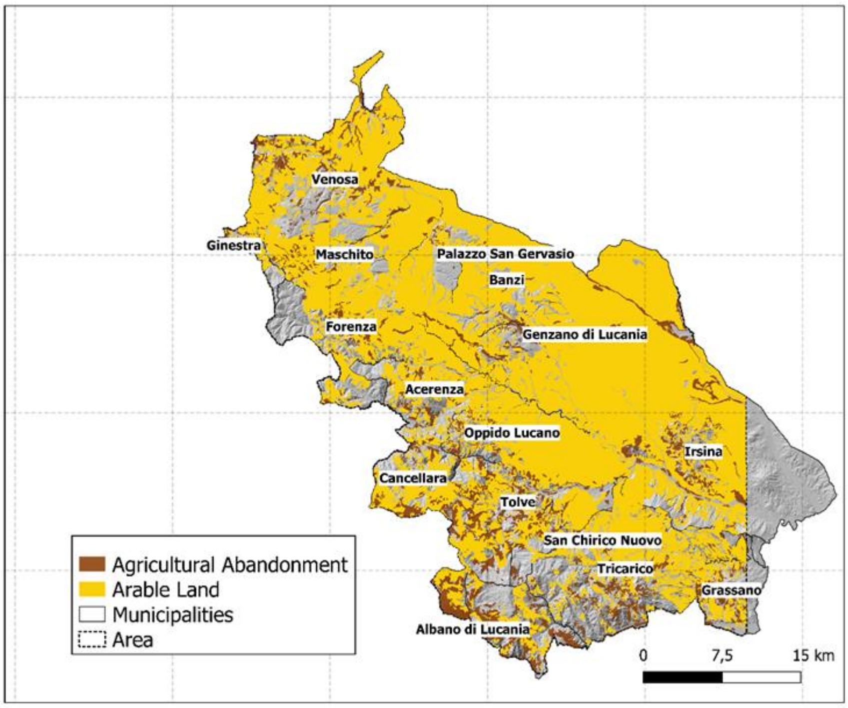


Figure 37.Mapping of arable land and abandoned agricultural areas against the actual study area

The investigation was based on statistics of average monthly and annual erosion values with respect to arable and post-cultivated areas. The data are shown in Table 15.

Table 15. Average monthly and annual RUSLE values (expressed in Mg-ha $^{-1}$ -year $^{-1}$) for arable lands and post-cultivation vegetation areas.

Period	**Post-Cultivation Vegetation Area**	**Arable Lands**
October 2019	1.81	2.10
November 2019	8.81	8.84
December 2019	0.42	0.34
March 2020	7.22	3.94
April 2020	0.90	0.35
May 2020	0.37	0.39
June 2020	1.95	2.19
July 2020	1.85	1.96
August 2020	2.29	1.33
September 2020	0.69	0.48
YEAR (2019 – 2020)	**26.23**	**22.92**

The analysis on annual values shows an erosion rate with same order of magnitude in two classes but with a slightly higher value in areas with post-crop vegetation. This small difference is extremely important to investigate because, generally high values are noted in arable crops as they have long periods of the year with bare soil. The reason could be that the areas with post-cultivation vegetation, present a type of cover (expressed by the C-factor) and the morphological context that could influence the erosion. Evaluating the arable crop classes, it can be seen that the month in which the highest values are present is November 2019. This is due to the amount of rainfall that has fallen and also that November is the month when arable land is without vegetative cover, as it is the transition period between the end of the agricultural year and the beginning of planting the following one. Since there is no vegetation cover, the month of March is ideal for investigating erosion-dependent soil degradation in arable land. In November, in fact, erosion is determined, with equal erosivity R due to rainfall, only by the stationary factors K and LS. This is called "natural potential" which does not consider the influence of vegetation. Areas where high erosivity values emerge can be referred to as those areas that are subject to greater susceptibility to land degradation and therefore should be given more attention. When considering areas of post-crop vegetation, it can be seen that the months of greatest interest are November and March. November has rather lower values than arable land, despite the difference in land cover in the two classes in this month. There could be many reasons for this, but require further investigation as several factors could be involved, related to morphological and physical factors as well as different stages of abandonment. In March the average value in the abandoned areas is almost double, presumably due to the fact that in this month the arable land already provides a certain degree of land cover and the herbaceous and shrub vegetation does not yet, since the growing season begins later than that of cereals and arable land. The application of Gi's local autocorrelation algorithm allowed us to identify areas for attention characterized by persistent erosion, which takes into account the spatial and geographical relationships that may exist between contiguous areas that emerge from monthly RUSLE calculations. The pixels marked in the map are spatially and geographically correlated with each other according to the intensity of the monthly RUSLE value.

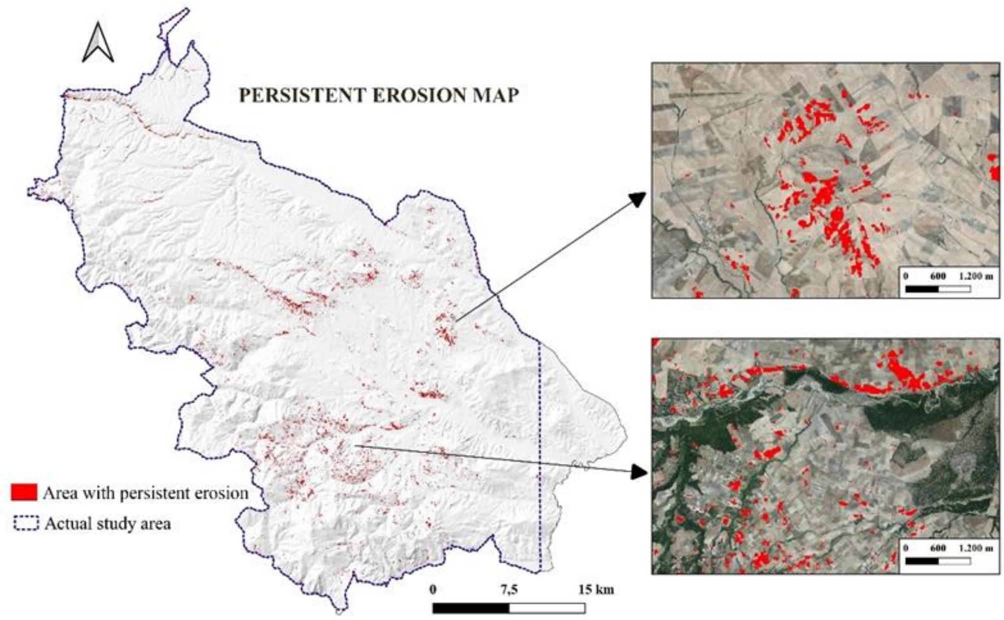


Figure 38. Map of permanent erosion between October 2019 and September 2020. On the right, two details on as many areas superimposed on the data from the Regional Technical Map (2013) of the Basilicata Region.

In this map (Fig 38.), the pixels have been reclassified so that they have only discrete 0-1 values. The areas of interest, which have value 1, are all those areas that during the period analysed, have positively autocorrelated RUSLE values. In these areas there is a constant erosional contribution during all months of analysis. To more clearly interpret this process, the results were related to land cover to evaluate which classes were most affected in terms of area by permanent erosion. The most significant classes (Table 16) are those related to arable land and grassland that have post-crop vegetation due to abandonment of agricultural activity. In addition, when relating the hectares in permanent erosion to the total land cover class area, it is possible to identify those most affected by a major erosion rate each month. From this analysis we note that the highest rates are found in classes that, given their own characteristics, are subject to erosion phenomena (Badlands, quarries and riverbeds); followed by land cover classes subject to agricultural abandonment processes.

Table 16. Surfaces in hectares and as a percentage of areas in permanent erosion.

Land Cover Classes	**Hectares (ha) in persisten erosion**	**% of total persistently eroded area**
Arable Land	493.96	22.48
Post-Cultivation Vegetation Area	1343.11	61.13
Olive groves, vineyards and orchards	143.89	6.55
Forests and shrublands	29.57	1.35
Riparian vegetation area	18.52	0.84
Gully area	149.48	6.80
Urban area, quarries, industrial site	18.76	0.85

The spatial statistical analysis shows that arable land and areas with post-crop vegetation are exactly those with higher erosion values than the others, with the latter in particular accounting for more than 61 percent. The results of these activities allowed to produce preliminary maps of susceptibility to soil degradation for arable land and areas with post-crop vegetation. The results of the mapping allow, in general terms, to identify large areas or clusters (Fig. 39) that need to be monitored both for further studies and for planning as they are precisely those areas that may be subject to land degradation. Areas currently under cultivation (arable land) which may be susceptible to land degradation are highly fragmented. Less than 95 per cent of the area falls into this band. These areas are susceptible because they have erosion values higher than the average of the most critical month (March 2020); variable but permanent erosion throughout the year of analysis. Finally, regarding the use of this information from a practical point of view, being arable land predominantly occupied by cereals, they are subject to different periods with bare soil and mechanized tillage types which would make these areas even more subject to soil degradation. As regards the areas with post-crop vegetation, elaborations of areas that could be susceptible to soil degradation were evaluated on the basis of the RUSLE values of November 2019.

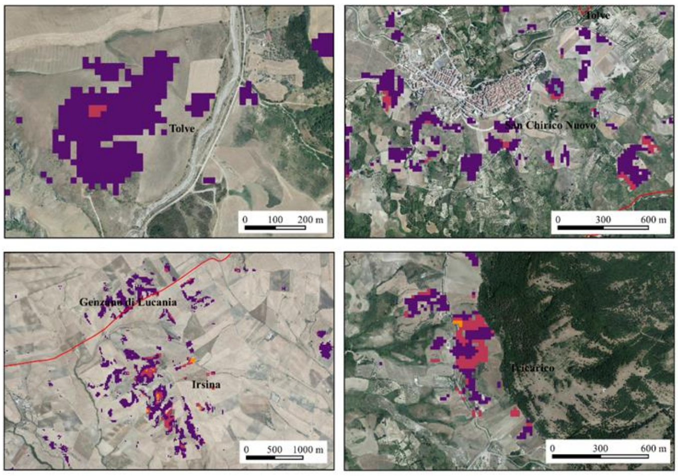


Figure 39. Four examples of mapping susceptibility to land degradation in as many different arable lands by territorial context. Orthophoto 2017 AGEA.

4.3.3 Identification of Abandoned Arable Land

The results showed widespread agricultural land abandonment in the study area (Fig. 40). However, such high classification accuracy requires multidata images, ideally one image for each spring, summer and fall and winter period for each individual year. However, some suboptimal combinations of image dates (data with fewer multi-seasonal image dates) can produce maps of farmland abandonment with high detail. In general, "abandoned arable land" was mapped more accurately than "abandoned managed grassland." We observed that the classifications for “abandoned arable land” were statistically significantly more accurate when Spring and Fall images. Having a spring image to accurately identify "abandoned arable land" was important for several reasons; in fact, the April months image distinguished between new vegetative growth of winter crops and senescent vegetation on fallow fields, and exposed soil after tillage for summer crops accounted for much of the total arable land area in 1990 and 2020. The summer image of July and August does not accurately distinguish arable land since at this stage of the year crops are advancing and mature and the land is worked by view. The autumn image captured the soil exposed after harvest and summer crops, and separated actively managed grasslands from abandoned farmland with abundant herbaceous vegetation. From the perspective of remote sensing, the change in reflectance that occurred when arable land is abandoned is very pronounced, making it easier to classify abandoned arable land than the more gradual transition of other land cover types from maintained to abandoned. To accurately monitor agricultural areas at the regional level with Landsat satellite images with 30m resolution, it is suggested to combine as many satellite images as possible with fall and spring images, especially when arable land is the dominant land cover. Usually, the abandonment of cultivated land a result in a succession of weeds or grasses and eventually in rinaturalization with the establishment of shrubs or trees. On the contrary, uncultivated land characterized by sparse herbaceous vegetation could be part of a crop rotation cycle (e.g., periods of alfalfa as a soil conservation tool), making it difficult to assess whether or not a land has truly been abandoned when only one season /year is taken into account [221,222].

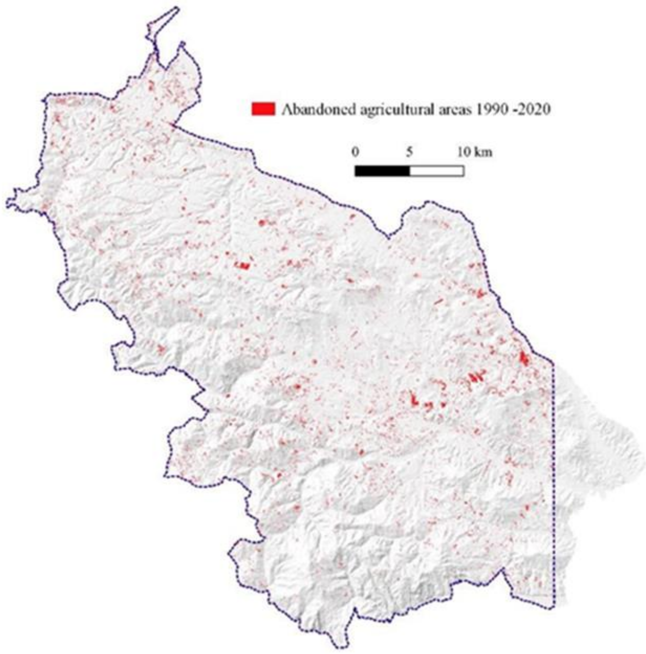


Figure 40. Mapping abandoned farmland between 1990 and 2020.

The investigation based on NDVI values calculated from 1990 to 2020 and the subsequent change detection analysis on the time series showed that from 1990 to the present, the areas that have never been cultivated with arable crops amount to about 595 km^2 while those that have undergone any land use change and/or abandonment amount to about 430 km^2 as shown in Figure 40 and in Table 17.

Table 17. Agricultural land use in km^2 resulting from the historical analysis of the NDVI series.

Arable Land (km^2)	Other Land Cover (km^2)	Agricultural transition – abandoned (km^2)
432.93	596.512	40.76

Areas reported as "Agricultural Transitions" indicate areas that have undergone agricultural abandonment or change from arable farming to another type of land use during the 30-year period 1990-2020.
The results obtained were subsequently cross-referenced with those obtained in previous analyses. The data obtained from overlaying the maps of transitional agricultural areas, divided into 3 decades, with those of the Nature Map made it possible to identify which agricultural areas have been subject to agricultural land use change and/or abandonment. It is more difficult to discriminate and evaluate abandonment from 2010 to the present, as these areas may be subject to vegetative rest and/or crop rotation, and thus need further evaluative analysis. Sources of possible errors in the procedure for classifying and identifying areas defined as agricultural transition areas and/or agricultural abandonment are due to errors in identifying spectral signatures of arable land in the dNDVI. Additional sources of error need to be considered, which could be due to classification errors reported in official land use maps, as they are out of date. To address these classification errors, each map was checked through photointerpretation and photo correction using orthophotos. The areas considered "agricultural transition" intersecting the non-agricultural and non-forest classes of the Nature Map amount to about 185 km^2. These areas were divided into decades, and for each individual decade the average value of soil erosion as of 2019-2020 was calculated, using the soil erosion map obtained by applying the RUSLE model from previous analyses. From 1990 to 2020, continuously

cultivated areas amount to about 400 km^2, these areas were intersected and compared with the agricultural classes of the Nature Map, and then with the average value of eroded soil for each individual class (Table 18).

Figure 41. Example of abandoned agricultural area where the difference between abandoned agricultural area and agricultural area with cereal crops are clear.

Overall, the average value of RUSLE in agricultural areas is about 19 (Mg-ha $^{-1}$ -year $^{-1}$), if we consider the erosion values only for the classes of arable land, we arrive at about 17 (Mg-ha $^{-1}$ - year $^{-1}$) and about 33 (Mg-ha $^{-1}$ -year $^{-1)}$ for extensive crops and complex agricultural systems. In conclusion, it is possible to deduce from the analyses carried out that the soils cultivated for arable land in the period considered show values of soil lost lower than those of the abandoned soils in the three decades analysed. This first analysis shows that the lands abandoned in the first decade have lower values of lost soil than in the following decades, this is because these areas have probably rinaturalized and stabilized over time. It is more difficult to discriminate and evaluate the abandonment from 2010 to today, as these areas may be subject to vegetative rest and/or crop rotation, and therefore require further evaluation analyses. It was possible to map the arable land, highlighting areas where the protective contribution of vegetation on the soil does not limit erosion by indicating that area as a likely area of degradation.

Table 18. Average values of eroded soil in 2019-2020 in relation to the decade of probable abandonment.

DECADES non-agricultural and non-forested classes.	**Average RUSLE (2019/2020) (Mg· ha –1 · year –1)**
1 Decade (1990/2000)	22
2 Decade (2000/2010)	37
3 Decade (2010/2020)	31

The areas analysed in March 2020 represent the areas where erosion is strongly correlated with factor C. In order to be able to define with good probability that these are throughout the year, it is necessary to supplement the data with the Getis Map of the entire area study area obtained through spatial autocorrelation, covering the areas under permanent erosion permanent from October 2019 to September 2020. The intersection gives as final result a map of soil degradation related to arable land that not only shows values of RUSLE high during the growing season, but maintain it throughout the year. The usability of this methodology, in addition to scientific assessments, can be useful for monitoring and planning activities at different administrative levels (Fig 42).

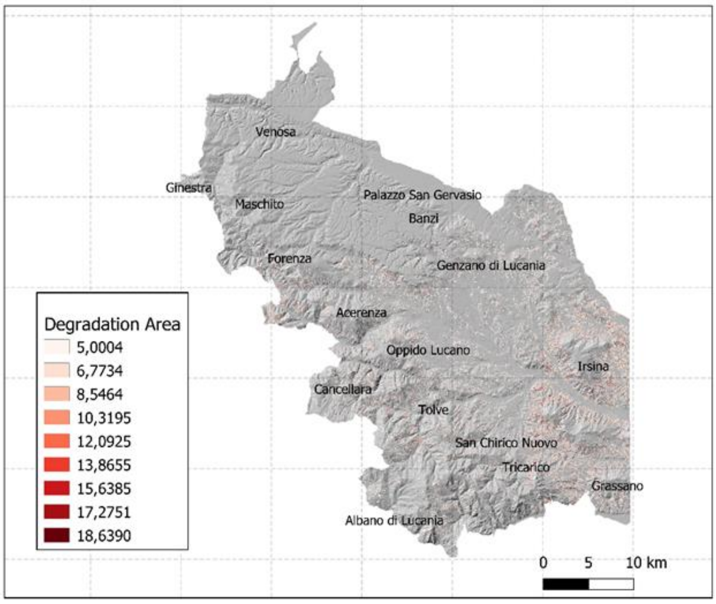


Figure 42. Map of degradation areas.

Table 19 summarizes the result obtained from the creation of a map for the identification of arable land areas strongly correlated to the vegetation factor C. The municipalities falling within the study area are shown in the first column. The second column shows the surface in hectares of degraded arable land for each municipality. In the third column the total area dedicated to arable land was reported, and in the following column the average value of erosion of the degraded areas was calculated for each municipality, and finally compared, the area calculated with the methodology and the arable area with respect to each municipality. Tolve is the area with the most hectares in degradation with an average A of 7.36 [Mg-ha -1 -year -1], and a percentage of the total area of around 0.97%. Another fact that is interesting to highlight is the area of San Chirico Nuovo which has the highest percentage of degraded area of 1.48% compared to the arable land area with an average erosion of 7.65 [Mg-ha -1 -year -1]. The data referring to the municipalities of Irsina and Grassano is partial because the study area does not include the entire municipal territory.

Table 19. Extension of the areas subject to degradation cultivated with arable land in degradation with respect to the factor C.

Municipality	Degradation of arable land (ha)	Arable lands area (ha)	RUSLE (A) Average	Degradation Area/Arable land (%)
Tolve	70.32	7255.93	7.37	0.97
Genzano di Lucania	63.48	17918.36	6.95	0.35
Tricarico	36.20	8520.47	9.07	0.42
Irsina	19.48	14953.28	8.58	0.13
Forenza	14.72	6461.10	7.33	0.23
Acerenza	13.00	4497.24	6.87	0.29
San Chirico Nuovo	12.52	841.49	7.65	1.49
Venosa	6.44	11430.61	5.79	0.05
Banzi	3.08	6786.59	6.46	0.05
Oppido Lucano	2.68	3909.05	6.71	0.07
Ginestra	2.24	536.66	5.94	0.42
Cancellara	2.12	2205.97	7.61	0.10
Palazzo San Gervasio	1.68	4584.13	6.93	0.04
Albano di Lucania	0.76	1445.75	7.74	0.05

Maschito	0.48	3569.22	5.57	0.01
Grassano	0	1231.17	0	0

Figure 43 and 44 shows detailed examples over four different areas. Pixels overlapping the orthophoto identify the clusters where soil degradation is most likely to occur. There may be a variety of causes for this phenomenon, one of which could be, for example, intensive exploitation (excessive mechanization and use of chemicals), resulting in loss of organic content that leads to deterioration of soil structure and thus facilitating the initiation of erosion.

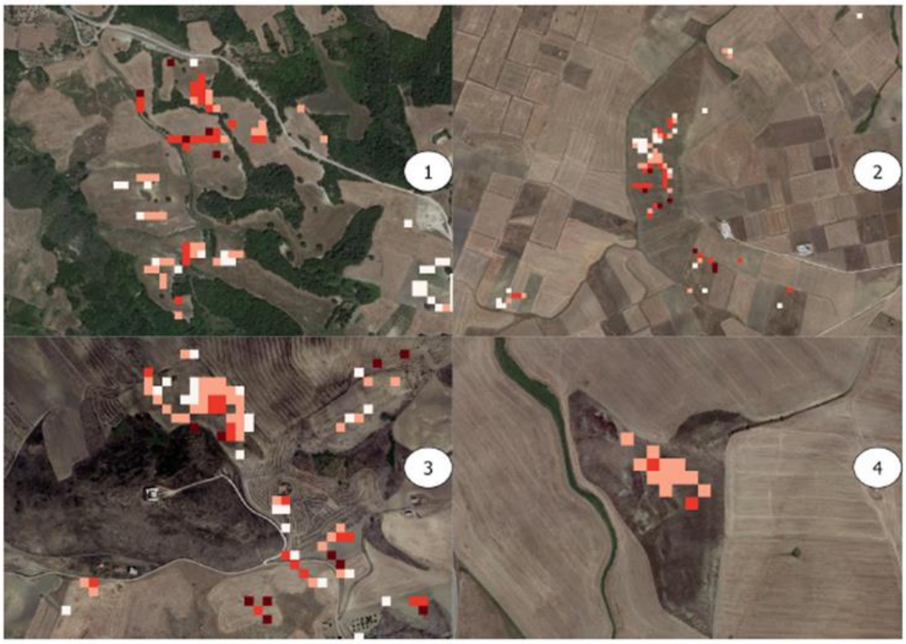


Figure 43. Detailed examples of areas subject to land degradation on arable land in four different areas. arable land 1 and 2 are located in the municipality of Tolve - 3 (Genzano di Lucania), 4 - Municipality of Irsina.

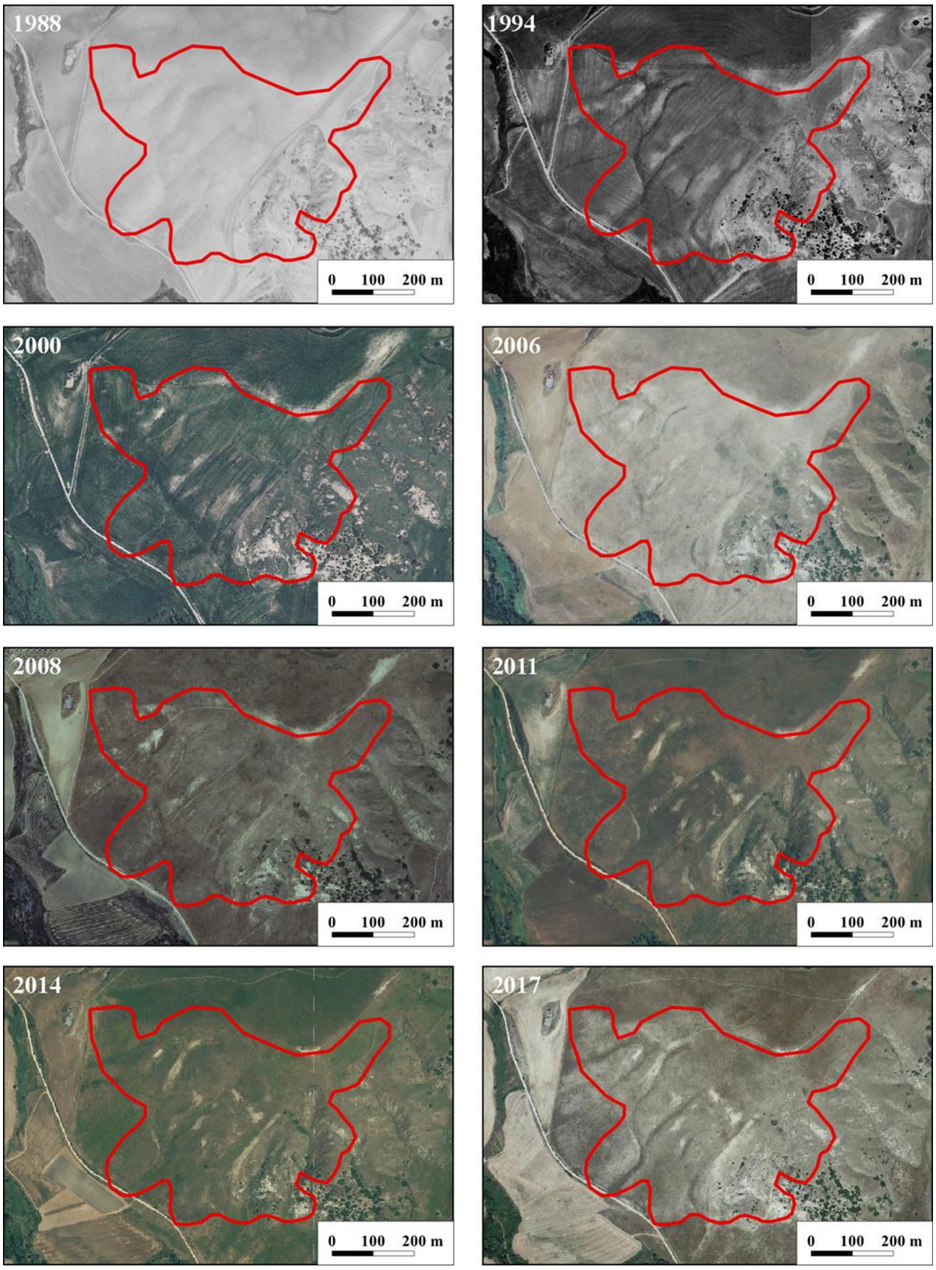


Figure 44. Outline of the identified cluster with respect to orthophotos of different years (1988 - 1994 - 2000 - 2006 - 2008 - 2011 - 2014 - 2017).

4.4 Agricultural sector in Basilicata

Rural areas in Basilicata have been subject to depopulation processes caused by progressive urbanization since the post-World War II period. This, as we saw in Chapter 2, is caused by the concentration of resources and services in urban areas. Consequences of this phenomenon include rural and agricultural marginality, which is reflected in the process of agricultural land abandonment with the occurrence of degradation phenomena such as erosion. Agricultural marginality is considered to be a process, induced by a combination of social, economic, political and environmental factors, due to which, in specific areas, agricultural activity stopped being economically profitable, given the present land use pattern and socio-economic structure.

Agricultural marginalization is, moreover, to be listed among the many causes of land use changes. As seen above, these can lead to major and often irreversible changes at the landscape level; therefore, there is a need for careful analysis and specific land-use monitoring in order to support future policy decisions and verify the effects of past actions. These two aspects of the problem led the European Commission to propose marginality as one of the indicators for integrating environmental concerns into the CAP (COM 2000/20) and to define the basis for its calculation and procedures for its use (COM 2001/144). The concentration of population at lower altitudes and in larger centres, followed by the displacement of productive activities, has greatly reduced anthropogenic pressure (e.g., agriculture-related productive activities) in inland areas. However, this has also aggravated the processes of agricultural marginalization in these areas, which have suffered processes of agricultural abandonment and spontaneous post-crop vegetation. At the same time, where anthropogenic pressure has increased significantly, processes of agricultural intensification and expansion of urbanized areas have increased, with significant ecological and sustainability implications[223]
Basilicata from the nineteenth century to the early decades of the twentieth century was subject to massive deforestation linked mainly to population growth, but also to the deep social transformations of the last century. The transformation of the feudal system into a new landowner class led to a gradual reconversion of land for agricultural use. After this period of intense degradation, a law was signed in 1923 to stop the destruction of forests and promote land regeneration measures. At the same time, the "Battle of the Grain" led to further expansion of cultivated areas and a reduction in the impact of the measures promoted for land conversion.

Agricultural activity, while representing the main industry at the regional level, was still a system of subsistence after World War II, featuring low investment, difficult access to credit and an ownership structure still linked to large landholdings. From an employment point of view, it was also a traditional system, centred on the direct activity of the owner and the labour force of his family. From a production point of view, there was a prevalence of cereal crops, in stark contrast to the morphological and climatic characteristics of a predominantly mountainous region. Specialization in cereal cultivation did not yield the economic results expected, not only because of the morphological and climatic conditions. However, the low level of productivity was not only due to the geomorphological characteristics of the region, but also to the way agricultural activities were carried out. In particular, the subsistence agricultural economy that marked Basilicata at least until the mid-1960s did not provide the availability of investment capital in equipment, fertilizer, appropriate for increasing cereal productivity. The low level of regional development, linked to conditions of geographic marginality, weakness of infrastructure provision, a quite low level of human capital (aggravated by substantial migration) and the region's marked and persistent isolation, were not the only regional territorial and economic disadvantages. In fact, a central factor for the low potential for competitiveness can be attributed to the land ownership system. The low competitiveness of small family farms, followed by the persistence of a low standard of living of the farming classes, has also been an element in amplifying the depopulation processes of inland and marginal areas. In fact, the agricultural activity, although family-based, of inland areas still represented a form of land protection, through water regulation activities and landscaping works. The gradual abandonment of these areas, aggravated after the second half of the 1960s by the occupational prospects of early industrial activities, set the stage for a renovated emergency in land management in depopulation areas. A marked increase in forested areas occurred in the 1980s as a result of regional incentives to reforest erosion-sensitive areas. Parallel to the reforestation process, which affected many public areas, deforestation continued to affect private properties to allow for an increase in areas for agriculture. This was a direct consequence of the measures promoted by the EU to support the agricultural sector, which led to a continuous increase in areas devoted to arable land. In the following decades there was a trend that saw a strong contraction of the Utilized Agricultural Area (UAA) and the number of farms. The development policies financed by the Cassa del Mezzogiorno had significant consequences for the agricultural sector as well; in fact, many planned interventions consisted of the development of water basins, substantial land drainage works and road infrastructure with which the region was poorly equipped. Spatial policies financed by the Cassa del Mezzogiorno thus assumed a fundamental role in redrawing the region's agricultural geography, because while it is true that hydrological and territorial works were carried out, it is also true that massive land reclamation works affected territories closer to the flat areas, such as the Metapontino and lower Materano or the Vulture areas. Certainly, the works carried out had an important social role, as they improved the living conditions of agricultural populations, although on the one side they contributed to increasing the advantages of some already more developed and dynamic areas. Already in the 1972 documents it is possible to find the outlines of the new regional agricultural geography, characterized by the abandonment of areas with more remote but less productive agricultural traditions. In addition to national programming, European programming actions have also been playing a key role, such as the CAP, which belongs to the Community's exclusive sphere of competence and was aimed at increasing the productivity of agriculture by developing technical progress, providing for the efficient development of agricultural production and better use of production factors (especially manpower), guaranteeing a reasonable standard of living for the agricultural population by improving the individual income of those working in agriculture; stabilizing markets and making security of supply; and providing just prices in deliveries to consumers. The CAP is one of the most important policies of the European Union (agricultural spending accounts for about 45 percent of the EU budget). It initially allowed the Community to quickly achieve self-sufficiency, but over time its operation became increasingly expensive due to overproduction and the excessive level of European prices compared to world market prices. The 1992 Mac Sharry reform corrected the situation through the reduction of guaranteed agricultural prices offset by compensatory payments linked to inputs and the establishment of so-called "accompanying" measures. The 1999 reform, based on Agenda 2000, consolidates the changes made in 1992 and identifies food security, environmental protection and the promotion of sustainable agriculture as priority objectives. Non-market policy objectives have been brought together in rural development, which has become the second pillar of the CAP. In addition, the reform aims to increase the competitiveness of EU agricultural products, the simplification of agricultural legislation and its implementation, the strengthening of the Union's position in World Trade Organization (WTO) negotiations, and the stabilization of spending. To this end, a reduction in intervention prices offset by an increase in aid to farmers was decided. The latest reform in June 2003, also known as the Fischler reform, includes several changes, such as simplification of market support measures and direct aid by decoupling direct payments to farmers from production; strengthening rural development by transferring funds from the first pillar of the CAP to rural development through modulation; and a financial discipline mechanism (limitation of market support expenditure and direct aid between 2007 and 2013). Community actions include set-aside, which is the laying fallow (fallow) of agricultural land, generally for the purpose of reducing the production of a particular crop. In Europe, set aside has been adopted under the CAP since 1988 (EEC Reg. No. 1094/88), with the aim of reducing cereal supply in a period of structural surplus. With the MacSharry reform (Reg. 1765/92), a compulsory set-aside quota was provided coupled with the possibility for farmers to voluntarily leave a portion of their farmland above the compulsory set-aside quota in exchange for aid. Subsequently, set-aside underwent numerous variations, which in fact strengthened its agri-environmental role: with the Fischler reform (EC Reg. 1782/2003), for example, cross-compliance requirements were also applied to set-aside land. Set-aside was finally abolished in 2008 as part of the CAP reform known as "Health Check." The results produced by the analyses described in the previous chapters described the innovative methodological approach to identifying and monitoring abandoned agricultural soils and the level of degradation due to soil erosion. As described above, actions dictated by community and regional policies, including in agriculture, can affect the process of agricultural abandonment and the resulting erosion. Based on these considerations, it is interesting to compare these data with the information collected by ISTAT in the general agricultural censuses over the 30-year period studied. The general census of agriculture represents a snapshot of the agricultural sector in Italy; the information obtained concerns the number of farms, the title of land ownership and its use, the size of herds, the labour force employed and the activities carried out in parallel with agricultural production activity. Comparison with previous censuses confirms the ongoing process of contraction in the agricultural sector. Since 1982, more sustained contractions are observed in the number of farms than in UAA (Utilized Agricultural Area) and SAT (Total Agricultural Area). In Italy, farms decline by 30.1 percent, SUA by 2.5 percent and SAT by 3.6 percent (the decline in UAA is in line with that observed in the previous 2010 decade) (Tab..20).

Table 20. Farms, UAA and SAT in the last 5 agricultural censuses.

YEAR	FARMS	SAU (he)	SAT (he)
1982	3133118	15833	16474
1990	2848136	15026	17081
2000	2393161	13181	18767
2010	1615590	12856	21628
2020	1133023	12535	22398

ISTAT data on agricultural censuses show a decreasing trend in the number of mainly arable crop farms until 2010, after which a slight increase in the number of farms was recorded at the regional level; the trend is also confirmed by the analysis of the data of the Chamber of Commerce of Basilicata (Fig.45-46).
In summary, the signals that emerge from the provisional data from the comparison of the data of the general censuses of agriculture, which Istat has made available, represent the picture of an agriculture in which important processes of change are underway.

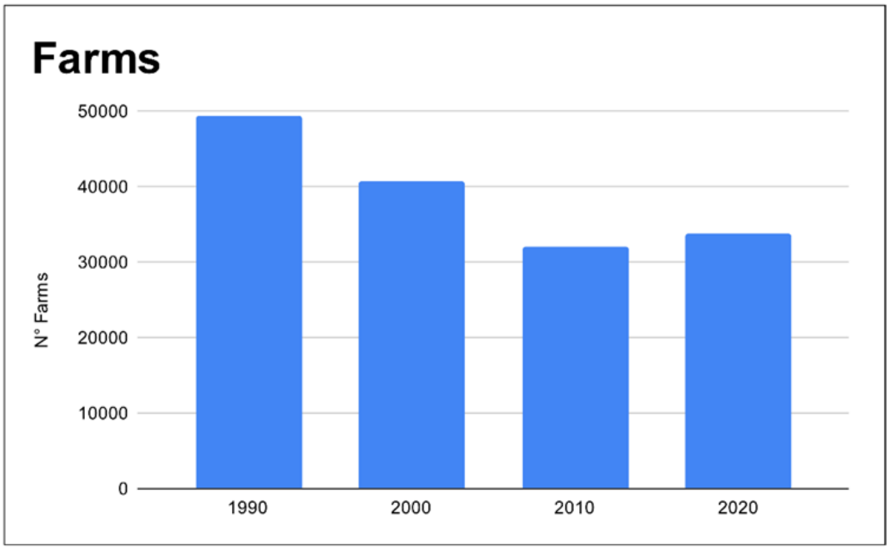


Figure 45. Number of farms in Basilicata from 1990 to 2020. (Source: Istat Agricultural Censuses).

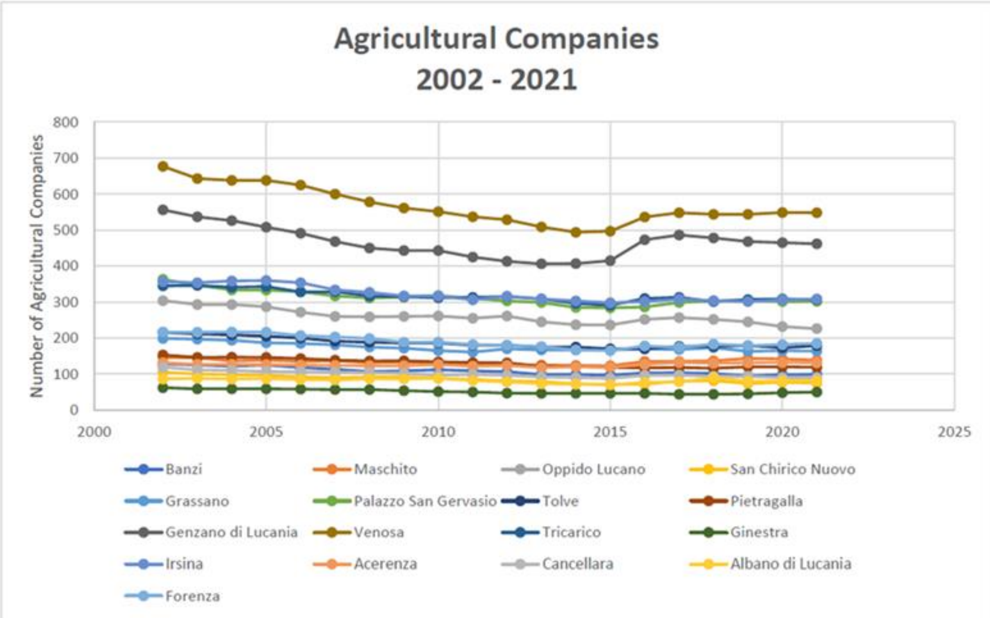


Figure 46. Number of farms present in the municipalities of the study area from 2002 to 2021. (Data source: Chamber of Commerce of Basilicata).

If the data from previous censuses suggested a process of defragmentation of the Italian and regional agricultural reality, with a decrease in the number of farms specializing in cereal crops and UAA, starting in 2010 a reversal of the trend begins to emerge, as we have seen in the number of farms. In fact, comparing the data from the last two agricultural censuses (Fig.47) we see that indeed the UAA is decreasing, while the number of hectares devoted to arable crops is increasing. This is probably due to all the forms of incentives of agricultural support actions promoted by the FEARS Community Funds.

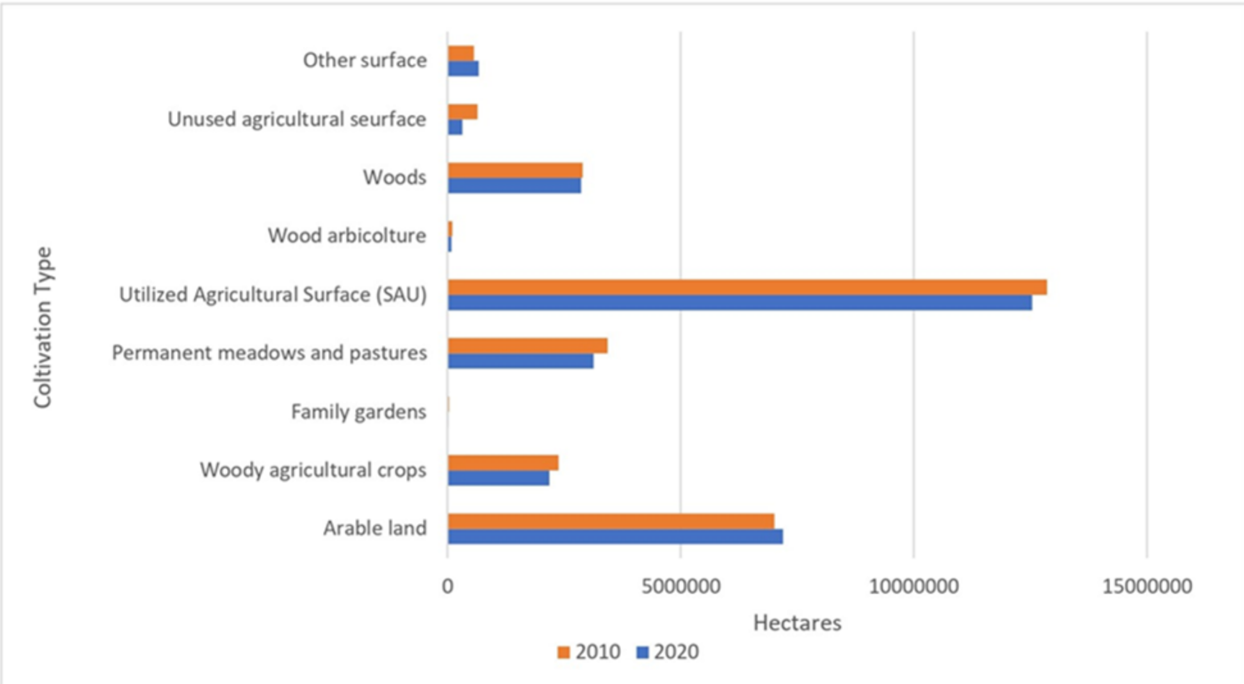


Figure 47. Comparison of agricultural census data (2010 - 2020).

Furthermore, land abandonment due to emigration has a strong social impact, because it leads to further isolation of the communities living in these marginal areas. In chapter two the theme of depopulation and marginalization of the regional territory was addressed. The results demonstrated a negative population trend in the period 1981 - 2021. Analysing the population data in the municipalities studied in this chapter, a similar result emerges (Fig.48).

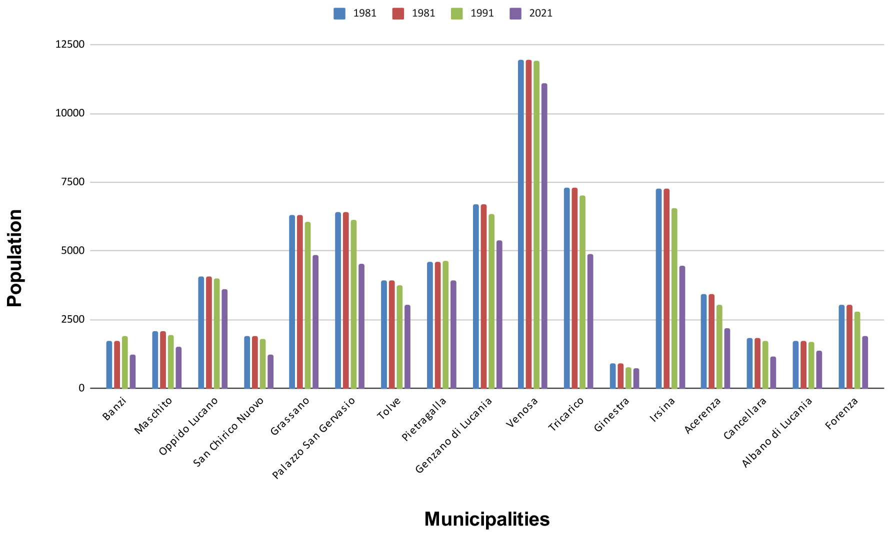


Figure 48. Evolution of the population in the 17 municipalities analysed. The graph shows a trend similar to other regional contexts characterized by depopulation.

Over the course of history, regional agriculture has often experienced phases of expansion and contraction in terms of area. These phases resulted from the demographic changes that occurred over time, causing a higher percentage of the population employed in agriculture and a relative rigidity of agricultural yields, thus having a direct proportionality relationship: an increase in population corresponds to an increase in cultivated area. The most important factors of land abandonment are economic, demographic and sociocultural [224,225], while environmental, political and institutional factors play a minor role. Moreover, results have shown that land abandonment is driven by the complex interrelationship of these drivers of change [226].

4.5 Conclusions

The abandonment of agricultural land is one of the most important manifestations of changes in the use of cultivated land. However, knowledge about the spatial distribution of abandoned land in the studied area is limited. This thesis work has produced the first maps describing the distribution of abandoned farmland and an initial analysis of the susceptibility of these areas to degradation and erosion. Therefore, this study provides a first insight into the state of farmland abandonment in the analysed municipalities. Our analysis showed that abandoned agriculture can be mapped by Landsat satellite images. The analyses applied in this work made it possible to assess the existing relationships between changes in agricultural land use and degradation processes, since erosion processes occur more in areas that have undergone changes in land use and/or abandonment, while in permanent agricultural areas the impact of the erosion process is less. With the methodologies applied in this study, it was possible to create different data sets, both tabular and in the form of maps, for an assessment of the land degradation process related to land use and land cover dynamics. The transitional phase of these areas towards low-density urbanisation has a marginal influence on the degradation process compared to the phenomena of agricultural abandonment and/or transition (transition from one type of arable land cultivation to another). The implementation of the NDVI time series for arable land from 1990 to 2020 and the subsequent evaluation of the differences (ΔNDVI) made it possible to identify and map the areas that have undergone a process of agricultural abandonment during this time period as they have several consecutive years with no cereal crops. The total number of abandoned hectares is approximately 4033, distributed mainly in patches of the same size as the single pixel (0.09 ha), showing that the analyses must be supplemented with subsequent spatial analyses to better determine abandonment. Through random validation by photo-interpretation with orthophotos (1990 and 2020), the overall accuracy of the identified areas was verified. The procedure shows that time series and change detection are the benchmark for this type of investigation and that NDVI is certainly sensitive but must be supplemented with other spectral indices. One problem is due to the temporal resolution of the Landsat missions, which have a return time over the same area of 16 days, and this leads to gaps in the time series when cloud cover is high. In the future, the use of Sentinel-2, even if it allows time series from 2015, will be essential because the return time is reduced to 5 days. Hence, land abandonment may be determined by the interaction of global causes such as migration, socioeconomic patterns and public policies, while local causes may determine the specific areas where abandonment occurs. Abandonment of agricultural land presents a policy challenge, as its management is debated because of interests related to the loss of agricultural landscapes and, most importantly, potential impacts on biodiversity, ecosystem services, and increased soil degradation. Land abandonment may be determined by the interaction of global causes such as migration, socio-economic patterns and public policies, while local causes may determine the specific areas where abandonment occurs. The process of abandonment poses a political challenge, as its management is debated due to interests related to impacts on biodiversity and ecosystem services, the presence of phenomena and forms of degradation such as erosion. However, most policies have addressed abandonment as an agricultural problem, rather than as a dynamic process driven by a variety of factors, including socio-economic, cultural and environmental trends, policy-related factors and spatio-temporal processes. As we have seen, most of the policy efforts applied to land abandonment have been through the Common Agricultural Policy (CAP) and its support for agricultural development. Among the impacts of the CAP Biodiversity loss and soil erosion have been called into question with policy recommendations focusing on the expansion of direct CAP payments to farmers for environmental services. The CAP has thus been conceptualised as a single-project action focused on agriculture, ignoring the social, cultural, political and economic factors that lead to land abandonment and rural degradation. In order to preserve rural areas from degradation and abandonment, it is necessary to consider that current policy responses to land abandonment must move away from the agricultural-oriented programmes of the CAP and incorporate a series of independent rural development programmes orienting the rural environment towards multifunctionality. A particular example of initiatives aimed at promoting multifunctional rural landscapes is the Farm to Fork strategy, which aims to decrease the environmental footprint of food systems, ensure food security and create a circular economy [227]in which food systems to address climate change and land degradation to environmental degradation are considered a key aspect to be taken into account. Reutilising and reusing abandoned agricultural land is one way to achieve multifunctionality in rural areas. Since agricultural abandonment varies depending on the socio-cultural context, a better understanding of the determinants, impacts and trade-offs of the activation processes is essential [228]. The Italian agroforestry territory, with its phases of expansion and reduction of forests, abandoned areas, and areas at hydrogeological risk, has undergone many changes over time. The past scenarios of the territory and the transformations that have occurred on it, if not evaluated, may not allow a correct criticism and evaluation of the current dynamics. The erosive impact of abandoned and uncultivated land raises important questions about the implementation of soil conservation programmes. It is difficult to collaborate with those involved in soil conservation and land degradation prevention efforts and to involve farmers whose animals graze on unused land. Therefore, as many landowners choose to move to urban areas and seek more comfortable lifestyles or abandon land due to declining productivity, erosion accelerates by increasing topsoil losses. The abandonment of agriculture in some cases has had negative consequences, especially in economic and social terms, as marginal areas are increasingly isolated and far from services and increasingly victims of depopulation. Sustainable rural land use and management through integrated planning could mitigate this ongoing process and above all avoid negative impacts. In order for planning to be functional, it is necessary to implement replicable and updatable techniques and methodologies to quantify and analyse the abandonment of agricultural activities at the highest level of detail. Abandonment of agricultural land, therefore, is one of the most important manifestations of change in the use of cultivated land, and is a complex process that requires a multidisciplinary approach to study its causes and consequences. Agricultural land is generally abandoned due to a combination of economic aspects and natural factors that cause the area to be set aside for long periods of time. As introduced in Chapter 1, the terms 'land use' and 'land cover' are used extensively in the literature and the lack of a universal definition causes confusion. Land Use is defined as the use by man of a specific area of land, i.e., its socio-economic function. Land Cover, on the other hand, is the observed biophysical coverage of the earth's surface, the type of surface layer of a specific area of land, including vegetation, bare soil and artificial surfaces observable in the field and recorded by orthophotos.

Thesis Conclusions

In order to achieve some of the Sustainable Development Goals of the 2030 Agenda, the role of environmental planning is crucial in addressing spatial problems, such as agricultural land abandonment and land consumption, which cause negative impacts on biodiversity. At the end of 2021, the European Commission approved the new EU Soil Strategy 2030 to reiterate how soil health is essential for achieving the climate and biodiversity targets of the European Green Deal [229–231]. This strategy sets out a framework and concrete measures to protect and restore soils and ensure their sustainable use. The Commission is also committed to passing a new soil health law by 2023 to ensure a level playing field and a high level of environmental and health protection. Sustainable land use planning aims to integrate ecological principles with socio-economic principles for a comprehensive vision of sustainable land management for present and future generations. To implement land-use planning strategies, it is essential to collect, process and distribute timely and accurate data and apply advanced land assessment technologies to create scientific knowledge useful for appropriate decision support systems. It is essential to implement tools that provide an overview of the land, meeting the needs of public decision makers to verify past management policies and develop new strategies. The approach illustrated in this thesis work allows the extrapolation of land cover and land use information from remotely sensed data and rapid analysis, could be the basic approach for the development of future studies.

Data on land use and land cover are key resources to be able to conduct analyses of environmental impacts, define indices of well-being, assess human impacts, and monitor habitats and ecosystem services. Updating data on land characterization and the spatial distribution of changes in land use and land cover that are taking place is essential for proper and sustainable management of the soil resource, as it helps to better investigate the link between the physical environment and the socioeconomic aspects acting in that environment.

In fact, LULCC data are fundamental in environmental studies, decision making, land use planning and design, and natural resource management policies because they can be used as input data for applying models and techniques to monitor and assess land changes such as land take, land degradation, agricultural land abandonment, and urban expansion.

Assessing land use dynamics is a fundamental step in understanding land use and land cover change. The study of LULCC dynamics can suggest an alternative technical strategy to make land more liveable, with particular reference to natural resource management. Without proper land resource management and policy intervention, land use patterns will act against the healthiness of the environment of urban and rural areas. The identification and allocation of land resources based on land use patterns is essential to this assessment. The application of geospatial tools such as remote sensing techniques and Geographic Information System tools contribute to multi-temporal satellite data processing and analysis of LULC changes in urban and rural areas. Land use and land cover are two interrelated fields in the analysis of phenomena and processes that characterise the evolution of the territory. These transformations have substantial consequences on human beings' welfare and on the state of the environment at a global, regional and local level. It is therefore necessary to develop monitoring support tools that can support the definition and implementation of adequate government and sustainable land management policies in an organic form. In this context, although some dynamics, such as land take, are well known, the availability of an integrated monitoring and assessment system of the state and evolutionary dynamics of land cover and its use has historically been limited in our country. On the other hand, the increasing need for information with a high spatial, temporal and thematic resolution, which is indispensable for the description of complex contemporary spatial dynamics, has led to the creation of numerous independent products at global, European, national and local level, characterised by different levels of spatial and temporal detail and based on different relationships between land use and land cover. Furthermore, when we talk about land use and land cover change, it is important to underline the difference between land consumption and land take. Land take has a different meaning than land take because it refers to all land cover transformation processes such as urban sprawl and land use for agricultural purposes. In this thesis work two aspects of land use and land cover change have been analysed: the sealing processes with the phenomenon of land take and agricultural abandonment and its impacts on land degradation in the form of erosion. Land use planning is the systematic evaluation of territorial land changes, land use scenarios and economic and social conditions of a territory in order to select and adopt the best land use options. The structure and dynamics of the population, and in general the socio-economic, political and legislative aspects are important drivers in the field of sustainable soil management. Comparison of socio-economic analyses with land use and land cover change can highlight the need to modify existing policies or implement new ones. In chapter two the socio-economic aspects of the Basilicata region were investigated, considered as drivers in land use changes. The joint assessment of socio-economic and environmental trends is increasingly required to provide an integrated and comprehensive analysis of territorial dynamics [85]. Providing an objective way to identify the drivers of socioeconomic disparities based on their potential for change and in relation to land use is relevant to regional science. The descriptive analyses in Chapter 2 illustrated the complex relationship between the multiple dimensions of a local and regional system that potentially informs policies aimed at inverting spatial inequality. This study confirms how the classical model based on a monotonic descending density function from the metropolitan centre seems to have been replaced by other models based on polycentric structures. Among the implications of this study, the application of other methodologies such as parametric and non-parametric models could be used to better study sub-centres [232]. The proposed assessment tool is a first step in identifying and evaluating the spatial drivers that influence territorial divisions in several socio economic and environmental dimensions [233]. The methodology can be complemented with qualitative analyses and the use of local-scale indicators to more accurately identify regional differences resulting from spatial divisions by merging sustainable development issues with a traditional regional science perspective focused on spatial divisions and heterogeneity.[61,97,234] Spatial indicators comparable over long period are essential tool for these studies. Historically, Basilicata lacks a consolidated urban network in terms of relations on a regional scale, the only lines of force that can be found in recent times were those oriented by the two provincial capitals, with a quite limited territorial scope, which lapped at most the areas immediately adjacent, and those in any case better interconnected with the main road axes. The isolation and mountainous features of the territory represent those basic factors on which historical evolution has failed to hinge forms of development suitable for producing an adequate urban framework and more generally services. These problems still represent elements characterizing the evolution of the regional system, which has experienced the growth of the tertiary sector in a small number of smaller towns, suitable for being able to communicate functionally with the two provincial capitals linked to changes in land use or infrastructure cannot be answered with universal validity. With a view to intensifying territorial relations on a regional scale, it is necessary to keep in mind the productive and economic specializations which the different territories have assumed to date. Specifically, we observe a strengthening of relations between the regional capital and Melfi, following the location of the FIAT factory. On the other hand, we observe the evolution of the Metaponto plain which seems to have by now defined its economic identity in the agro-industry, in tourist and cultural services. Another matter must be referred to Matera which seems to have further strengthened its extra-regional ties, seriously discussing the need for a greater strengthening of the bond between the two capitals, above all in the context of the development of strategic enhancement strategies deriving also from the plans Europeans.[136,235,236] The development of innovative solutions and applications for the management of urban services is constantly growing, driven by technological progress (sectors such as IoT, Big Data, cloud-based services, etc.). The advantages in terms of service optimization, the efficiency in the use of resources and social inclusion are tangible. However, a problem that can not being underestimated concerns the not always availability of data that allows the integration and updating of the datasets built in order to enable the approach and the study of the economic dynamics of the centres in order to be able to relate them to the dynamics of transformation of the territory. This work has allowed a new vision of investigation of the urban and extra-urban framework as a system of heterogeneous service provider provided without adequate infrastructural support to guarantee its use [232,237,238]. Studies on city management show that increased use of urban services by citizens has great benefits for local governments, especially in economic terms. Greater use leads to economies of scale for many urban services[239] . Municipalities also benefit from economies of scope in providing local public services sharing fixed administrative costs, the benefits of introducing and sharing services, improving the networked and multimodal transport network, supported by an institutional resource plan and marketing actions are observed [95]. The current debate on urban sustainability often adopts a long-term relational perspective, based on the social, environmental and economic sustainability of urban management [240,241].In order to achieve both efficiency and sustainability, local authorities need programmes that enable the combination and sharing of services between different municipalities that can create closer relationships with citizens, oriented towards a more sustainable land and soil management.[95,242,243]

The first part of the chapter 3 concerned an overview of land take at a regional level, underlining the distinction between land take and land consumption. Land take refers only to artificial soil sealing processes[244].Land take is irreversible, while soil consumption, based on the intensity of its transformation, could be reversible in the medium to long term. The aim of the chapter was to create an expeditious monitoring methodology for the identification and classification of the consumed soil. The first part was characterized by the implementation of an experimental methodology for the classification and historical analysis of the phenomenon based mainly on Landsat satellite data (analysis of the historical land take trend). It has been observed that the increase in urbanized areas is not accompanied by adequate population growth. The second part of chapter 2 research aims to develop a methodology capable of providing detailed maps of land take due to the installation of renewable energy sources using data from Sentinel 2 and Landsat. Renewable energy sources (above all wind farms) imply an intensive use of the land and the relationship with land consumption and the spatial dimension of the plants is a fundamental aspect to take into consideration. From 2010 to 2018, land consumption due to the presence of wind sources increased and the trend is continuously growing. The environmental effects of the land take are consequent to the conversion of agricultural land into built-up areas and the resulting impacts include the loss of the ecological functionality of the soil, the loss of ecosystem services and the phenomenon of soil degradation [54,170]. Land take that is not monitored and legislated has not only environmental impacts but also social costs. The social costs related to longer travel times to reach essential services, dependence on the use of own cars due to the absence of public transport, social marginalization. The construction of small centres distant from each other and from the main centres, to remedy the marginalization phenomena typical of inland areas, require the creation of new services, new road infrastructures accompanied by an adequate increase in population [94,245]. The particular geomorphological conditions of Basilicata and those of its economic system which even today, despite attempts at industrialization and weak tertiarization, remain strongly characterized by agricultural activity, have profoundly characterized the demographic evolution of the region. The two provincial capitals can be identified as rural. In fact, on the basis of the population density criterion adopted by the National Strategic Plan, Matera with a population density of less than 150 inhab/km^2 is identified as rural. The same goes for Potenza, which despite having a population density of more than 150 inhab/km^2 is defined as rural on the basis of the predominance of agricultural use of the provincial area: about 70% used for agricultural and forestry use [246].

The centrality of the role of the agricultural sector in Basilicata is certainly the main source of reflections on soil degradation (Chapter 4). In the previous paragraphs we have analysed the transformation of the territory deriving from European policies (CAP), highlighting the link between soil degradation, depopulation phenomena and policies. The approach followed in this contribution, in addition to creating a monitoring system of abandoned areas that can be replicated in other territorial contexts, tried to compare the transformations due to abandonment and to assess overall the negative impacts mainly due to erosion of policies that have acted on the land, exploring some relationships between land abandonment, the agricultural vocation of the land and public policies. In particular, it is noted that the provision of public funds from various community and national policy actions has not helped to combat land abandonment. In order to counter land take and agricultural abandonment, the creation of a multilevel governance system would be fundamental in which policies are no longer sectorised but multifunctional to sustainable development. In the rural sphere, the new CAP, with the important innovations in terms of greening, measures against land degradation can therefore be an opportunity for one new governance of the territory and the landscape [167]. Most of the works based on the evaluation of land take are related to the problem of the use of spatial data, which can be inhomogeneous and not replicable over time. This is because the data considered are often raster or vector cartography of different origins, scales, reference systems, etc. These are cartographies that often do not cover the entire study area and have different nominal scale values. Furthermore, replicating the study, also for the sake of monitoring the phenomenon, becomes problematic given that the data used are not available over time and in the same ways. For all these weaknesses, for the technological progress that has taken place in the field of Remote Sensing data management, for the free use of data and for an innovative study on soil consumption, in this research project the information base is determined by satellite data. This guarantees to be able to monitor the phenomenon and to replicate the studies over time and in different territorial contexts. Sustainable urbanization is a key driver of the 2030 Agenda for Sustainable Development. Achieving SDG 11 and its targets will require political will and commitment, innovative and integrated planning and design, and collaboration among all stakeholders at all levels. Achieving sustainable urbanization requires addressing the social, economic, and environmental dimensions of development, with the goal of ensuring that cities and human settlements are inclusive, safe, resilient, and sustainable.

In conclusion, this thesis provides a concrete example of the contribution of Earth Observation and innovative geospatially derived data in support of the Sustainable Development Goals. The SDGs were formulated in tandem with a comprehensive and ambitious monitoring system. However, this monitoring system is currently hindered by a lack of available data and statistical capacity to monitor it effectively. Earth Observations are positioned as a critical source of information to support SDG monitoring: they enhance data availability, provide precise and appropriate data spanning long time periods, and have a wide geographical range that complements traditional methods[1,10]. To provide a practical application in this area, a LULCC classification methodology was estimated at a local scale, capable of providing tools and methods useful for achieving the SDG 11.3 and 15.3 objectives of the 2030 Agenda. The results obtained make up a dataset heterogeneous range of data and tools, harmonized in space and time, concerning the spatial distribution of built-up areas, abandoned and eroding agricultural areas, that can satisfy the data requirements of the SDGs.

Glossary

LAND ABANDONMENT: Land abandonment refers to the process by which cultivated or managed land is no longer used for agricultural, forestry, or other purposes, and is left to revert to its natural state or undergoes a spontaneous reforestation. This can occur due to a range of factors, including changes in land use policies, economic factors, rural-urban migration, environmental degradation, and natural disasters. The abandoned land may be left to regenerate naturally or may require active restoration efforts to ensure its recovery. The abandonment of land can have significant ecological, economic, and social impacts, including changes in ecosystem services, loss of biodiversity, and impacts on local communities [124,247,248].

LAND CONSUMPTION: land consumption means: (1) the expansion of built-up area which can be directly measured; (2) the absolute extent of land that is subject to exploitation by agriculture, forestry or other economic activities and (3) the over-intensive exploitation of land that is used for agriculture and forestry [30].

LAND COVER: The physical coverage of land, usually expressed in terms of vegetation cover (natural or planted) or lack of it. Related to, but not synonymous with, land use. Land cover refers to the physical and biological cover on the Earth's surface, including vegetation, water bodies, bare soil, and human-made structures. Land cover can be classified into different categories based on the dominant type of cover, such as forests, grasslands, wetlands, croplands, urban areas, and water bodies. These categories are often used to understand the distribution and characteristics of different land cover types and their implications for ecosystem services, biodiversity, climate, and human well-being. [6,29].

LAND DEGRADATION: Land degradation refers to the deterioration of the quality and productivity of land, often as a result of human activities. It involves the decline in the natural fertility and biological diversity of the soil, as well as the reduction in the ability of the land to support plant growth and other ecosystem services. Land degradation can occur through a variety of processes, such as soil erosion, deforestation, overgrazing, land-use change, and pollution. It can have significant impacts on food security, water availability, and the sustainability of ecosystems, and it is often linked to poverty, social conflict, and migration [29,30,248–250].

LAND TAKE: there are various synonyms for land take [17]: (1) the area of land that is taken by infrastructure and other facilities that necessarily go along with the infrastructure, such as filling stations on roads and railway stations [30,123]; (2) also referred to as land consumption describes an increase of settlement areas over time. This process includes the development of scattered settlements in rural areas, the expansion of urban areas around an urban nucleus (including urban sprawl), and the conversion of land within an urban area (densification). Depending on local circumstances, a greater or smaller part of the land take will result in actual soil sealing [251]; the amount of agriculture, forest, semi-natural/natural land, wetlands or water taken by urban and other artificial land development, as defined in the EEA Land take indicator (CSI 014/LSI 001; EEA, 2005)[252]. This indicator provides information on the change from agricultural, forestry and semi-natural/ natural land, wetlands or water to urban land cover as a consequence of urban residential development, development of economic sites and infrastructures (including the creation of industrial, commercial and transport units, but excluding the conversion of previously developed land to sport and leisure facilities) and development of green urban areas on previously undeveloped land. To this end, the indicator uses Corine Land Cover (CLC) data, containing a hybrid of land cover and land use data. Land take is also referred to as 'land consumption' in some cases, although the actual meaning may differ from the EEA's definition of land take [244];

LAND USE: Human activities, which are directly related to the land, making use of its resources, or having an impact upon it. A given land use may take place on one or more than one piece of land, and several land uses may occur on the same piece of land. Land use refers to the various ways in which land is utilized or managed by humans, including the activities and functions that take place on the land. It encompasses both natural and human-made features on the earth's surface, including agriculture, forestry, urban development, transportation, mining, recreation, and conservation. Land use can be categorized into different types, such as residential, commercial, industrial, institutional, and agricultural. Land use planning is the process of deciding on the best use of land to meet the needs of the society while considering environmental, social, and economic factors. Effective land use management is critical for ensuring sustainable development and the conservation of natural resources. [29,123,253].

SOIL EROSION: Soil erosion refers to the loss of soil due to the movement of water, wind, ice, or other natural agents, as well as human activities such as agriculture and deforestation. Soil erosion can lead to the loss of topsoil, which is the most fertile layer of soil that contains the most nutrients and organic matter necessary for plant growth. When topsoil is lost, it can have negative impacts on crop productivity, water quality, and biodiversity. Soil erosion is a major environmental concern, particularly in areas with steep slopes, intense rainfall, or unsustainable land use practices. It is also one of the major contributors to sedimentation in rivers, lakes, and reservoirs, which can lead to reduced water storage capacity and increased flooding. Therefore, soil erosion prevention and control measures are critical for protecting the environment and promoting sustainable land use [48,254].

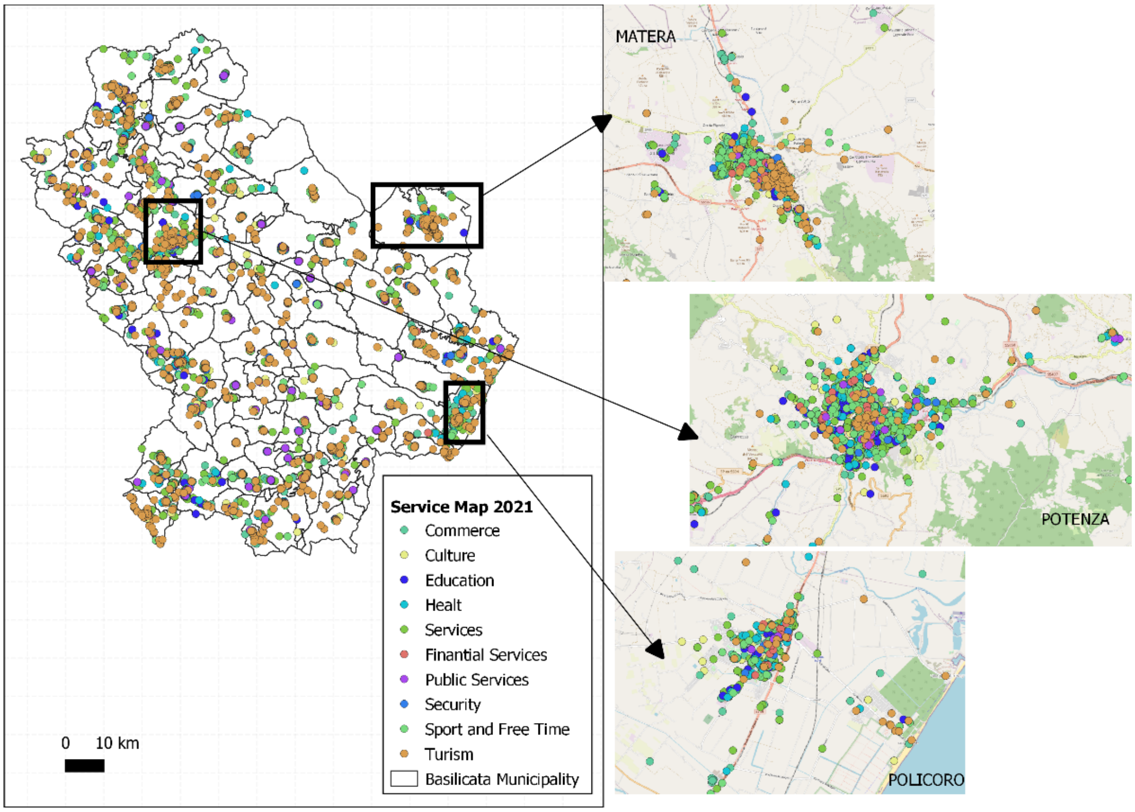
SOIL SEALING: Soil sealing refers to the permanent covering of soil with impermeable materials such as asphalt, cement, bricks, metal, and other artificial materials. This process transforms natural soil into an impermeable surface, preventing the absorption of water and the exchange of air and nutrients between the soil and atmosphere. Soil sealing can have negative consequences on the environment, such as reduced biodiversity, increased risk of flooding, decreased air quality, and the urban heat island effect. Additionally, soil sealing can negatively impact the quality of life for people, such as the loss of green spaces, increased traffic, and noise pollution [25,30].

URBANIZATION: is a result of population migration from rural areas in addition to natural urban demographic growth[255]. Urbanization is the process by which an increasing proportion of a population lives in urban areas or cities, and there is a corresponding decrease in the proportion of people living in rural areas. Urbanization is often associated with economic and social development, as cities tend to be centres of commerce, education, and innovation. Urbanization can also lead to changes in lifestyle, culture, and the environment. It can have both positive and negative impacts on society, including increased access to services, higher levels of pollution, and changes in land use patterns [256–258].

Appendix

A 1. Tables and Figure

- *Map of Services and Equipment (2021).*



▪ *Tables 1 Distribution of resident population by municipality from 1981 to 2021 (Class 6).*

Class 6														
ID	**Munucipality**	**1981**	**ID**	**Munucipality**	**1991**	**ID**	**Munucipality**	**2001**	**ID**	**Munucipality**	**2011**	**ID**	**Munucipality**	**2021**
1	Calvera	754	1	Armento	946	1	Armento	800	1	Armento	667	1	Aliano	891
2	Cersosimo	896	2	Brindisi Monta	949	2	Brindisi Monta	905	2	Brindisi Montagna	904	2	Armento	577
3	Cirigliano	578	3	Calvera	662	3	Calciano	983	3	Calciano	797	3	Brindisi Montagna	840
4	Fardella	911	4	Cersosimo	882	4	Calvera	584	4	Calvera	437	4	Calciano	678
5	Ginestra	841	5	Cirigliano	532	5	Campomaggio	980	5	Campomaggiore	853	5	Calvera	361
6	Guardia Pertica	872	6	Craco	971	6	Carbone	853	6	Carbone	704	6	Campomaggiore	746
7	Missanello	757	7	Fardella	857	7	Castelluccio Su	987	7	Castelluccio Superiore	864	7	Carbone	550
8	Oliveto Lucano	768	8	Ginestra	783	8	Castelmezzano	970	8	Castelmezzano	855	8	Castelgrande	841
9	San Paolo Alba	545	9	Guardia Pertica	817	9	Cersosimo	847	9	Cersosimo	716	9	Castelluccio Superiore	739
10	Teana	771	10	Missanello	713	10	Cirigliano	445	10	Cirigliano	365	10	Castelmezzano	744
11	Trivigno	893	11	Oliveto Lucano	762	11	Craco	796	11	Craco	754	11	Castronuovo di Sant'Andrea	943
			12	San Paolo Alba	529	12	Fardella	765	12	Fardella	628	12	Cersosimo	571
			13	Teana	874	13	Ginestra	726	13	Gallicchio	887	13	Cirigliano	297
			14	Trivigno	868	14	Guardia Pertica	758	14	Ginestra	732	14	Craco	651
						15	Missanello	604	15	Gorgoglione	992	15	Fardella	559
						16	Oliveto Lucano	587	16	Guardia Perticara	609	16	Gallicchio	824
						17	San Costantino	884	17	Missanello	554	17	Ginestra	721
						18	San Martino d'	969	18	Noepoli	983	18	Gorgoglione	888
						19	San Paolo Alba	416	19	Oliveto Lucano	499	19	Guardia Perticara	524
						20	Sasso di Castal	871	20	San Costantino Albane	784	20	Missanello	533
						21	Teana	750	21	San Martino d'Agri	813	21	Noepoli	773
						22	Trivigno	794	22	San Paolo Albanese	313	22	Oliveto Lucano	374
									23	Sasso di Castalda	822	23	Pietrapertosa	945
									24	Teana	652	24	Rapone	908
									25	Trivigno	710	25	Ruvo del Monte	993
												26	San Chirico Raparo	955
												27	San Costantino Albanese	624
												28	San Martino d'Agri	685
												29	San Paolo Albanese	226
												30	Sasso di Castalda	766
												31	Teana	551
												32	Trivigno	603

▪ *Tables 2 Distribution of resident population by municipality from 1981 to 2021 (Class 5)*

Class 5														
ID	**Munucipality**	**1981**	**ID**	**Munucipality**	**1991**	**ID**	**Munucipality**	**2001**	**ID**	**Munucipality**	**2011**	**ID**	**Munucipality**	**2021**
1	Albano di Lucar	1706	1	Albano di Luca	1682	1	Abriola	1808	1	Abriola	1578	1	Abriola	1329
2	Aliano	1635	2	Aliano	1495	2	Albano di Luca	1612	2	Accettura	1989	2	Accettura	1679
3	Armento	1069	3	Banzi	1903	3	Aliano	1284	3	Albano di Lucania	1468	3	Albano di Lucania	1369
4	Banzi	1742	4	Calciano	1049	4	Anzi	1949	4	Aliano	1035	4	Anzi	1573
5	Calciano	1189	5	Campomaggio	1109	5	Banzi	1514	5	Anzi	1787	5	Balvano	1751
6	Campomaggior	1047	6	Cancellara	1715	6	Cancellara	1598	6	Balvano	1859	6	Banzi	1230
7	Cancellara	1784	7	Carbone	1171	7	Castelgrande	1231	7	Banzi	1402	7	Calvello	1775
8	Carbone	1372	8	Castelgrande	1358	8	Castelsaracen	1730	8	Calvello	1922	8	Cancellara	1166
9	Castelgrande	1249	9	Castelluccio Su	1142	9	Castronuovo d	1439	9	Cancellara	1408	9	Castelluccio Inferiore	1955
10	Castelluccio Su	1158	10	Castelmezzano	1063	10	Colobraro	1535	10	Castelgrande	1016	10	Castelsaraceno	1243
11	Castelmezzano	1123	11	Castronuovo d	1691	11	Episcopia	1656	11	Castelsaraceno	1486	11	Chiaromonte	1778
12	Castronuovo di	1773	12	Colobraro	1756	12	Gallicchio	1018	12	Castronuovo di Sant'Ar	1136	12	Colobraro	1086
13	Colobraro	1997	13	Episcopia	1735	13	Garaguso	1193	13	Chiaromonte	1963	13	Episcopia	1276
14	Craco	1014	14	Gallicchio	1130	14	Gorgoglione	1179	14	Colobraro	1340	14	Forenza	1901
15	Episcopia	1690	15	Garaguso	1270	15	Grumento Nov	1839	15	Episcopia	1444	15	Garaguso	1001
16	Gallicchio	1109	16	Gorgoglione	1395	16	Maschito	1864	16	Garaguso	1126	16	Grumento Nova	1598
17	Garaguso	1225	17	Grumento Nov	1956	17	Montemurro	1555	17	Grumento Nova	1720	17	Laurenzana	1642
18	Gorgoglione	1383	18	Maschito	1951	18	Nemoli	1561	18	Laurenzana	1979	18	Maschito	1511
19	Grumento Nov	1985	19	Montemurro	1648	19	Noepoli	1189	19	Maschito	1725	19	Montemilone	1438
20	Montemurro	1703	20	Nemoli	1598	20	Pietrapertosa	1312	20	Montemilone	1751	20	Montemurro	1144
21	Nemoli	1493	21	Noepoli	1348	21	Rapone	1203	21	Montemurro	1330	21	Nemoli	1402
22	Noepoli	1521	22	Pietrapertosa	1447	22	Ripacandida	1767	22	Nemoli	1511	22	Pescopagano	1727
23	Pietrapertosa	1563	23	Rapone	1336	23	Roccanova	1759	23	Pescopagano	1999	23	Ripacandida	1594
24	Rapone	1447	24	Ruvo del Mont	1453	24	Ruvo del Mont	1262	24	Pietrapertosa	1103	24	Roccanova	1345
25	Ruvo del Monte	1757	25	San Chirico Nu	1801	25	San Chirico Nu	1632	25	Rapone	1018	25	San Chirico Nuovo	1225
26	San Chirico Nuo	1839	26	San Chirico Ra	1695	26	San Chirico Ra	1304	26	Ripacandida	1717	26	San Giorgio Lucano	1091
27	San Chirico Rap	1735	27	San Costantino	1077	27	San Giorgio Lu	1510	27	Roccanova	1639	27	San Mauro Forte	1310
28	San Costantino	1206	28	San Giorgio Lu	1820	28	San Severino L	1923	28	Ruvo del Monte	1094	28	San Severino Lucano	1419
29	San Giorgio Luc	1964	29	San Martino d'	1243	29	Sant'Angelo Le	1472	29	San Chirico Nuovo	1528	29	Sant'Angelo Le Fratte	1331
30	San Martino d'A	1313	30	Sant'Angelo Le	1656	30	Sarconi	1351	30	San Chirico Raparo	1154	30	Sarconi	1405
31	Sant'Angelo Le	1587	31	Sarconi	1307	31	Savoia di Lucar	1236	31	San Giorgio Lucano	1284	31	Savoia di Lucania	1018
32	Sarconi	1112	32	Sasso di Castal	1115	32	Spinoso	1778	32	San Mauro Forte	1706	32	Spinoso	1362
33	Sasso di Castal	1098	33	Savoia di Lucar	1351	33	Terranova di P	1534	33	San Severino Lucano	1678	33	Terranova di Pollino	1065
34	Savoia di Lucar	1295	34	Spinoso	1852	34	Valsinni	1797	34	Sant'Angelo Le Fratte	1439	34	Vaglio Basilicata	1903
35	Spinoso	1788	35	Terranova di P	1815				35	Sarconi	1324	35	Valsinni	1384
36	Terranova di Po	1948	36	Valsinni	1965				36	Savoia di Lucania	1147			
									37	Spinoso	1562			
									38	Terranova di Pollino	1343			
									39	Valsinni	1607			

- *Tables 3 Distribution of resident population by municipality from 1981 to 2021 (Class 4)*

Class 4														
ID	**Munucipality**	**1981**	**ID**	**Munucipality**	**1991**	**ID**	**Munucipality**	**2001**	**ID**	**Munucipality**	**2011**	**ID**	**Munucipality**	**2021**
1	Abriola	2309	1	Abriola	2061	1	Accettura	2436	1	Acerenza	2513	1	Acerenza	2204
2	Accettura	2669	2	Accettura	2740	2	Acerenza	3010	2	Atella	3801	2	Atella	3744
3	Acerenza	3391	3	Acerenza	3043	3	Atella	3726	3	Baragiano	2597	3	Baragiano	2536
4	Anzi	2178	4	Anzi	2158	4	Balvano	2007	4	Barile	2809	4	Barile	2664
5	Atella	3486	5	Atella	3519	5	Baragiano	2751	5	Brienza	4039	5	Bella	4796
6	Balvano	2205	6	Balvano	2296	6	Barile	3229	6	Castelluccio Inferiore	2137	6	Brienza	3873
7	Baragiano	2499	7	Baragiano	2716	7	Brienza	4067	7	Corleto Perticara	2598	7	Corleto Perticara	2351
8	Barile	3457	8	Barile	3262	8	Calvello	2212	8	Filiano	3090	8	Filiano	2800
9	Brienza	4016	9	Brienza	4144	9	Castelluccio In	2344	9	Forenza	2178	9	Francavilla in Sinni	3987
10	Calvello	3034	10	Calvello	2362	10	Chiaromonte	2148	10	Francavilla in Sinni	4203	10	Grassano	4865
11	Castelluccio Inf	2630	11	Castelluccio In	2617	11	Corleto Pertica	3018	11	Grottole	2365	11	Grottole	2088
12	Castelsaracenc	2064	12	Castelsaracen	2020	12	Filiano	3298	12	Latronico	4781	12	Irsina	4459
13	Chiaromonte	2489	13	Chiaromonte	2410	13	Forenza	2546	13	Marsico Nuovo	4401	13	Latronico	4173
14	Corleto Pertica	3658	14	Corleto Pertica	3345	14	Francavilla in S	4367	14	Miglionico	2554	14	Maratea	4837
15	Filiano	3151	15	Filiano	3318	15	Grottole	2607	15	Moliterno	4246	15	Marsico Nuovo	3910
16	Forenza	3058	16	Forenza	2807	16	Laurenzana	2250	16	Oppido Lucano	3798	16	Miglionico	2395
17	Francavilla in S	4147	17	Francavilla in S	4044	17	Marsicovetere	4703	17	Palazzo San Gervasio	4846	17	Moliterno	3663
18	Grottole	3130	18	Grottole	3006	18	Miglionico	2630	18	Paterno	3394	18	Muro Lucano	4999
19	Laurenzana	2996	19	Laurenzana	2640	19	Moliterno	4592	19	Pietragalla	4238	19	Oppido Lucano	3627
20	Marsicovetere	3431	20	Marsicovetere	4098	20	Oppido Lucano	3968	20	Pomarico	4167	20	Palazzo San Gervasio	4540
21	Maschito	2052	21	Miglionico	2718	21	Paterno	3994	21	Rapolla	4379	21	Paterno	3100
22	Miglionico	2568	22	Montemilone	2122	22	Pescopagano	2147	22	Rivello	2814	22	Pietragalla	3930
23	Moliterno	4922	23	Oppido Lucano	4004	23	Pietragalla	4532	23	Rotonda	3481	23	Pomarico	3884
24	Montemilone	2614	24	Paterno	4170	24	Pomarico	4482	24	Rotondella	2621	24	Rapolla	4146
25	Oppido Lucano	4092	25	Pescopagano	2392	25	Rapolla	4648	25	Ruoti	3525	25	Rivello	2591
26	Paterno	3964	26	Pietragalla	4633	26	Rivello	3010	26	Salandra	2928	26	Rotonda	3282
27	Pescopagano	3088	27	Pignola	4681	27	Rotonda	3888	27	San Fele	3165	27	Rotondella	2489
28	Pietragalla	4583	28	Rapolla	4447	28	Rotondella	3233	28	Satriano di Lucania	2313	28	Ruoti	3383
29	Pignola	3982	29	Ripacandida	2072	29	Ruoti	3687	29	Stigliano	4679	29	Salandra	2595
30	Rapolla	4073	30	Rivello	3153	30	Salandra	3109	30	Tolve	3322	30	San Fele	2654
31	Ripacandida	2307	31	Roccanova	2023	31	San Fele	3832	31	Tramutola	3123	31	Satriano di Lucania	2254
32	Rivello	3001	32	Rotonda	4011	32	San Mauro For	2306	32	Trecchina	2309	32	Stigliano	3768
33	Roccanova	2022	33	Rotondella	3712	33	Satriano di Luc	2353	33	Tursi	4908	33	Tolve	3047
34	Rotonda	3892	34	Ruoti	3777	34	Tolve	3620	34	Vaglio Basilicata	2072	34	Tramutola	2946
35	Rotondella	3989	35	Salandra	3363	35	Tramutola	3251	35	Vietri di Potenza	2895	35	Trecchina	2159
36	Ruoti	3440	36	San Fele	4186	36	Trecchina	2404	36	Viggianello	3140	36	Tricarico	4890
37	Salandra	3478	37	San Mauro For	3025	37	Vaglio Basilica	2217	37	Viggiano	3035	37	Tursi	4849
38	San Mauro For	2961	38	San Severino L	2224	38	Vietri di Poten	3096				38	Vietri di Potenza	2694
39	San Severino Lu	2352	39	Satriano di Luc	2424	39	Viggianello	3500				39	Viggianello	2790
40	Satriano di Luc	2081	40	Tolve	3766	40	Viggiano	3208				40	Viggiano	3269
41	Tito	4870	41	Tramutola	3244									
42	Tolve	3934	42	Trecchina	2508									
43	Tramutola	3544	43	Vaglio Basilica	2320									
44	Trecchina	2530	44	Vietri di Poten	3255									
45	Vaglio Basilicat	2145	45	Viggianello	3985									
46	Valsinni	2013	46	Viggiano	3161									
47	Vietri di Potenz	3444												
48	Viggianello	4274												
49	Viggiano	3044												

- *Tables 4 Distribution of resident population by municipality from 1981 to 2021 (Class 3)*

Class 3														
ID	**Munucipality**	**1981**	**ID**	**Munucipality**	**1991**	**ID**	**Munucipality**	**2001**	**ID**	**Munucipality**	**2011**	**ID**	**Munucipality**	**2021**
1	Bella	5916	1	Bella	5789	1	Bella	5440	1	Bella	5051	1	Ferrandina	8137
2	Ferrandina	9172	2	Ferrandina	9427	2	Ferrandina	9358	2	Ferrandina	8857	2	Genzano di Lucania	5377
3	Genzano di Luc	6731	3	Genzano di Lu	6330	3	Genzano di Lu	6115	3	Genzano di Lucania	5816	3	Lagonegro	5192
4	Grassano	6281	4	Grassano	6065	4	Grassano	5792	4	Grassano	5350	4	Marsicovetere	5536
5	Irsina	7237	5	Irsina	6558	5	Irsina	5732	5	Irsina	5138	5	Montalbano Jonico	6874
6	Lagonegro	6264	6	Lagonegro	6260	6	Lagonegro	6146	6	Lagonegro	5774	6	Montescaglioso	9224
7	Latronico	5787	7	Latronico	5507	7	Latronico	5279	7	Maratea	5214	7	Nova Siri	6663
8	Maratea	5108	8	Maratea	5261	8	Maratea	5261	8	Marsicovetere	5360	8	Picerno	5687
9	Marsico Nuovo	6010	9	Marsico Nuovo	5610	9	Marsico Nuovo	5134	9	Montalbano Jonico	7488	9	Pignola	6830
10	Montalbano Jo	9093	10	Moliterno	5033	10	Montalbano Jo	7991	10	Muro Lucano	5635	10	Sant'Arcangelo	6062
11	Montescaglioso	9265	11	Montalbano Jo	8688	11	Muro Lucano	5134	11	Nova Siri	6638	11	Scanzano Jonico	7635
12	Muro Lucano	7529	12	Muro Lucano	6380	12	Nova Siri	6418	12	Picerno	5997	12	Senise	6656
13	Nova Siri	5475	13	Nova Siri	5922	13	Palazzo San Ge	5184	13	Pignola	6604	13	Tito	7162
14	Palazzo San Ge	6514	14	Palazzo San Ge	6138	14	Picerno	6186	14	Sant'Arcangelo	6381			
15	Picerno	5543	15	Picerno	5976	15	Pignola	5483	15	Scanzano Jonico	6790			
16	Pomarico	5012	16	Pomarico	5018	16	Sant'Arcangelo	6637	16	Senise	7064			
17	San Fele	5907	17	Sant'Arcangelo	7270	17	Scanzano Joni	6711	17	Tito	6922			
18	Sant'Arcangelo	6781	18	Scanzano Joni	6210	18	Senise	7182	18	Tricarico	5674			
19	Scanzano Jonic	5945	19	Senise	7316	19	Stigliano	5616						
20	Senise	7248	20	Stigliano	6576	20	Tito	6387						
21	Stigliano	7269	21	Tito	5722	21	Tricarico	6318						
22	Tricarico	7197	22	Tricarico	7017	22	Tursi	5510						
23	Tursi	6080	23	Tursi	6003									

- *Tables 5 Distribution of resident population by municipality from 1981 to 2021 (Class 2)*

Class 2														
ID	Munucipality	1981	ID	Munucipality	1991	ID	Munucipality	2001	ID	Munucipality	2011	ID	Munucipality	2021
1	Avigliano	11592	1	Avigliano	11761		Avigliano	12025		Avigliano	11668	1	Avigliano	10796
2	Bernalda	11803	2	Bernalda	12037		Bernalda	11958		Bernalda	11761	2	Bernalda	12050
3	Lauria	13675	3	Lauria	13752		Lauria	13801		Lauria	13330	3	Lauria	12166
4	Lavello	13292	4	Lavello	13215		Lavello	13247		Lavello	13649	4	Lavello	13139
5	Melfi	15661	5	Melfi	15757		Melfi	16110		Melfi	17379	5	Melfi	17196
6	Pisticci	17793	6	Montescaglioso	10104		Montescaglioso	10121		Montescaglioso	10127	6	Pisticci	16889
7	Policoro	12174	7	Pisticci	18311		Pisticci	17811		Pisticci	17043	7	Policoro	17762
8	Rionero in Vult	12679	8	Policoro	14551		Policoro	15096		Policoro	15415	8	Rionero in Vulture	12652
9	Venosa	12060	9	Rionero in Vulture	13201		Rionero in Vulture	13441		Rionero in Vulture	13085	9	Venosa	11093
			10	Venosa	11905		Venosa	12148		Venosa	11830			

- *Tables 6 Distribution of resident population by municipality from 1981 to 2021 (Class 1)*

Class 1														
ID	Munucipality	1981	ID	Munucipality	1991	ID	Munucipality	2001	ID	Munucipality	2011	ID	Munucipality	2021
1	Matera	51261	1	Matera	54919		Matera	57785		Matera	59813	1	Matera	59794
2	Potenza	65698	2	Potenza	65714		Potenza	69060		Potenza	66302	2	Potenza	65420

- *Table 7 Resident population in age groups.*

Municipality	Old_1981	Old_2021	Population_1981	Population_2021	Aldult_1981	Adult_2021	Youth_1981	Child_1981	Child_2021
Abriola	304	369	2309	1329	740	579	529	736	187
Accettura	564	462	2669	1679	850	693	507	748	238
Acerenza	602	593	3391	2204	494	933	708	903	274
Albano di Lucania	254	317	1706	1369	545	586	353	554	188
Aliano	254	301	1635	891	566	346	325	490	104
Anzi	293	394	2178	1573	756	665	453	676	212
Armento	229	89	1069	577	372	314	185	283	77
Atella	408	811	3486	3744	1206	1585	741	1131	618
Avigliano	1367	2461	11592	10796	4137	4795	2297	3791	1657
Balvano	306	447	2205	1751	886	729	325	688	268
Banzi	251	196	1742	1230	600	657	356	535	173
Baragiano	348	615	2499	2536	794	1090	613	744	410
Barile	542	603	3457	2664	1153	1137	782	980	397
Bella	716	1149	5916	4796	2018	2015	1342	1840	768
Bernalda	1207	2770	11803	12050	3822	5131	2835	3939	2082
Brienza	537	917	4016	3873	1371	1633	930	1178	595
Brindisi Montagna	129	170	1000	840	314	387	248	309	117
Calciano	172	210	1189	678	453	279	245	319	81
Calvello	407	489	3034	1775	988	701	732	907	276
Calvera	91	127	754	361	235	154	154	274	25
Campomaggiore	139	208	1047	746	316	313	256	336	94
Cancellara	343	335	1784	1166	582	485	389	470	156
Carbone	285	227	1372	550	466	216	272	349	38
Castelgrande	243	271	1249	841	412	353	256	338	82

Castelluccio Inferiore	351	535	2630	1955	868	811	587	824	267
Castelluccio Superiore	168	221	1158	739	414	297	242	334	98
Castelmezzano	215	246	1123	744	367	304	238	303	82
Castelsaraceno	289	373	2064	1243	671	527	474	630	156
Castronuovo di Sant'Andrea	346	358	1773	943	673	371	334	420	83
Cersosimo	131	187	896	571	314	239	199	252	59
Chiaromonte	364	493	2489	1778	864	773	548	713	234
Cirigliano	156	99	578	297	204	140	98	120	18
Colobraro	336	326	1997	1086	668	459	396	597	134
Corleto Perticara	650	603	3658	2351	1246	1025	747	1015	307
Craco	146	173	1014	651	323	266	217	328	99
Episcopia	193	373	1690	1276	606	515	388	503	199
Fardella	132	186	911	559	321	222	190	268	61
Ferrandina	1118	2053	9172	8137	2890	3401	2059	3105	1240
Filiano	466	679	3151	2800	1099	1228	705	881	372
Forenza	581	531	3058	1901	1029	800	610	838	253
Francavilla in Sinni	474	927	4147	3987	1301	1719	1003	1369	659
Gallicchio	133	206	1109	824	370	340	232	374	108
Garaguso	162	224	1225	1001	400	420	264	399	192
Genzano di Lucania	1115	1466	6731	5377	2170	2215	1399	2047	844
Ginestra	157	181	841	721	291	294	162	231	131
Gorgoglione	223	231	1383	888	483	378	279	398	116
Grassano	912	1244	6281	4865	2022	1962	1456	1891	792
Grottole	407	524	3130	2088	935	889	703	1085	315
Grumento Nova	250	411	1985	1598	722	682	451	562	235
Guardia Perticara	172	136	872	524	327	236	153	220	47
Irsina	1020	1246	7237	4459	2469	1764	1531	2217	640
Lagonegro	697	1289	6264	5192	2018	2254	1552	1997	739
Latronico	900	1290	5787	4173	2079	1732	1253	1555	509
Laurenzana	496	465	2996	1642	1020	719	662	818	211
Lauria	1574	2970	13675	12166	4603	5291	3275	4223	1711
Lavello	1669	2789	13292	13139	4113	5557	3166	4344	2385
Maratea	731	1317	5108	4837	1605	2110	1257	1515	642
Marsico Nuovo	747	1137	6010	3910	2166	1588	1369	1728	519
Marsicovetere	310	1023	3431	5536	1039	2391	909	1173	1104
Maschito	403	437	2052	1511	703	623	383	563	209
Matera	4495	13866	51261	59794	16719	25529	12749	17298	10102
Melfi	1993	3188	15661	17196	4614	7392	3771	5283	3195
Miglionico	361	583	2568	2395	805	1003	620	782	360
Missanello	117	126	757	533	265	226	181	194	66

Moliterno	310	1101	4922	3663	2158	1540	1100	1354	485
Montalbano Jonico	908	1666	9093	6874	2921	2922	2204	3060	1064
Montemilone	487	393	2614	1438	869	621	471	787	184
Montemurro	305	327	1703	1144	572	449	360	466	159
Montescaglioso	1038	2129	9265	9224	2968	3768	2191	3068	1592
Muro Lucano	1107	1364	7529	4999	2487	2185	1772	2163	648
Nemoli	243	388	1493	1402	481	598	381	388	194
Noepoli	270	251	1521	773	540	338	328	383	70
Nova Siri	521	1421	5475	6663	1663	2835	1317	1974	1128
Oliveto Lucano	127	147	768	374	294	151	122	225	34
Oppido Lucano	590	921	4092	3627	1288	1495	924	1290	569
Palazzo San Gervasio	965	1007	6514	4540	1951	1959	1479	2119	733
Paterno	434	819	3964	3100	1262	1295	946	1322	461
Pescopagano	444	513	3088	1727	1075	726	695	874	232
Picerno	671	1394	5543	5687	1847	2426	1343	1682	843
Pietragalla	855	977	4583	3930	1527	1695	1005	1196	571
Pietrapertosa	283	270	1563	945	523	374	281	476	109
Pignola	379	1210	3982	6830	1152	3144	1065	1386	1238
Pisticci	2014	3992	17793	16889	5892	7167	4092	5795	2751
Policoro	652	3398	12174	17762	3524	7747	3286	4712	3167
Pomarico	733	1003	5012	3884	1599	1606	1207	1473	582
Potenza	5663	16183	65698	65420	22420	28657	16255	21360	9908
Rapolla	498	433	4073	4146	1224	2158	972	1379	762
Rapone	234	256	1447	908	517	378	289	407	103
Rionero in Vulture	1776	2730	12679	12652	3901	5629	2926	4076	2001
Ripacandida	490	394	2307	1594	831	690	411	575	239
Rivello	527	683	3001	2591	1007	1067	606	861	387
Roccanova	338	392	2022	1345	677	520	406	601	162
Rotonda	515	909	3892	3282	1387	1376	885	1105	431
Rotondella	506	641	3989	2489	1388	1063	904	1191	339
Ruoti	458	763	3440	3383	1121	1799	777	1084	560
Ruvo del Monte	351	309	1757	993	585	396	363	458	119
Salandra	429	668	3478	2595	1020	1078	818	1211	378
San Chirico Nuovo	265	365	1839	1225	593	522	418	563	149
San Chirico Raparo	313	318	1735	955	631	379	315	476	114
San Costantino Albanese	212	224	1206	624	491	261	199	304	52
San Fele	757	879	5907	2654	2038	1087	1379	1733	292
San Giorgio Lucano	358	380	1964	1091	671	424	377	558	130
San Martino d'Agri	221	224	1313	685	440	277	278	374	89
San Mauro Forte	410	388	2961	1310	1014	553	651	886	142

San Paolo Albanese	146	102	545	226	214	79	94	91	15
San Severino Lucano	385	446	2352	1419	855	586	508	604	148
Sant'Angelo Le Fratte	216	327	1587	1331	583	-269	337	451	1047
Sant'Arcangelo	776	1381	6781	6062	2003	3354	1670	2332	202
Sarconi	148	340	1112	1405	409	671	223	332	110
Sasso di Castalda	151	255	1098	766	388	25	206	353	358
Satriano di Lucania	280	494	2081	2254	755	978	454	592	358
Savoia di Lucania	195	274	1295	1018	421	434	299	380	139
Scanzano Jonico	444	1480	5945	7635	1745	3214	1565	2191	1402
Senise	740	1479	7248	6656	2165	2919	1731	2612	974
Spinoso	278	354	1788	1362	575	586	383	552	174
Stigliano	1377	1271	7269	3768	2538	1514	1565	1789	368
Teana	99	176	771	551	265	221	180	227	63
Terranova di Pollino	269	364	1948	1065	686	440	433	560	94
Tito	532	1270	4870	7162	1555	3285	1249	1534	1383
Tolve	659	751	3934	3047	1248	1312	859	1168	420
Tramutola	472	724	3544	2946	1139	1267	814	1119	462
Trecchina	411	638	2530	2159	838	909	570	711	278
Tricarico	1024	1356	7197	4890	2267	2025	1620	2286	645
Trivigno	146	170	893	603	286	261	220	241	66
Tursi	653	1203	6080	4849	1840	2016	1449	2138	701
Vaglio Basilicata	332	516	2145	1903	729	837	461	623	266
Valsinni	271	380	2013	1384	694	583	468	580	172
Venosa	1531	2561	12060	11093	3630	4830	2683	4216	1769
Vietri di Potenza	473	679	3444	2694	1008	1151	842	1121	374
Viggianello	574	898	4274	2790	1494	1162	964	1242	358
Viggiano	433	596	3044	3269	1018	1417	678	915	631
Basilicata	75823	131558	609514	545130	199769	233630	140968	192270	84758
Matera Province	22998	45835	405896	352490	134122	152304	91918	127764	53650
Potenza Province	52825	85723	203618	192640	65647	81326	49050	64506	31108

A2. Methodogical annexess

- The *service endowment* index was calculated for each municipality:

$$\sum \frac{x_i}{f_i}$$

Where X_i represents the total endowment of services and f_i the resident population. In general, the index is based on dividing the number of services available in a geographical area by the population residing in the same area. However, this indicator shows some critical issues especially in relation to the difficulty of comparing different geographical areas and the need to also consider other factors, such as the socio-economic conditions of the population, the quality of services, accessibility to transport and distance from infrastructure.

- *Depopulation Index:*

$$Depopulation\ Index = \left(\frac{Actual\ population - Previous\ Population}{Previous\ Population}\right) * 100$$

The result of the depopulation index is a percentage value which indicates the percentage increase or decrease of the population in the period considered. A positive depopulation index indicates a decrease in population, while a negative depopulation index indicates an increase in population.

- *Dependence Index:* Ratio between the non-autonomous population due to age and the working population.

$$Dependece\ Index = \frac{(Populantion \leq 14y + Population\ \geq 65)}{\leq 15yPopulation \leq 64y} * 100$$

The dependency ratio is considered an indicator of economic and social relevance. The numerator is made up of the population which, due to age, considers itself to be non-autonomous - i.e., dependent - and the denominator by the segment of the population which, being active, should provide for its livelihood.
It is an indicator that is affected by the economic structure of the population: for example, in societies with an important agricultural component, very young or elderly subjects cannot be considered economically or socially dependent on adults; on the contrary, in the more advanced structures, a part of the individuals considered in the denominator index are actually employees as students or unemployed. The indicator in developing countries takes on higher values than in more advanced populations economically; this is largely due to the greater presence of young individuals due to their higher fecundity.

- *LS Factor equation*

Many authors have developed equations to estimate the LS factor [259–262], the formula proposed by Mitasova [205,263] was used to calculate the topographic LS-factor relative to a point r on a hillslope, that includes into a single factor LS the parameters relating to slope length L and slope S, using a formulation that better interprets the topographical complexity of the examined region:

$$LS_{(r)} = (\mu + 1)\left[a_{(r)}/a_0\right]^{\mu}\left[\sin b_{(r)}\,/b_0\right]^{n}$$

where $a_{(r)}$ is the upslope contributing area per unit contour width, in this study assessed by the product of QGIS with GRASS function r.flow), b is the slope, μ is the slope length exponent [264], n is a parameters whose value has been set up 1.2 [262], a_0= 22.1 m is the standard USLE plot length, and b_0= 9% is the slope grade of the standard USLE plot. The LS factor was estimated using the 20 m gridded DEM with the support of QGIS software, in fact most of the algorithms for LS estimation are implemented within GIS software. The LS product factor is dimensionless and was assumed to be constant over the entire observation period of observation[205].

References

1. Cai, G.; Zhang, J.; Du, M.; Li, C.; Peng, S. Identification of urban land use efficiency by indicator-SDG 11.3.1. *PLoS One* **2020**, *15*, 1–14, doi:10.1371/journal.pone.0244318.

2. Ehrlich, D.; Kemper, T.; Pesaresi, M.; Corbane, C. Built-up area and population density: Two Essential Societal Variables to address climate hazard impact. *Environ. Sci. Policy* **2018**, *90*, 73–82, doi:10.1016/j.envsci.2018.10.001.

3. Nor, A.N.M.; Corstanje, R.; Harris, J.A.; Brewer, T. Impact of rapid urban expansion on green space structure. *Ecol. Indic.* **2017**, *81*, 274–284, doi:10.1016/j.ecolind.2017.05.031.

4. Council, S. Critical milestones towards a coherent, efficient, and inclusive follow-up and review of the 2030 Agenda at the global level. **2015**.

5. Bonsu, N.O.; Tyreehageman, J.; Kele, J. Beyond agenda 2030: Future-oriented mechanisms in localising the sustainable development goals (sdgs). *Sustain.* **2020**, *12*, 1–21, doi:10.3390/su12239797.

6. United Nations Transforming Our World: The 2030 Agenda for Sustainable Development. Available online: https://sdgs.un.org/2030agenda (accessed on Feb 15, 2023).

7. Colglazier, B.W.; Na-, U. Sustainable development agenda: 2030. **2015**, 4–6.

8. Weiland, S.; Hickmann, T.; Lederer, M.; Marquardt, J.; Schwindenhammer, S. The 2030 agenda for sustainable development: Transformative change through the sustainable development goals? *Polit. Gov.* **2021**, *9*, 90–95, doi:10.17645/PAG.V9I1.4191.

9. Tóth, G.; Hermann, T.; da Silva, M.R.; Montanarella, L. Monitoring soil for sustainable development and land degradation neutrality. *Environ. Monit. Assess.* **2018**, *190*, doi:10.1007/s10661-017-6415-3.

10. Melchiorri, M.; Pesaresi, M.; Florczyk, A.J.; Corbane, C.; Kemper, T. Principles and applications of the global human settlement layer as baseline for the land use efficiency indicator—SDG 11.3.1. *ISPRS Int. J. Geo-Information* **2019**, *8*, doi:10.3390/ijgi8020096.

11. Wang, Y.; Huang, C.; Feng, Y.; Zhao, M.; Gu, J. Using earth observation for monitoring SDG 11.3.1-ratio of land consumption rate to population growth rate in Mainland China. *Remote Sens.* **2020**, *12*, 1–21, doi:10.3390/rs12030357.

12. Kust, G.; Andreeva, O.; Cowie, A. Land Degradation Neutrality: Concept development, practical applications and assessment. *J. Environ. Manage.* **2017**, *195*, 16–24, doi:https://doi.org/10.1016/j.jenvman.2016.10.043.

13. Santarsiero, V.; Nolè, G.; Lanorte, A.; Tucci, B.; Baldantoni, P.; Murgante, B. Evolution of Soil Consumption in the Municipality of Melfi (Southern Italy) in Relation to Renewable Energy. *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)* **2019**, *11621 LNCS*, 675–682, doi:10.1007/978-3-030-24302-9_48.

14. Santarsiero, V.; Nolè, G.; Lanorte, A.; Tucci, B.; Cillis, G.; Murgante, B. Remote Sensing and Spatial Analysis for Land-Take Assessment in Basilicata Region (Southern Italy). **2022**, doi:10.3390/rs14071692.

15. Saganeiti, L.; Pilogallo, A.; Scorza, F.; Mussuto, G.; Murgante, B. Spatial Indicators to Evaluate Urban

Fragmentation in Basilicata Region. *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)* **2018**, *10964 LNCS*, 100–112, doi:10.1007/978-3-319-95174-4_8.

16. Seto, K.; Güneralp, B.; the, L.H.-P. of; 2012, undefined Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. *Natl. Acad Sci.*, doi:10.1073/pnas.1211658109.

17. Marquard, E.; Bartke, S.; Font, J.G. i; Humer, A.; Jonkman, A.; Jürgenson, E.; Marot, N.; Poelmans, L.; Repe, B.; Rybski, R.; et al. Land Consumption and Land Take: Enhancing Conceptual Clarity for Evaluating Spatial Governance in the EU Context. *Sustain. 2020, Vol. 12, Page 8269* **2020**, *12*, 8269, doi:10.3390/SU12198269.

18. Schiavina, M.; Melchiorri, M.; Corbane, C.; Florczyk, A.J.; Freire, S.; Pesaresi, M.; Kemper, T. Multi-scale estimation of land use efficiency (SDG 11.3.1) across 25 Years Using Global Open and Free Data. *Sustain.* **2019**, *11*, 1–25, doi:10.3390/su11205674.

19. Patel, L.; Singh, R.; Thottathil, S.D. Land use drivers of riverine methane dynamics in a tropical river basin, India. *Water Res.* **2023**, *228*, 119380, doi:10.1016/j.watres.2022.119380.

20. Santarsiero, V.; Nolè, G.; Lanorte, A.; Tucci, B.; Cillis, G.; Scorza, F.; Murgante, B.; Nolè, G.; Lanorte, A.; Santarsiero, V.; et al. Understanding Land Changes for Sustainable Environmental Management: The Case of Basilicata Region (Southern Italy). *Pollutants* **2021**, *1*, 217–233, doi:10.3390/pollutants1040018.

21. Santarsiero, V.; Nolè, G.; Scorza, F.; Murgante, B. *Geographic Information and Socio-Economic Indicators: A Reading of Recent Territorial Processes in the Test Area of Basilicata Region*; Springer International Publishing, 2022; Vol. 482 LNNS; ISBN 9783031068249.

22. Wohlfart, C.; Mack, B.; Liu, G.; Kuenzer, C. Multi-faceted land cover and land use change analyses in the Yellow River Basin based on dense Landsat time series: Exemplary analysis in mining, agriculture, forest, and urban areas. *Appl. Geogr.* **2017**, *85*, 73–88, doi:10.1016/j.apgeog.2017.06.004.

23. Turner, B.L.; Lambin, E.F.; Reenberg, A. The emergence of land change science for global environmental change and sustainability. *Proc. Natl. Acad. Sci. U. S. A.* **2007**, *104*, 20666–20671, doi:10.1073/pnas.0704119104.

24. Joshi, N.; Baumann, M.; Ehammer, A.; Fensholt, R.; Grogan, K.; Hostert, P.; Jepsen, M.R.; Kuemmerle, T.; Meyfroidt, P.; Mitchard, E.T.A.; et al. A Review of the Application of Optical and Radar Remote Sensing Data Fusion to Land Use Mapping and Monitoring. *Remote Sens. 2016, Vol. 8, Page 70* **2016**, *8*, 70, doi:10.3390/RS8010070.

25. *Consumo di suolo, dinamiche territoriali e servizi ecosistemici Edizione 2021 Rapporto ISPRA SNPA*; ISBN 9788844810597.

26. Bocco, G.; Mendoza, M.; Velázquez, A. Remote sensing and GIS-based regional geomorphological mapping- A tool for land use planning in developing countries. *Geomorphology* **2001**, *39*, 211–219, doi:10.1016/S0169-555X(01)00027-7.

27. Aung, H.P.P.; Aung, S.T. Analysis of land cover change detection using satellite images in Patheingyi Township. *Adv. Intell. Syst. Comput.* **2019**, *744*, 364–373, doi:10.1007/978-981-13-0869-7_41/TABLES/3.

28. Land Take Indicator Available online: https://www.eea.europa.eu/data-and-maps/indicators/land-take-3/assessment (accessed on Feb 21, 2023).

29. World Overview of Conservation Approaches and Technologies WOAT Glossary Available online: https://www.wocat.net/en/glossary/#heading-l (accessed on Feb 21, 2023).

30. EEA *Land take and land degradation in functional urban areas — European Environment Agency*; 2021; ISBN 978-92-9480-465-5.

31. Abuelaish, B.; Teresa, M.; Olmedo, C. Scenario of land use and land cover change in the Gaza Strip using remote sensing and GIS models. *Arab. J. Geosci.*, doi:10.1007/s12517-015-2292-7.

32. Rahman, A.; Kumar, S.; Fazal, S.; Siddiqui, M.A. Assessment of Land use/land cover Change in the North-West District of Delhi Using Remote Sensing and GIS Techniques. *J. Indian Soc. Remote Sens.* **2012**, *40*, 689–697, doi:10.1007/S12524-011-0165-4/TABLES/4.

33. Yonaba, R.; Koïta, M.; Mounirou, L.A.; Tazen, F.; Queloz, P.; Biaou, A.C.; Niang, D.; Zouré, C.; Karambiri, H.; Yacouba, H. Spatial and transient modelling of land use/land cover (LULC) dynamics in a Sahelian landscape under semi-arid climate in northern Burkina Faso. *Land use policy* **2021**, *103*, 105305, doi:10.1016/j.landusepol.2021.105305.

34. Zoungrana, B.J.B.; Conrad, C.; Amekudzi, L.K.; Thiel, M.; Da, E.D.; Forkuor, G.; Löw, F. Multi-temporal landsat images and ancillary data for land use/cover change (LULCC) detection in the Southwest of Burkina Faso, West Africa. *Remote Sens.* **2015**, *7*, 12076–12102, doi:10.3390/rs70912076.

35. Kadavi, P.R.; Lee, C.W. Land cover classification analysis of volcanic island in Aleutian Arc using an artificial neural network (ANN) and a support vector machine (SVM) from Landsat imagery. *Geosci. J. 2018 224* **2018**, *22*, 653–665, doi:10.1007/S12303-018-0023-2.

36. Agapiou, A. Land Cover Mapping from Colorized CORONA Archived Greyscale Satellite Data and Feature Extraction Classification. **2021**, doi:10.3390/land10080771.

37. Eskandari, S.; Jaafari, M.R.; Oliva, P.; Ghorbanzadeh, O.; Blaschke, T. Mapping Land Cover and Tree Canopy Cover in Zagros Forests of Iran: Application of Sentinel-2, Google Earth, and Field Data. **1912**, *12*, 1912, doi:10.3390/rs12121912.

38. Di Palma, F.; Amato, F.; Nolè, G.; Martellozzo, F.; Murgante, B. A SMAP Supervised Classification of Landsat Images for Urban Sprawl Evaluation. *ISPRS Int. J. Geo-Information 2016, Vol. 5, Page 109* **2016**, *5*, 109, doi:10.3390/IJGI5070109.

39. Goldblatt, R.; Deininger, K.; Hanson, G. Utilizing publicly available satellite data for urban research: Mapping built-up land cover and land use in Ho Chi Minh City, Vietnam. *Dev. Eng.* **2018**, *3*, 83–99, doi:10.1016/j.deveng.2018.03.001.

40. Rogan, J.; Miller, J.; Stow, D.; Franklin, J.; Levien, L.; Fischer, C. Land-cover change monitoring with classification trees using Landsat TM and ancillary data. *Photogramm. Eng. Remote Sensing* **2003**, *69*, 793–804, doi:10.14358/PERS.69.7.793.

41. Smiraglia, D.; Ceccarelli, T.; Bajocco, S.; Perini, L.; Salvati, L. Unraveling Landscape Complexity: Land Use/Land Cover Changes and Landscape Pattern Dynamics (1954–2008) in Contrasting Peri-Urban and Agro-Forest Regions of Northern Italy. *Environ. Manage.* **2015**, *56*, 916–932, doi:10.1007/s00267-015-0533-x.

42. Meyfroidt, P.; Roy Chowdhury, R.; de Bremond, A.; Ellis, E.C.; Erb, K.H.; Filatova, T.; Garrett, R.D.; Grove, J.M.; Heinimann, A.; Kuemmerle, T.; et al. Middle-range theories of land system change. *Glob. Environ. Chang.* **2018**, *53*, 52–67, doi:10.1016/J.GLOENVCHA.2018.08.006.

43. Briassoulis, H. The Web Book of Regional Science Sponsored by Analysis of Land Use Change : Theoretical and Modeling Approaches By Helen Briassoulis. **2019**, 248.

44. Nedd, R.; Light, K.; Owens, M.; James, N.; Johnson, E.; Anandhi, A. Knowledge Gaps on a Global Landscape. *Land* **2021**, 1–30.

45. Duhamel, C.; Cover, L. M SC PL O E – C EO M SC PL O E – C EO. *I*.

46. Sallustio, L.; Munafò, M.; Riitano, N.; Lasserre, B.; Fattorini, L.; Marchetti, M. Integration of land use and land cover inventories for landscape management and planning in Italy. *Environ. Monit. Assess.* **2016**, *188*, 1–20, doi:10.1007/s10661-015-5056-7.

47. Azad, A.; Wang, X. Land use change ontology and traffic prediction through recurrent neural networks: A case study in Calgary, Canada. *ISPRS Int. J. Geo-Information* **2021**, *10*, doi:10.3390/ijgi10060358.

48. Keesstra, S.D.; Bouma, J.; Wallinga, J.; Tittonell, P.; Smith, P.; Cerdà, A.; Montanarella, L.; Quinton, J.N.; Pachepsky, Y.; Van Der Putten, W.H.; et al. The significance of soils and soil science towards realization of the United Nations Sustainable Development Goals. **2016**, *2*, 111–128, doi:10.5194/soil-2-111-2016.

49. Jansen, L.J.M.; Di Gregorio, A. Land-use data collection using the "land cover classification system": Results from a case study in Kenya. *Land use policy* **2003**, *20*, 131–148, doi:10.1016/S0264-8377(02)00081-9.

50. Brief, F.A. Land use statistics and indicators. *L. use Stat. Indic.* **2022**, doi:10.4060/cc0963en.

51. Kaiser, E.J.; Godschalk, D.J.; Jr, F.S.C.; Chapin, F.S. Book Review Urban Land Use Planning Book Review. **2015**, 1–3.

52. Meyfroidt, P.; Roy Chowdhury, R.; de Bremond, A.; Ellis, E.C.; Erb, K.H.; Filatova, T.; Garrett, R.D.; Grove, J.M.; Heinimann, A.; Kuemmerle, T.; et al. Middle-range theories of land system change. *Glob. Environ. Chang.* **2018**, *53*, 52–67, doi:10.1016/j.gloenvcha.2018.08.006.

53. Bounoua, L.; DeFries, R.; Collatz, G.J.; Sellers, P.; Khan, H. Effects of land cover conversion on surface climate. *Clim. Change* **2002**, *52*, 29–64, doi:10.1023/A:1013051420309.

54. Ramankutty, N.; Foley, J.A. Characterizing patterns of global land use: An analysis of global croplands data. *Global Biogeochem. Cycles* **1998**, *12*, 667–685, doi:10.1029/98GB02512.

55. Aic, B. Le fonti informative per il monitoraggio del consumo di suolo Information sources for monitoring land take. **2014**, 36–55.

56. Babu, R.G.; Maheswari, K.U.; Zarro, C.; Parameshachari, B.D.; Ullo, S.L. Land-Use and Land-Cover Classification Using a Human Group-Based Particle Swarm Optimization Algorithm with an LSTM Classifier on Hybrid Pre-Processing Remote-Sensing Images. *Remote Sens.* **2020**, *12*, 1–28, doi:10.3390/rs12244135.

57. Rozenstein, O.; Karnieli, A. Comparison of methods for land-use classification incorporating remote sensing and GIS inputs. *Appl. Geogr.* **2011**, *31*, 533–544, doi:10.1016/j.apgeog.2010.11.006.

58. De Fioravante, P.; Luti, T.; Cavalli, A.; Giuliani, C.; Dichicco, P.; Marchetti, M.; Chirici, G.; Congedo, L.; Munafò, M. Multispectral sentinel-2 and sar sentinel-1 integration for automatic land cover classification. *Land* **2021**, *10*, 1–35, doi:10.3390/land10060611.

59. Strollo, A.; Smiraglia, D.; Bruno, R.; Assennato, F.; Congedo, L.; De Fioravante, P.; Giuliani, C.; Marinosci, I.; Riitano, N.; Munafò, M. Land consumption in Italy. *J. Maps* **2020**, *16*, 113–123, doi:10.1080/17445647.2020.1758808.

60. De Fioravante, P.; Strollo, A.; Assennato, F.; Marinosci, I.; Congedo, L.; Munafò, M. High resolution land cover integrating copernicus products: A 2012–2020 map of Italy. *Land* **2022**, *11*, 1–30, doi:10.3390/land11010035.

61. Trisurat, Y.; Shirakawa, H.; Johnston, J.M. Land-use/land-cover change from socio-economic drivers

and their impact on biodiversity in Nan Province, Thailand. *Sustain.* **2019**, *11*, doi:10.3390/su11030649.

62. Barberis, R. CONSUMO DI SUOLO E QUALITÀ DEI SUOLI URBANI.

63. Garcia-Ayllon, S. Urban transformations as indicators of economic change in post-communist Eastern Europe: Territorial diagnosis through five case studies. **2017**, doi:10.1016/j.habitatint.2017.11.004.

64. Obubu, J.P.; Odong, R.; Alamerew, T.; Fetahi, T.; Mengistou, S. Application of DPSIR model to identify the drivers and impacts of land use and land cover changes and climate change on land, water, and livelihoods in the L. Kyoga basin: implications for sustainable management. *Environ. Syst. Res.* **2022**, *11*, doi:10.1186/s40068-022-00254-8.

65. Geist, H.J.; Lambin, E.F. Proximate causes and underlying driving forces of tropical deforestation. *Bioscience* **2002**, *52*, 143–150, doi:10.1641/0006-3568(2002)052[0143:PCAUDF]2.0.CO;2.

66. Guzmán, G.I.; González de Molina, M.; Alonso, A.M. The land cost of agrarian sustainability. An assessment. *Land use policy* **2011**, *28*, 825–835, doi:10.1016/j.landusepol.2011.01.010.

67. Nayak, S.; Mandal, M. Impact of land use and land cover changes on temperature trends over India. *Land use policy* **2019**, *89*, 104238, doi:10.1016/j.landusepol.2019.104238.

68. Afrin, S.; Gupta, A.; Farjad, B.; Ahmed, M.R.; Achari, G.; Hassan, Q.K. Development of Land-Use/Land-Cover Maps Using Landsat-8 and MODIS Data, and Their Integration for Hydro-Ecological Applications. *Sensors* **2019**, *19*, 4891, doi:10.3390/s19224891.

69. Roy Haines-Young, by; Potschin, M. *Common International Classification of Ecosystem Services (CICES) V5.1 Guidance on the Application of the Revised Structure*; 2018;

70. Hamad, R. An Assessment of Artificial Neural Networks, Support Vector Machines and Decision Trees for Land Cover Classification Using Sentinel-2A Data. *Appl. Ecol. Environ. Sci.* **2020**, *8*, 459–464, doi:10.12691/aees-8-6-18.

71. Townshend, J.; Justice, C.; Li, W.; Gurney, C.; McManus, J. Global land cover classification by remote sensing: present capabilities and future possibilities. *Remote Sens. Environ.* **1991**, *35*, 243–255, doi:10.1016/0034-4257(91)90016-Y.

72. Belay, T.; Mengistu, D.A. Land use and land cover dynamics and drivers in the Muga watershed, Upper Blue Nile basin, Ethiopia. *Remote Sens. Appl. Soc. Environ.* **2019**, *15*, 100249, doi:10.1016/j.rsase.2019.100249.

73. Lu, D.; Weng, Q. A survey of image classification methods and techniques for improving classification performance. *https://doi.org/10.1080/01431160600746456* **2007**, *28*, 823–870, doi:10.1080/01431160600746456.

74. Thai, L.H.; Hai, T.S.; Thuy, N.T. Image Classification using Support Vector Machine and Artificial Neural Network. *Int. J. Inf. Technol. Comput. Sci.* **2012**, *4*, 32–38, doi:10.5815/ijitcs.2012.05.05.

75. Löw, F.; Fliemann, E.; Abdullaev, I.; Conrad, C.; Lamers, J.P.A. Mapping abandoned agricultural land in Kyzyl-Orda, Kazakhstan using satellite remote sensing. *Appl. Geogr.* **2015**, *62*, 377–390, doi:10.1016/J.APGEOG.2015.05.009.

76. Radoux, J.; Chomé, G.; Jacques, D.C.; Waldner, F.; Bellemans, N.; Matton, N.; Lamarche, C.; D’Andrimont, R.; Defourny, P. Sentinel-2’s potential for sub-pixel landscape feature detection. *Remote Sens.* **2016**, *8*, doi:10.3390/rs8060488.

77. Estel, S.; Kuemmerle, T.; Alcántara, C.; Levers, C.; Prishchepov, A.; Hostert, P. Mapping farmland

abandonment and recultivation across Europe using MODIS NDVI time series. *Remote Sens. Environ.* **2015**, *163*, 312–325, doi:10.1016/j.rse.2015.03.028.

78. Alshari, E.A.; Gawali, B.W. Development of classification system for LULC using remote sensing and GIS. *Glob. Transitions Proc.* **2021**, *2*, 8–17, doi:10.1016/j.gltp.2021.01.002.

79. Salah, M. A survey of modern classification techniques in remote sensing for improved image classification. *J. Geomatics* **2017**, *11*, 20.

80. Zhu, G.; Blumberg, D.G. Classification using ASTER data and SVM algorithms: The case study of Beer Sheva, Israel. *Remote Sens. Environ.* **2002**, *80*, 233–240, doi:10.1016/S0034-4257(01)00305-4.

81. Burges, C.J.C. A Tutorial on Support Vector Machines for Pattern Recognition. *Data Min. Knowl. Discov. 1998 22* **1998**, *2*, 121–167, doi:10.1023/A:1009715923555.

82. Joshi, N.; Baumann, M.; Ehammer, A.; Fensholt, R.; Grogan, K.; Hostert, P.; Jepsen, M.R.; Kuemmerle, T.; Meyfroidt, P.; Mitchard, E.T.A.; et al. A review of the application of optical and radar remote sensing data fusion to land use mapping and monitoring. *Remote Sens.* **2016**, *8*, 1–23, doi:10.3390/rs8010070.

83. Jin, M.; Dickinson, R.E.; Zhang, D.L. The footprint of urban areas on global climate as characterized by MODIS. *J. Clim.* **2005**, *18*, 1551–1565, doi:10.1175/JCLI3334.1.

84. Battaglia, M.; Annesi, N.; Pierantoni, I.; Sargolini, M. Future perspectives of sustainable development: An innovative planning approach to inner areas. Experience of an Italian alpine region. *Futures* **2019**, *114*, 102468, doi:10.1016/j.futures.2019.102468.

85. Salvati, L.; Zitti, M.; Carlucci, M. In-between regional disparities and spatial heterogeneity: a multivariate analysis of territorial divides in Italy. *J. Environ. Plan. Manag.* **2017**, *60*, 997–1015, doi:10.1080/09640568.2016.1192023.

86. Harris, C.D.; Ullman, E.L. The nature of cities. *Ann. Am. Acad. Pol. Soc. Sci.* **1945**, *242*, 7–17.

87. Report, I. AN AGENDA FOR A REFORMED COHESION POLICY A place-based approach to meeting European Union challenges and expectations. **2009**.

88. Ufficio, D.; Ercole, M.D.; Romano, R. Schede regionali 2018. **2019**.

89. Saganeiti, L.; Mustafa, A.; Teller, J.; Murgante, B. Modeling urban sprinkling with cellular automata. *Sustain. Cities Soc.* **2021**, *65*, 102586, doi:10.1016/J.SCS.2020.102586.

90. Saganeiti, L.; Pilogallo, A.; Scorza, F.; Mussuto, G.; Murgante, B. Spatial indicators to evaluate urban fragmentation in basilicata region. *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)* **2018**, *10964 LNCS*, 100–112, doi:10.1007/978-3-319-95174-4_8.

91. Romano, B.; Zullo, F.; Fiorini, L.; Marucci, A.; Ciabò, S. Land transformation of Italy due to half a century of urbanization. *Land use policy* **2017**, *67*, 387–400, doi:10.1016/j.landusepol.2017.06.006.

92. Pilogallo, A.; Saganeiti, L.; Scorza, F.; Murgante, B. Soil Ecosystem Services and Sediment Production: The Basilicata Region Case Study. In; Springer, Cham, 2020; pp. 421–435.

93. Scorza, F.; Pilogallo, A.; Saganeiti, L.; Murgante, B. Natura 2000 Areas and Sites of National Interest (SNI): Measuring (un)Integration between Naturalness Preservation and Environmental Remediation Policies. *Sustainability* **2020**, *12*, 2928, doi:10.3390/su12072928.

94. Manganelli, B.; Murgante, B.; Saganeiti, L. The social cost of urban sprinkling. *Sustain.* **2020**, *12*, 2236, doi:10.3390/su12062236.

95. Belanche, D.; Casaló, L. V; Orús, C. City attachment and use of urban services: Benefits for smart cities. *Cities* **2016**, *50*, 75–81.

96. Mattingly, K.; Morrissey, J. Housing and transport expenditure: Socio-spatial indicators of affordability in Auckland. *Cities* **2014**, *38*, 69–83, doi:10.1016/j.cities.2014.01.004.

97. Curatella, L.; Scorza, F. Polycentrism and Insularity Metrics for In-Land Areas. *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)* **2020**, *12255 LNCS*, 253–261, doi:10.1007/978-3-030-58820-5_20.

98. Opdam, P.; Wascher, D. Climate change meets habitat fragmentation : linking landscape and biogeographical scale levels in research and conservation. **2004**, *117*, 285–297, doi:10.1016/j.biocon.2003.12.008.

99. Scorza, F.; Las Casas, G.B.; Murgante, B.; Francesco, S.; Las Casas, G.B.; Beniamino, M. That's ReDO: Ontologies and Regional Development Planning. In *Computational Science and Its Applications – ICCSA 2012*; Springer Berlin Heidelberg, 2012; Vol. 7334, pp. 640–652.

100. Las Casas, G.; Scorza, F.; Murgante, B. New Urban Agenda and Open Challenges for Urban and Regional Planning. In *New Metropolitan Perspectives. ISHT 2018*; Calabrò, F., Della Spina, L., Bevilacqua, C., Eds.; Springer: Cham, 2019; Vol. 100, pp. 282–288 ISBN 9783319920986.

101. Tuia, D.; Kaiser, C.; Da Cunha, A.; Kanevski, M. Detection of urban socio-economic patterns using clustering techniques. *Geocomputation urban Plan.* **2009**, *176*, 19–36.

102. Scorza, F.; Pilogallo, A.; Saganeiti, L.; Murgante, B.; Pontrandolfi, P. Comparing the territorial performances of renewable energy sources' plants with an integrated ecosystem services loss assessment: A case study from the Basilicata region (Italy). *Sustain. Cities Soc.* **2020**, *56*, 102082, doi:10.1016/J.SCS.2020.102082.

103. Bacci, E.; Cotella, G.; Vitale Brovarone, E. La sfida dell'accessibilità nelle aree interne: riflessioni a partire dalla Valle Arroscia. *TERRITORIO* **2021**, 77–85, doi:10.3280/TR2021-096007.

104. Zheng, G.; Barbieri, E.; Di Tommaso, M.R.; Zhang, L. Development zones and local economic growth: Zooming in on the Chinese case. *China Econ. Rev.* **2016**, *38*, 238–249.

105. Pollio, C.; Barbieri, E.; Rubini, L.; Di Tommaso, M.R. Attrarre basta per innovare? La via cinese nell'industria dell'auto. *L'industria* **2016**, *37*, 537–564.

106. Abdelfattah, L.; Deponte, D.; Fossa, G. The 15-minute city: Interpreting the model to bring out urban resiliencies. *Transp. Res. procedia* **2022**, *60*, 330–337.

107. Istat.it - Censimento permanente popolazione e abitazioni Available online: https://www.istat.it/it/censimenti/popolazione-e-abitazioni (accessed on Feb 3, 2022).

108. Webster, C. Pricing accessibility: Urban morphology, design and missing markets. *Prog. Plann.* **2010**, *73*, 77–111, doi:10.1016/j.progress.2010.01.001.

109. Alonso, W. A theory of the urban land market. In *Readings in urban analysis*; Routledge, 2017; pp. 1–10 ISBN 1315128063.

110. Carol, H. The hierarchy of central functions within the city. *Ann. Assoc. Am. Geogr.* **1960**, *50*, 419–438.

111. De Toni, A.; Vizzarri, M.; Di Febbraro, M.; Lasserre, B.; Noguera, J.; Di Martino, P. Aligning Inner Peripheries with rural development in Italy: Territorial evidence to support policy contextualization. *Land use policy* **2021**, *100*, 104899, doi:10.1016/J.LANDUSEPOL.2020.104899.

112. Kompil, M.; Aurambout, J.; Ribeiro Barranco, R.; Barbosa, A.; Jacobs-Crisioni, C.; Pisoni, E.; Zulian, G.; Vandecasteele, I.; Trombetti, M.; Vizcaino, M.P.; et al. *European cities: territorial analysis of characteristics and trends - An application of the LUISA Modelling Platform (EU Reference Scenario 2013 - Updated Configuration 2014)*; 2015; ISBN 978-92-79-54594-8 (PDF).

113. Bonaiuto, M.; Fornara, F.; Bonnes, M. Indexes of perceived residential environment quality and neighbourhood attachment in urban environments: a confirmation study on the city of Rome. *Landsc. Urban Plan.* **2003**, *65*, 41–52, doi:10.1016/S0169-2046(02)00236-0.

114. Borlini, B.; Memo, F. Ripensare l'accessibilità urbana. **2009**.

115. Cetin, M. Using GIS analysis to assess urban green space in terms of accessibility: Case study in Kutahya. *Int. J. Sustain. Dev. World Ecol.* **2015**, *22*, 420–424, doi:10.1080/13504509.2015.1061066.

116. Žlender, V.; Ward Thompson, C. Accessibility and use of peri-urban green space for inner-city dwellers: A comparative study. *Landsc. Urban Plan.* **2017**, *165*, 193–205, doi:10.1016/j.landurbplan.2016.06.011.

117. Berry, B.J.L. *Geography of market centers and retail distribution*; Englewood Cliffs, NJ: Prentice-Hall, 1967; Vol. 10; ISBN 0133513041.

118. Ferrario, M. L'accessibilità alle opportunità urbane: uffici postali e altri servizi della città di Milano. **2019**.

119. Saganeiti, L.; Favale, A.; Pilogallo, A.; Scorza, F.; Murgante, B. Assessing urban fragmentation at regional scale using sprinkling indexes. *Sustain.* **2018**, *10*, 3274, doi:10.3390/su10093274.

120. Nesticò, A.; Fiore, P.; D'Andria, E. Enhancement of small towns in inland areas. A novel indicators dataset to evaluate sustainable plans. *Sustain.* **2020**, *12*, doi:10.3390/SU12166359.

121. Baldantoni, P.; Nolè, G.; Lanorte, A.; Tucci, B.; Santarsiero, V.; Murgante, B. Trend Definition of Soil Consumption in the Period 1994–2014 - Municipalities of Potenza, Matera and Melfi. *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)* **2019**, *11621 LNCS*, 683–691, doi:10.1007/978-3-030-24302-9_49.

122. Yuan, Y.; Chen, D.; Wu, S.; Mo, L.; Tong, G.; Total, D.Y.-S. of the; 2019, undefined Urban sprawl decreases the value of ecosystem services and intensifies the supply scarcity of ecosystem services in China. *Elsevier*.

123. Land take in Europe — European Environment Agency Available online: https://www.eea.europa.eu/data-and-maps/indicators/land-take-3/assessment (accessed on Nov 23, 2021).

124. European Environment Agency *EEA Signals 2019-Land and soil in Europe*; 2019; ISBN 9789294800954.

125. Luti, T.; De Fioravante, P.; Marinosci, I.; Strollo, A.; Riitano, N.; Falanga, V.; Mariani, L.; Congedo, L.; Munafò, M. Land consumption monitoring with sar data and multispectral indices. *Remote Sens.* **2021**, *13*, 1–26, doi:10.3390/rs13081586.

126. Richardson, H.W.; Bae, C.H.C. Urban sprawl in Western Europe and the United States. *Urban Spraw. West. Eur. United States* **2017**, 1–325, doi:10.4324/9781315235226/URBAN-SPRAWL-WESTERN-EUROPE-UNITED-STATES-CHANG-HEE-CHRISTINE-BAE-HARRY-RICHARDSON.

127. Fiorini, L.; Zullo, F.; Marucci, A.; Romano, B. Land take and landscape loss: Effect of uncontrolled urbanization in Southern Italy. *J. Urban Manag.* **2019**, *8*, 42–56, doi:10.1016/j.jum.2018.09.003.

128. Tankosić, J.V. Environmental Policy and Air Quality Standards of the European Union. **2022**, *5*, 818–

825.

129. Imbrenda, V.; Quaranta, G.; Salvia, R.; Egidi, G.; Salvati, L.; Prokopovà, M.; Coluzzi, R.; Lanfredi, M. Land degradation and metropolitan expansion in a peri-urban environment. *Geomatics, Nat. Hazards Risk* **2021**, *12*, 1797–1818, doi:10.1080/19475705.2021.1951363.

130. van Vliet, J.; Eitelberg, D.A.; Verburg, P.H. A global analysis of land take in cropland areas and production displacement from urbanization. *Glob. Environ. Chang.* **2017**, *43*, 107–115, doi:10.1016/J.GLOENVCHA.2017.02.001.

131. Puertas, O.L.; Henríquez, C.; Meza, F.J. Assessing spatial dynamics of urban growth using an integrated land use model. Application in Santiago Metropolitan Area, 2010-2045. *Land use policy* **2014**, *38*, 415–425, doi:10.1016/j.landusepol.2013.11.024.

132. Romano, B.; Zullo, F.; Ciabò, S.; Fiorini, L.; Marucci, A. Geografie e modelli di 50 anni di consumo di suolo in Italia. *Scienze&Ricerche* **2015**, *6*, 17–28.

133. Romano, B.; Zullo, F.; Fiorini, L.; Ciabò, S.; Marucci, A. Sprinkling: An approach to describe urbanization dynamics in Italy. *Sustain.* **2017**, *9*, doi:10.3390/su9010097.

134. Amato, F.; Maimone, B.A.; Martellozzo, F.; Nolé, G.; Murgante, B. The effects of urban policies on the development of urban areas. *Sustain.* **2016**, *8*, 297, doi:10.3390/su8040297.

135. Nolè, G.; Murgante, B.; Calamita, G.; Lanorte, A.; Lasaponara, R. Evaluation of urban sprawl from space using open source technologies. *Ecol. Inform.* **2015**, *26*, 151–161, doi:10.1016/J.ECOINF.2014.05.005.

136. Scorza, F.; Saganeiti, L.; Pilogallo, A.; Murgante, B. Ghost planning : the inefficiency of energy sector policies in a low population density region. *Ghost Plan. inefficiency energy Sect. policies a low Popul. density Reg.* **2020**, 34–55, doi:10.3280/ASUR2020-127-S1003.

137. Schatz, E.M.; Bovet, J.; Lieder, S.; Schroeter-Schlaack, C.; Strunz, S.; Marquard, E. Land take in environmental assessments: Recent advances and persisting challenges in selected EU countries. *Land use policy* **2021**, doi:10.1016/j.landusepol.2021.105730.

138. Ghayour, L.; Neshat, A.; Paryani, S.; Shahabi, H.; Shirzadi, A.; Chen, W.; Al-Ansari, N.; Geertsema, M.; Amiri, M.P.; Gholamnia, M.; et al. Performance evaluation of sentinel-2 and landsat 8 OLI data for land cover/use classification using a comparison between machine learning algorithms. *Remote Sens.* **2021**, *13*, doi:10.3390/RS13071349.

139. Birdi, P.K.; Kale, K. V. Accuracy assessment of classification on landsat-8 data for land cover and land use of an urban area by applying different image fusion techniques and varying training samples. *Lect. Notes Electr. Eng.* **2019**, *521*, 189–198, doi:10.1007/978-981-13-1906-8_21/FIGURES/4.

140. Brodley, C.E.; Friedl, M.A. Decision tree classification of land cover from remotely sensed data. *Remote Sens. Environ.* **1997**, *61*, 399–409, doi:10.1016/S0034-4257(97)00049-7.

141. Lu, D.; Weng, Q.; Weng{, Q. International Journal of Remote Sensing A survey of image classification methods and techniques for improving classification performance A survey of image classification methods and techniques for improving classification performance. **2007**, doi:10.1080/01431160600746456.

142. Jia, K.; Wei, X.; Gu, X.; Yao, Y.; Xie, X.; Li, B. Land cover classification using Landsat 8 Operational Land Imager data in Beijing, China. *https://doi.org/10.1080/10106049.2014.894586* **2014**, *29*, 941–951, doi:10.1080/10106049.2014.894586.

143. Shao, Y.; Lunetta, R.S. Comparison of support vector machine, neural network, and CART algorithms

for the land-cover classification using limited training data points. *ISPRS J. Photogramm. Remote Sens.* **2012**, *70*, 78–87, doi:10.1016/J.ISPRSJPRS.2012.04.001.

144. Heydari, S.; Environment, G.M.-R.S. of; 2018, undefined Effect of classifier selection, reference sample size, reference class distribution and scene heterogeneity in per-pixel classification accuracy using 26 Landsat. *Elsevier*.

145. Kwan, C.; Ayhan, B.; Budavari, B.; Lu, Y.; Perez, D.; Li, J.; Bernabe, S.; Plaza, A. remote sensing Deep Learning for Land Cover Classification Using Only a Few Bands., doi:10.3390/rs12122000.

146. Naushad, R.; Kaur, T.; Ghaderpour, E. Deep Transfer Learning for Land Use and Land Cover Classification: A Comparative Study. **2021**, doi:10.3390/s21238083.

147. Zheng, B.; Myint, S.W.; Thenkabail, P.S.; Aggarwal, R.M. A support vector machine to identify irrigated crop types using time-series Landsat NDVI data. *Int. J. Appl. Earth Obs. Geoinf.* **2015**, *34*, 103–112, doi:10.1016/j.jag.2014.07.002.

148. Zheng, B.; Myint, S.W.; Thenkabail, P.S.; Aggarwal, R.M. A support vector machine to identify irrigated crop types using time-series Landsat NDVI data. *Int. J. Appl. Earth Obs. Geoinf.* **2015**, *34*, 103–112, doi:10.1016/J.JAG.2014.07.002.

149. Nath, S.S.; Mishra, G.; Kar, J.; Chakraborty, S.; Dey, N. A survey of image classification methods and techniques. *2014 Int. Conf. Control. Instrumentation, Commun. Comput. Technol. ICCICCT 2014* **2014**, 554–557, doi:10.1109/ICCICCT.2014.6993023.

150. Plaza, A.; Benediktsson, J.A.; Boardman, J.W.; Brazile, J.; Bruzzone, L.; Camps-Valls, G.; Chanussot, J.; Fauvel, M.; Gamba, P.; Gualtieri, A.; et al. Recent advances in techniques for hyperspectral image processing. *Remote Sens. Environ.* **2009**, *113*, S110–S122, doi:10.1016/J.RSE.2007.07.028.

151. Santarsiero, V.; Nolè, G.; Lanorte, A.; Tucci, B.; Cillis, G.; Murgante, B. Remote Sensing and Spatial Analysis for Land-Take Assessment in Basilicata Region (Southern Italy). *Remote Sens.* **2022**, *14*, 1–19, doi:10.3390/rs14071692.

152. Wu, P.; Dietterich, T.G. Improving SVM accuracy by training on auxiliary data sources. *Proceedings, Twenty-First Int. Conf. Mach. Learn. ICML 2004* **2004**, 871–878, doi:10.1145/1015330.1015436.

153. Eskandari, S. Mapping the land uses and analysing the landscape elements in south-western Iran: Application of Landsat-7, field data, and landscape metrics Identification of suitable lands for wood farming by Eucalyptus in Khuzestan Province View project.

154. Adam, E.; Mutanga, O.; Odindi, J.; Abdel-Rahman, E.M. Land-use/cover classification in a heterogeneous coastal landscape using RapidEye imagery: evaluating the performance of random forest and support vector machines classifiers. *http://dx.doi.org/10.1080/01431161.2014.903435* **2014**, *35*, 3440–3458, doi:10.1080/01431161.2014.903435.

155. Jia, K.; Wei, X.; Gu, X.; Yao, Y.; Xie, X.; Li, B. Land cover classification using Landsat 8 Operational Land Imager data in Beijing, China. *https://doi.org/10.1080/10106049.2014.894586* **2014**, *29*, 941–951, doi:10.1080/10106049.2014.894586.

156. Ioannidis, R.; Koutsoyiannis, D. A review of land use, visibility and public perception of renewable energy in the context of landscape impact. *Appl. Energy* **2020**, *276*, 115367, doi:10.1016/J.APENERGY.2020.115367.

157. Saganeiti, L.; Pilogallo, A.; Faruolo, G.; Scorza, F.; Murgante, B. Territorial fragmentation and renewable energy source plants: Which relationship? *Sustain.* **2020**, *12*, doi:10.3390/su12051828.

158. Zhang, X.; Lovati, M.; Vigna, I.; Widén, J.; Han, M.; Gal, C.; Feng, T. A review of urban energy systems

at building cluster level incorporating renewable-energy-source (RES) envelope solutions. *Appl. Energy* **2018**, *230*, 1034–1056, doi:10.1016/j.apenergy.2018.09.041.

159. Scorza, F.; Pilogallo, A.; Saganeiti, L.; Murgante, B.; Pontrandolfi, P. Comparing the territorial performances of renewable energy sources' plants with an integrated ecosystem services loss assessment: A case study from the Basilicata region (Italy). *Sustain. Cities Soc.* **2020**, *56*, 102082, doi:10.1016/j.scs.2020.102082.

160. Sesto, E.; Casale, C. Exploitation of wind as an energy source to meet the world's electricity demand. *J. Wind Eng. Ind. Aerodyn.* **1998**, *74–76*, 375–387, doi:10.1016/S0167-6105(98)00034-8.

161. Poggi, F.; Firmino, A.; Amado, M. Planning renewable energy in rural areas: Impacts on occupation and land use. *Energy* **2018**, *155*, 630–640, doi:10.1016/j.energy.2018.05.009.

162. Waddell, P.; Berry, B.J.L.; Hoch, I. Housing price gradients: The intersection of space and built form. *Geogr. Anal.* **1993**, *25*, 5–19.

163. Falcucci, A.; Maiorano, L.; Boitani, L. Changes in land-use/land-cover patterns in Italy and their implications for biodiversity conservation. *Landsc. Ecol.* **2007**, *22*, 617–631, doi:10.1007/s10980-006-9056-4.

164. Bajocco, S.; Smiraglia, D.; Scaglione, M.; Raparelli, E.; Salvati, L. Exploring the role of land degradation on agricultural land use change dynamics. *Sci. Total Environ.* **2018**, *636*, 1373–1381, doi:10.1016/j.scitotenv.2018.04.412.

165. Bivand, R.; Piras, G. Comparing implementations of estimation methods for spatial econometrics. *J. Stat. Softw.* **2015**, *63*, 1–36, doi:10.18637/jss.v063.i18.

166. Gabellieri, N. La Comunità Europea e il paesaggio rurale : il caso del Set Aside (1988-1993). **2013**, 205–220.

167. Lazio, R. Il consumo di suolo tra politiche ambientali e poli- tiche economiche : un ' analisi dell ' impatto dei Pro- grammi di Sviluppo Rurale nelle aree protette della Regione Lazio. **2015**.

168. Quaranta, G.; Salvia, R.; Salvati, L.; Paola, V. De; Coluzzi, R.; Imbrenda, V.; Simoniello, T. Long-term impacts of grazing management on land degradation in a rural community of Southern Italy: Depopulation matters. *L. Degrad. Dev.* **2020**, *31*, 2379–2394, doi:10.1002/ldr.3583.

169. Statuto, D.; Cillis, G.; Picuno, P. Using Historical Maps within a GIS to Analyze Two Centuries of Rural Landscape Changes in Southern Italy. *L. 2017, Vol. 6, Page 65* **2017**, *6*, 65, doi:10.3390/LAND6030065.

170. Imbrenda, V.; Quaranta, G.; Salvia, R.; Egidi, G.; Salvati, L. Land degradation and metropolitan expansion in a peri-urban environment. *Geomatics, Nat. Hazards Risk* **2021**, *12*, 1797–1818, doi:10.1080/19475705.2021.1951363.

171. Pacheco, F.A.L.; Sanches Fernandes, L.F.; Valle Junior, R.F.; Valera, C.A.; Pissarra, T.C.T. Land degradation: Multiple environmental consequences and routes to neutrality. *Curr. Opin. Environ. Sci. Heal.* **2018**, *5*, 79–86, doi:10.1016/J.COESH.2018.07.002.

172. Land Degradation and Society. **2015**, doi:10.4324/9781315685366.

173. Chalise, D.; Kumar, L.; Kristiansen, P. Land degradation by soil erosion in Nepal: A review. *Soil Syst.* **2019**, *3*, 1–18, doi:10.3390/soilsystems3010012.

174. Wunder, S.; Kaphengst, T.; Frelih-Larsen, A. Implementing Land Degradation Neutrality (SDG 15.3) at National Level: General Approach, Indicator Selection and Experiences from Germany BT - International Yearbook of Soil Law and Policy 2017. In; Ginzky, H., Dooley, E., Heuser, I.L., Kasimbazi,

E., Markus, T., Qin, T., Eds.; Springer International Publishing: Cham, 2018; pp. 191–219 ISBN 978-3-319-68885-5.

175. Nachtergaele, F.O.; Petri, M.; Biancalani, R. *Land degradation*; 2016; ISBN 9781439844519.

176. Sims, N.C.; Barger, N.N.; Metternicht, G.I.; England, J.R. A land degradation interpretation matrix for reporting on UN SDG indicator 15.3.1 and land degradation neutrality. *Environ. Sci. Policy* **2020**, *114*, 1–6, doi:10.1016/j.envsci.2020.07.015.

177. Salvati, L.; Zitti, M.; Carlucci, M. Territorial systems, regional disparities and sustainability: Economic structure and soil degradation in Italy. *Sustain.* **2014**, *6*, 3086–3104, doi:10.3390/su6053086.

178. van der Zanden, E.H.; Verburg, P.H.; Schulp, C.J.E.; Verkerk, P.J. Trade-offs of European agricultural abandonment. *Land use policy* **2017**, *62*, 290–301, doi:10.1016/j.landusepol.2017.01.003.

179. Terres, J.M.; Scacchiafichi, L.N.; Wania, A.; Ambar, M.; Anguiano, E.; Buckwell, A.; Coppola, A.; Gocht, A.; Källström, H.N.; Pointereau, P.; et al. Farmland abandonment in Europe: Identification of drivers and indicators, and development of a composite indicator of risk. *Land use policy* **2015**, *49*, 20–34, doi:10.1016/j.landusepol.2015.06.009.

180. Leal Filho, W.; Mandel, M.; Al-Amin, A.Q.; Feher, A.; Chiappetta Jabbour, C.J. An assessment of the causes and consequences of agricultural land abandonment in Europe. *Int. J. Sustain. Dev. World Ecol.* **2017**, *24*, 554–560, doi:10.1080/13504509.2016.1240113.

181. Keenleyside, C.; Tucker, G. Farmland Abandonment in the EU: an Assessment of Abandonment in the EU: an Assessment of Trends and Prospects A report for WWF Netherlands Clunie Keenleyside and Graham Tucker With contributed data from Tiffany Key Abandonment in the EU: an Assessment of. **2010**.

182. Arnaez, J.; Lasanta, T.; Errea, M.P.; Ortigosa, L. Land abandonment, landscape evolution, and soil erosion in a Spanish Mediterranean mountain region: The case of Camero Viejo. *L. Degrad. Dev.* **2011**, *22*, 537–550, doi:10.1002/ldr.1032.

183. Estel, S.; Kuemmerle, T.; Alcántara, C.; Levers, C.; Prishchepov, A.; Hostert, P. Mapping farmland abandonment and recultivation across Europe using MODIS NDVI time series. *Remote Sens. Environ.* **2015**, *163*, 312–325, doi:10.1016/J.RSE.2015.03.028.

184. Kitano, S. Estimation of determinants of farmland abandonment and its data problems. *Land* **2021**, *10*, doi:10.3390/land10060596.

185. Piekarczyk, J.; Kaźmierowski, C.; Królewicz, S. Relationships between soil properties of the abandoned fields and spectral data derived from the advanced spaceborne thermal emission and reflection radiometer (ASTER). *Adv. Sp. Res.* **2012**, *49*, 280–291, doi:10.1016/j.asr.2011.09.010.

186. Xu, D.; Deng, X.; Guo, S.; Liu, S. Labor migration and farmland abandonment in rural China: Empirical results and policy implications. *J. Environ. Manage.* **2019**, *232*, 738–750, doi:10.1016/j.jenvman.2018.11.136.

187. Grədinaru, S.R.; Iojə, C.I.; Onose, D.A.; Gavrilidis, A.A.; Pətru-Stupariu, I.; Kienast, F.; Hersperger, A.M. Land abandonment as a precursor of built-up development at the sprawling periphery of former socialist cities. *Ecol. Indic.* **2015**, *57*, 305–313, doi:10.1016/j.ecolind.2015.05.009.

188. Lasanta, T.; Arnáez, J.; Pascual, N.; Ruiz-Flaño, P.; Errea, M.P.; Lana-Renault, N. Space–time process and drivers of land abandonment in Europe. *Catena* **2017**, *149*, 810–823, doi:10.1016/j.catena.2016.02.024.

189. Chen, Q.; Xie, H.; Zhai, Q. Management Policy of Farmers' Cultivated Land Abandonment Behavior

Based on Evolutionary Game and Simulation Analysis. *Land* **2022**, *11*, doi:10.3390/land11030336.

190. Renwick, A.; Jansson, T.; Verburg, P.H.; Revoredo-Giha, C.; Britz, W.; Gocht, A.; McCracken, D. Policy reform and agricultural land abandonment in the EU. *Land use policy* **2013**, *30*, 446–457, doi:10.1016/j.landusepol.2012.04.005.

191. Munroe, D.K.; van Berkel, D.B.; Verburg, P.H.; Olson, J.L. Alternative trajectories of land abandonment: Causes, consequences and research challenges. *Curr. Opin. Environ. Sustain.* **2013**, *5*, 471–476, doi:10.1016/j.cosust.2013.06.010.

192. van Leeuwen, C.C.E.; Cammeraat, E.L.H.; de Vente, J.; Boix-Fayos, C. The evolution of soil conservation policies targeting land abandonment and soil erosion in Spain: A review. *Land use policy* **2019**, *83*, 174–186, doi:10.1016/j.landusepol.2019.01.018.

193. Martínez-Valderrama, J.; Ibáñez, J.; Del Barrio, G.; Sanjuán, M.E.; Alcalá, F.J.; Martínez-Vicente, S.; Ruiz, A.; Puigdefábregas, J. Present and future of desertification in Spain: Implementation of a surveillance system to prevent land degradation. *Sci. Total Environ.* **2016**, *563–564*, 169–178, doi:10.1016/j.scitotenv.2016.04.065.

194. García-Ruiz, J.M.; Lana-Renault, N. Hydrological and erosive consequences of farmland abandonment in Europe, with special reference to the Mediterranean region - A review. *Agric. Ecosyst. Environ.* **2011**, *140*, 317–338, doi:10.1016/j.agee.2011.01.003.

195. Goga, T.; Feranec, J.; Bucha, T.; Rusnák, M.; Sačkov, I.; Barka, I.; Kopecká, M.; Papčo, J.; Ot'ahel', J.; Szatmári, D.; et al. A review of the application of remote sensing data for abandoned agricultural land identification with focus on Central and Eastern Europe. *Remote Sens.* **2019**, *11*, doi:10.3390/rs11232759.

196. Perpiña Castillo, C.; Kavalov, B.; Diogo, V.; Jacobs-Crisioni, C.; Batista e Silvia, F.; Lavalle, C. Agricultural land abandonment in the EU within 2015-2030. *JRC113718, Eur. Comm.* **2018**, 1–7.

197. Levers, C.; Schneider, M.; Prishchepov, A. V.; Estel, S.; Kuemmerle, T. Spatial variation in determinants of agricultural land abandonment in Europe. *Sci. Total Environ.* **2018**, *644*, 95–111, doi:10.1016/j.scitotenv.2018.06.326.

198. Kabadayı, M.E.; Ettehadi Osgouei, P.; Sertel, E. Agricultural Land Abandonment in Bulgaria: A Long-Term Remote Sensing Perspective, 1950–1980. *Land* **2022**, *11*, doi:10.3390/land11101855.

199. Mallinis, G.; Emmanoloudis, D.; Giannakopoulos, V.; Maris, F.; Koutsias, N. Mapping and interpreting historical land cover/land use changes in a Natura 2000 site using earth observational data: The case of Nestos delta, Greece. *Appl. Geogr.* **2011**, *31*, 312–320, doi:10.1016/j.apgeog.2010.07.002.

200. Renard, K.G.; Foster, G.R.; Weesies, G.A.; Porter, J.P. RUSLE: Revised universal soil loss equation. *J. Soil Water Conserv.* **1991**, *46*, 30–33.

201. Majhi, A.; Shaw, R.; Mallick, K.; Patel, P.P. Towards improved USLE-based soil erosion modelling in India: A review of prevalent pitfalls and implementation of exemplar methods. *Earth-Science Rev.* **2021**, *221*, 103786, doi:10.1016/j.earscirev.2021.103786.

202. Houser, C.; Hamilton, S. Sensitivity of post-hurricane beach. *Earth Surf. Process. Landforms* **2009**, *34*, 613–628, doi:10.1002/esp.

203. Panagos, P.; Meusburger, K.; Ballabio, C.; Borrelli, P.; Alewell, C. Soil erodibility in Europe: A high-resolution dataset based on LUCAS. *Sci. Total Environ.* **2014**, *479–480*, 189–200, doi:10.1016/j.scitotenv.2014.02.010.

204. Farhan, Y.; Nawaiseh, S. Spatial assessment of soil erosion risk using RUSLE and GIS techniques.

Environ. Earth Sci. **2015**, *74*, 4649–4669, doi:10.1007/s12665-015-4430-7.

205. Mitasova, H.; Hofierka, J.; Zlocha, M.; Iverson, L.R. Modelling topographic potential for erosion and deposition using GIS. *Int. J. Geogr. Inf. Syst.* **1996**, *10*, 629–641, doi:10.1080/02693799608902101.

206. Ting Kuo, K.; Sekiyama, A.; Mihara, M. Determining C Factor of Universal Soil Loss Equation (USLE) Based on Remote Sensing. *IJERD-International J. Environ. Rural Dev.* **2016**, 7–9.

207. Sung, Y.; Lee, G.; Lee, G.; Han, J.; Kim, J.; Lim, K.J.; Kim, K.S. Study on improvement of USLE P factor considering topography and cultivation method. *J. Wetl. Res.* **2019**, *21*, 163–172.

208. Tobler, W.R. A Computer Movie Simulating Urban Growth in the Detroit Region. *Econ. Geogr.* **1970**, *46*, 234–240, doi:10.2307/143141.

209. Ord, J.K.; Getis, A. Local Spatial Autocorrelation Statistics: Distributional Issues and an Application. *Geogr. Anal.* **1995**, *27*, 286–306, doi:10.1111/J.1538-4632.1995.TB00912.X.

210. Peeters, A.; Zude, M.; Käthner, J.; Ünlü, M.; Kanber, R.; Hetzroni, A.; Gebbers, R.; Ben-Gal, A. Getis-Ord's hot- and cold-spot statistics as a basis for multivariate spatial clustering of orchard tree data Available online: http://dx.doi.org/10.1016/j.compag.2014.12.011.

211. Lanorte, A.; Danese, M.; Lasaponara, R.; Murgante, B. Multiscale mapping of burn area and severity using multisensor satellite data and spatial autocorrelation analysis. *Int. J. Appl. Earth Obs. Geoinf.* **2012**, *20*, 42–51, doi:10.1016/j.jag.2011.09.005.

212. Alcantara, C.; Kuemmerle, T.; Prishchepov, A. V.; Radeloff, V.C. Mapping abandoned agriculture with multi-temporal MODIS satellite data. *Remote Sens. Environ.* **2012**, *124*, 334–347, doi:10.1016/j.rse.2012.05.019.

213. Vicente-Serrano, S.M.; Cabello, D.; Tomás-Burguera, M.; Martín-Hernández, N.; Beguería, S.; Azorin-Molina, C.; Kenawy, A. El Drought Variability and Land Degradation in Semiarid Regions: Assessment Using Remote Sensing Data and Drought Indices (1982–2011). *Remote Sens. 2015, Vol. 7, Pages 4391-4423* **2015**, *7*, 4391–4423, doi:10.3390/RS70404391.

214. Anyamba, A.; Tucker, C.J. Analysis of Sahelian vegetation dynamics using NOAA-AVHRR NDVI data from 1981-2003. In Proceedings of the Journal of Arid Environments; 2005; Vol. 63, pp. 596–614.

215. Santarsiero, V.; Nolè, G.; Lanorte, A.; Tucci, B.; Cillis, G.; Scorza, F.; Murgante, B. A Remote Sensing Methodology to Assess the Abandoned Arable Land Using NDVI Index in Basilicata Region. *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)* **2021**, *12954 LNCS*, 695–703, doi:10.1007/978-3-030-86979-3_49.

216. Rivas-Tabares, D.A.; Saa-Requejo, A.; Martín-Sotoca, J.J.; Tarquis, A.M. Multiscaling NDVI series analysis of rainfed cereal in central Spain. *Remote Sens.* **2021**, *13*, 1–21, doi:10.3390/rs13040568.

217. Martínez, B.; Gilabert, M.A. Vegetation dynamics from NDVI time series analysis using the wavelet transform. *Remote Sens. Environ.* **2009**, *113*, 1823–1842, doi:10.1016/j.rse.2009.04.016.

218. Filizzola, C.; Corrado, R.; Falconieri, A.; Faruolo, M.; Genzano, N.; Lisi, M.; Mazzeo, G.; Paciello, R.; Pergola, N.; Tramutoli, V. On the use of temporal vegetation indices in support of eligibility controls for EU aids in agriculture. *Int. J. Remote Sens.* **2018**, *39*, 4572–4598, doi:10.1080/01431161.2017.1395973.

219. Wardlow, B.D.; Egbert, S.L. A comparison of MODIS 250-m EVI and NDVI data for crop mapping: A case study for southwest Kansas. *Int. J. Remote Sens.* **2010**, *31*, 805–830, doi:10.1080/01431160902897858.

220. Bradley, B.A.; Jacob, R.W.; Hermance, J.F.; Mustard, J.F. A curve fitting procedure to derive inter-

annual phenologies from time series of noisy satellite NDVI data. *Remote Sens. Environ.* **2007**, *106*, 137–145, doi:10.1016/j.rse.2006.08.002.

221. Loboda, T.; Krankina, O.; Savin, I.; Kurbanov, E.; Hall, J. *Land management and the impact of the 2010 extreme drought event on the agricultural and ecological systems of European Russia*; 2016; ISBN 9783319426389.

222. Kraemer, R.; Prishchepov, A. V.; Müller, D.; Kuemmerle, T.; Radeloff, V.C.; Dara, A.; Terekhov, A.; Frühauf, M. Long-term agricultural land-cover change and potential for cropland expansion in the former Virgin Lands area of Kazakhstan. *Environ. Res. Lett.* **2015**, *10*, doi:10.1088/1748-9326/10/5/054012.

223. Rivieccio, R.; Sallustio, L.; Paolanti, M.; Vizzarri, M.; Marchetti, M. Where land use changes occur: Using soil features to understand the economic trends in agricultural lands. *Sustain. (United States)* **2017**, *9*, doi:10.3390/su9010078.

224. Quintas-Soriano, C.; Buerkert, A.; Plieninger, T. Effects of land abandonment on nature contributions to people and good quality of life components in the Mediterranean region: A review. *Land use policy* **2022**, *116*, 106053, doi:10.1016/J.LANDUSEPOL.2022.106053.

225. Adebayo, T.S. Environmental consequences of fossil fuel in Spain amidst renewable energy consumption: a new insights from the wavelet-based Granger causality approach. *Int. J. Sustain. Dev. World Ecol.* **2022**, *29*, 579–592, doi:10.1080/13504509.2022.2054877.

226. Jiménez-Olivencia, Y.; Ibáñez-Jiménez, Á.; Porcel-Rodríguez, L.; Zimmerer, K. Land use change dynamics in Euro-mediterranean mountain regions: Driving forces and consequences for the landscape. *Land use policy* **2021**, *109*, doi:10.1016/j.landusepol.2021.105721.

227. Graskemper, V.; Yu, X.; Feil, J.H. Farmer typology and implications for policy design – An unsupervised machine learning approach. *Land use policy* **2021**, *103*, 105328, doi:10.1016/j.landusepol.2021.105328.

228. Valujeva, K.; Debernardini, M.; Freed, E.K.; Nipers, A.; Schulte, R.P.O. Abandoned farmland: Past failures or future opportunities for Europe’s Green Deal? A Baltic case-study. *Environ. Sci. Policy* **2022**, *128*, 175–184, doi:10.1016/j.envsci.2021.11.014.

229. Stringer, L. Can the UN Convention to Combat Desertification guide sustainable use of the world’s soils? *Front. Ecol. Environ.* **2008**, *6*, 138–144, doi:10.1890/070060.

230. Johnston, R.B. Arsenic and the 2030 Agenda for sustainable development. *Arsen. Res. Glob. Sustain. - Proc. 6th Int. Congr. Arsen. Environ. AS 2016* **2016**, 12–14, doi:10.1201/b20466-7.

231. World Bank *World Urbanization Prospects*; 2018; Vol. 12; ISBN 9789211483192.

232. Roca Cladera, J.; Marmolejo Duarte, C.R.; Moix, M. Urban structure and polycentrism: Towards a redefinition of the sub-centre concept. *Urban Stud.* **2009**, *46*, 2841–2868, doi:10.1177/0042098009346329.

233. Santarsiero, V.; Nolè, G.; Scorza, F.; Murgante, B. Evaluation of Spatial Variables Related to the Provision of Essential Services in the Basilicata Region. *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)* **2022**, *13376 LNCS*, 344–353, doi:10.1007/978-3-031-10450-3_29/FIGURES/7.

234. Pilogallo, A.; Scorza, F. Ecosystem services multifunctionality: An analytical framework to support sustainable spatial planning in Italy. *Sustainability* **2022**, *14*, 3346.

235. Pontrandolfi, P.; Dastoli, P.S. Comparing Impact Evaluation Evidence of EU and Local Development

Policies with New Urban Agenda Themes: The Agri Valley Case in Basilicata (Italy). *Sustain. 2021, Vol. 13, Page 9376* **2021**, *13*, 9376, doi:10.3390/SU13169376.

236. Dastoli, P.S.; Scorza, F.; Murgante, B. Impact Evaluation: An Experiment on Development Policies in Agri Valley (Basilicata, Italy) Compared with New Urban Agenda Themes. *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)* **2021**, *12957 LNCS*, 621–633, doi:10.1007/978-3-030-87013-3_48.

237. Talamo, C.; Pinto, M.R.; Viola, S.; Atta, N. Smart cities and enabling technologies: Influences on urban Facility Management services. *IOP Conf. Ser. Earth Environ. Sci.* **2019**, *296*, doi:10.1088/1755-1315/296/1/012047.

238. Yu, L.; Yu, T.; Wu, Y.; Wu, G. Rethinking the identification of urban centers from the perspective of function distribution: A framework based on point-of-interest data. *Sustain.* **2020**, *12*, doi:10.3390/su12041543.

239. Mohring, H. Optimization and scale economies in urban bus transportation. *Am. Econ. Rev.* **1972**, *62*, 591–604.

240. Neirotti, P.; De Marco, A.; Cagliano, A.C.; Mangano, G.; Scorrano, F. Current trends in Smart City initiatives: Some stylised facts. *Cities* **2014**, *38*, 25–36.

241. Balletto, G.; Ladu, M.; Milesi, A.; Borruso, G. A methodological approach on disused public properties in the 15-minute city perspective. *Sustainability* **2021**, *13*, 593.

242. Murgante, B.; Borruso, G.; Lapucci, A. Sustainable Development: Concepts and Methods for Its Application in Urban and Environmental Planning. *Stud. Comput. Intell.* **2011**, *348*, 1–15, doi:10.1007/978-3-642-19733-8_1.

243. Murgante, B.; Borruso, G.; Balletto, G.; Castiglia, P.; Dettori, M. Why Italy first? Health, geographical and planning aspects of the COVID-19 outbreak. *Sustain.* **2020**, *12*, doi:10.3390/su12125064.

244. Louwagie, G. Land recycling in Europe-approaches to measuring extent and impacts. *EEA Rep.* **2016**.

245. Camagni, R.; Cristina, M.; Rigamonti, P. 1-s2.0-S0921800901002543-main.pdf. **2002**, *40*, 199–216.

246. De Rubertis, M. Dinamiche insediative in Italia: spopolamento dei comuni rurali. *Perspect. Rural Dev.* **2019**, 71–96.

247. UNCCD Addressing desertification, land degradation and drought: From commitments to implementation. **2022**, 20.

248. United Nations Convention to Combat Desertification Available online: https://www.unccd.int/ (accessed on Feb 18, 2023).

249. Douglas, I. *Ecosystems and human well-being*; 2017; Vol. 1–5; ISBN 9780128096659.

250. UNITED NATIONS CONVENTION TO COMBAT DESERTIFICATION IN THOSE COUNTRIES EXPERIENCING SERIOUS DROUGHT AND/OR DESERTIFICATION, PARTICULARLY IN AFRICA.

251. Commission, E.; Environment, D.-G. for *Guidelines on best practice to limit, mitigate or compensate soil sealing*; Publications Office, 2014;

252. Terranova, O.; Antronico, L.; Coscarelli, R.; Iaquinta, P. Soil erosion risk scenarios in the Mediterranean environment using RUSLE and GIS: An application model for Calabria (southern Italy). *Geomorphology* **2009**, *112*, 228–245, doi:10.1016/j.geomorph.2009.06.009.

253. Marquard, E.; Bartke, S.; Gifreu I Font, J.; Humer, A.; Jonkman, A.; Jürgenson, E.; Marot, N.;

Poelmans, L.; Repe, B.; Rybski, R.; et al. Land Consumption and Land Take: Enhancing Conceptual Clarity for Evaluating Spatial Governance in the EU Context., doi:10.3390/su12198269.

254. Commission, E. WATER FRAMEWORK DIRECTIVE Available online: https://environment.ec.europa.eu/topics/water/water-framework-directive_en (accessed on Feb 20, 2023).

255. WHO | World Health Organization Available.

256. Sminkey, P. V.; Le Doux, J. *Case management ethics: High professional standards for health care's interconnected worlds*; 2016; Vol. 21; ISBN 9789211333954.

257. Montgomery, M.R. The urban transformation of the developing world. *Science (80-.).* **2008**, *319*, 761–764.

258. World Urbanization Prospects - Population Division - United Nations Available online: https://population.un.org/wup/ (accessed on Nov 3, 2021).

259. Wischmeier, W.H.; Smith, D.D. *Predicting rainfall erosion losses: a guide to conservation planning*; Department of Agriculture, Science and Education Administration, 1978;

260. Moore, I.D.; Wilson, J.P. Length-slope factors for the Revised Universal Soil Loss Equation: Simplified method of estimation. *J. soil water Conserv.* **1992**, *47*, 423–428.

261. Kolli, M.K.; Opp, C.; Groll, M. Estimation of soil erosion and sediment yield concentration across the Kolleru Lake catchment using GIS. *Environ. Earth Sci.* **2021**, *80*, doi:10.1007/s12665-021-09443-7.

262. Terranova, O.; Antronico, L.; Coscarelli, R.; Iaquinta, P. Soil erosion risk scenarios in the Mediterranean environment using RUSLE and GIS: An application model for Calabria (southern Italy). *Geomorphology* **2009**, *112*, 228–245, doi:10.1016/J.GEOMORPH.2009.06.009.

263. Cencetti, C.; P, D.E.R.; Fredduzzi, A.; Marchesini, I. Erosione dei suoli e grass gis: esempi di applicazione. *Geomatics Work. Vol. 5 - 6th Ital. GRASS users Meet. proceedings, Roma, 14-15 April. 2005* **2005**, 1–16.

264. Foster, G.R.; Meyer, L.D.; Onstad, C.A. An erosion equation derived from basic erosion principles. *Trans. ASAE* **1977**, *20*, 678–682.

Acknowledgements

Vorrei riservare questo spazio per ringraziare tutti coloro che hanno contribuito con il loro instancabile supporto, alla realizzazione ed al completamento di questa tesi di dottorato.

Innanzitutto, desidero ringraziare il Professor Beniamino Murgante, Tutor e guida scientifica, che in questi anni mi ha seguita con pazienza e competenza, punto di riferimento dell'intero percorso di Dottorato. Grazie per avermi accolta con entusiasmo all'interno del gruppo di ricerca presso il laboratorio LISUT dell'Università della Basilicata.

Ringrazio con profondo affetto e stima i miei Co-Tutor: l'Ing. Dott. Gabriele Nolè e il Dott. Antonio Lanorte per avermi dato la possibilità di interfacciarmi al mondo della ricerca, per la costruttiva esperienza scientifica svolta presso il CNR IMAA in questi anni. Grazie per avermi sempre incoraggiata e spronata in ogni fase della ricerca e del lavoro fatto insieme.

Ringrazio il Prof. Francesco Scorza per i continui confronti e dialoghi costruttivi e stimolanti.

Ringrazio i miei colleghi e colleghe del Laboratorio LISUT (Lucia, Angela, Priscilla, Luigi e Simone) per il tempo che mi hanno dedicato in questi anni. Grazie per i suggerimenti, i consigli, confronti, stimoli e i momenti di svago. Un ringraziamento particolare va alla Dott.ssa Ing. Lucia Saganeiti per esserci sempre con dolcezza e competenza, grazie per il supporto nelle fasi finali di stesura di questo elaborato.

Un ringraziamento speciale, colmo di affetto e gratitudine, va al mio collega Biagio, per tutto il lavoro svolto insieme presso il CNR IMAA, per l'aiuto, l'affetto ed il sostegno umano e scientifico.

Supplement

Papers on international and national peer reviewed journals indexed on Scopus during the PhD periods (2020, 2021 and 2022):

2020

Santarsiero, V., Nolè, G., Lanorte, A., Tucci, B., Saganeiti, L., Pilogallo, A., Scorza, F., & Murgante, B. (2020). "**Assessment of Post Fire Soil Erosion with ESA Sentinel-2 Data and RUSLE Method in Apulia Region (Southern Italy).**" *In: Gervasi O. et al. (eds) Computational Science and Its Applications – ICCSA 2020. ICCSA 2020. Lecture Notes in Computer* Science, vol 12252, 590–603.
DOI: https://doi.org/10.1007/978-3-030-58811-3_43

Muzzillo, V., Pilogallo, A., Saganeiti, L., Santarsiero, V., Murgante, B., & Bonifazi, A. (2021). "Res and habitat quality: Ecosystem services evidence based analysis in basilicata area." In: Bevilacqua C., Calabrò F., Della Spina L. (eds) New Metropolitan Perspectives. NMP 2020. Smart Innovation, Systems and Technologies, vol 178, 1714–1721.
DOI: https://doi.org/10.1007/978-3-030-48279-4_162

Nolè, L., Pilogallo, A., Saganeiti, L., Bonifazi, A., Santarsiero, V., Santos, L., & Murgante, B. (2021). "Land use change and habitat degradation: A case study from tomar (portugal)." 135 In: Bevilacqua C., Calabrò F., Della Spina L. (eds) New Metropolitan Perspectives. NMP 2020. Smart Innovation, Systems and Technologies, vol 178, 1722–1731.
DOI: https://doi.org/10.1007/978-3-030-48279-4_163

Scorza, F., Murgante, B., Pilogallo, A., Saganeiti, L., Santarsiero, V., Faruolo, G., Fortunato, G., Izzo, C., Piro, R., & Bonifazi, A. (2021). **"Best practices of agro-food sector in basilicata region (italy): Evidences from innovagro project."** *In: Bevilacqua C., Calabrò F., Della Spina L. (eds) New Metropolitan Perspectives. NMP 2020. Smart Innovation, Systems and Technologies, vol 178, 1706–1713.*
DOI: https://doi.org/10.1007/978-3-030-48279-4_161

Curatella, L., Fortunato, G., Pilogallo, A., Saganeiti, L., Santarsiero, V., Bonifazi, A., & Scorza, F. (2021). **"Polycentrism and effective territorial structures: Basilicata region case study."** *In: Bevilacqua C., Calabrò F., Della Spina L. (eds) New Metropolitan Perspectives. NMP 2020. Smart Innovation, Systems and Technologies, vol 178, 1689–1696*.
DOI: https://doi.org/10.1007/978-3-030-48279-4_159

Nolè, G., Santarsiero, V., Lanorte, A., Tucci, B., Capurso, V. A., Ronco, F. V., & Murgante, B. (2020, July). **"Model of Post Fire Erosion Assessment Using RUSLE Method, GIS Tools and ESA Sentinel DATA."** In *International Conference on Computational Science and Its Applications* (pp. 505-516). Springer, Cham.
DOI: https://doi.org/10.1007/978-3-030-58814-4_36

2021

Santarsiero, V., Nolè, G., Lanorte, A., Tucci, B., Cillis, G., Scorza, F., & Murgante, B. (2021, September). A remote sensing methodology to assess the abandoned arable land using NDVI index in Basilicata region. In *International Conference on Computational Science and Its Applications* (pp. 695-703). Springer, Cham.
DOI: https://doi.org/10.1007/978-3-030-86979-3_49

Cillis, G., Nolè, G., Lanorte, A., Santarsiero, V., Tucci, B., Scorza, F., & Murgante, B. (2021, September). Soil erosion and land degradation in rural environment: A preliminary GIS and remote-sensed approach. In *International Conference on Computational Science and Its Applications* (pp. 682-694). Springer, Cham.
DOI: https://doi.org/10.1007/978-3-030-86979-3_48

Tucci, B., Nolè, G., Lanorte, A., Santarsiero, V., Cillis, G., Scorza, F., & Murgante, B. (2021, September). Assessment and monitoring of soil erosion risk and land degradation in arable land combining remote sensing methodologies and rusle factors. In *International Conference on Computational Science and Its Applications* (pp. 704-716). Springer, Cham.
DOI: https://doi.org/10.1007/978-3-030-86979-3_50

Cillis, G., Tucci, B., Santarsiero, V., Nolè, G., & Lanorte, A. (2021). Understanding Land Changes for Sustainable Environmental Management: The Case of Basilicata Region (Southern Italy). *Pollutants*, *1*(4), 217-233.
DOI: https://doi.org/10.3390/pollutants1040018

Santarsiero, V., Nolè, G., Lanorte, A., Tucci, B., Ronco, F. V., Capurso, V. A., & Murgante, B. (2021, September). A Remote Sensing and Geo-Statistical Approaches to Mapping Burn Areas in Apulia Region (Southern Italy). In *International Conference on Computational Science and Its Applications* (pp. 670-681). Springer, Cham.
DOI: https://doi.org/10.1007/978-3-030-86979-3_47

2022

Santarsiero, V., Nolè, G., Lanorte, A., Tucci, B., Cillis, G., & Murgante, B. (2022). Remote Sensing and Spatial Analysis for Land-Take Assessment in Basilicata Region (Southern Italy). *Remote Sensing*, *14*(7), 1692.
DOI: https://doi.org/10.3390/rs14071692

Santarsiero, V., Nolè, G., Scorza, F., & Murgante, B. (2022). Geographic Information and Socio-Economic Indicators: A Reading of Recent Territorial Processes in the Test Area of Basilicata Region. In *INTERNATIONAL SYMPOSIUM: New Metropolitan Perspectives* (pp. 2104-2111). Springer, Cham.
DOI: https://doi.org/10.1007/978-3-031-06825-6_202

Santarsiero, V., Nolè, G., Lanorte, A., & Murgante, B. (2022). Towards Quantifying Rural Environment Soil Erosion: RUSLE Model and Remote Sensing Based Approach in Basilicata (Southern Italy). In *INTERNATIONAL SYMPOSIUM: New Metropolitan Perspectives* (pp. 2163-2172). Springer, Cham.
DOI: https://doi.org/10.1007/978-3-031-06825-6_208

Santarsiero, V., Lanorte, A., Nolè, G., Cillis, G., & Murgante, B. (2022). Land Use Change Evaluation in an Open-Source GIS Environment: A Case Study of the Basilicata Region (Southern Italy). In *International Conference on Computational Science and Its Applications* (pp. 364-372). Springer, Cham.
DOI: https://doi.org/10.1007/978-3-031-10450-3_31

Scorza, F., Santopietro, L., Corrado, S., Dastoli, P. S., Santarsiero, V., Gatto, R., & Murgante, B. (2022). Training for Territorial Sustainable Development Design in Basilicata Remote Areas: GEODESIGN Workshop. In *International Conference on Computational Science and Its Applications* (pp. 242-252). Springer, Cham.

DOI: https://doi.org/10.1007/978-3-031-10545-6_17

Santarsiero, V., Nolè, G., Scorza, F., & Murgante, B. (2022). Evaluation of Spatial Variables Related to the Provision of Essential Services in the Basilicata Region. In *International Conference on Computational Science and Its Applications* (pp. 344-353). Springer, Cham.
DOI: https://doi.org/10.1007/978-3-031-10450-3_29

Cillis, G., Santarsiero, V., Nolè, G., Lanorte, A., & Murgante, B. (2022). Abandoned Agricultural Areas: From Quantification to Qualification by Integration of GIS and Remote Sensing. In *International Conference on Computational Science and Its Applications* (pp. 354-363). Springer, Cham.
DOI: https://doi.org/10.1007/978-3-031-10450-3_30

Cillis, G., Lanorte, A., Nolè, G., Santarsiero, V., & Ronco, F. (2022). Fire Planning of Urban-Rural Interface in Open Source GIS Environment: Case Study of the Apulia Region (southern Italy). *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *48*, 4.
DOI: 10.5194/isprs-archives-XLVIII-4-W1-2022-97-2022

Saganeiti, L., Pilogallo, A., Scorza, F., Murgante, B., Santarsiero, V., & Nolè, G. (2022). Quantitative assessment of local warming based on urban dynamics. In *Multi-Chaos, Fractal and Multi-fractional Artificial Intelligence of Different Complex Systems* (pp. 277-289). Academic Press.
DOI: https://doi.org/10.1016/B978-0-323-90032-4.00017-1

Lanorte, Antonio and Cillis, Giuseppe and Nolè, Gabriele and Santarsiero, Valentina and Tucci, Biagio and Ronco, Francesco Vito, Simple Indices for Assessing Long-Term Fire Occurrence Prediction in the Mediterranean Area (Apulia Region-Italy) Using Ncep Seasonal Climate Forecasting System. Preliminary Results. Available at SSRN: https://ssrn.com/abstract=4173671 or http://dx.doi.org/10.2139/ssrn.4173671

Other papers on international and national peer reviewed journals indexed on Scopus during the 2019 year:

Santarsiero, V., Nolè, G., Lanorte, A., Tucci, B., Baldantoni, P., & Murgante, B. (2019, July). Evolution of soil consumption in the municipality of Melfi (Southern Italy) in relation to renewable energy. In *International Conference on Computational Science and Its Applications* (pp. 675-682). Springer, Cham.
DOI: https://doi.org/10.1007/978-3-030-24302-9_48

Baldantoni, P., Nolè, G., Lanorte, A., Tucci, B., Santarsiero, V., & Murgante, B. (2019, July). Trend Definition of Soil Consumption in the Period 1994–2014-Municipalities of Potenza, Matera and Melfi. In *International Conference on Computational Science and Its Applications* (pp. 683-691). Springer, Cham.
DOI: https://doi.org/10.1007/978-3-030-24302-9_49

Participation at national and international conferences

2020

- National conference: **“EGU general assembly – European Geosciences Union”**. *On-line conference.*
- International conference “**NMP - 2020: New Metropolitan Perspectives.”** *On-line conference.*
- International conference: **“ICCSA 2020 - International Conference on Computational Science and Applications”**. *On-line conference.*

2021

- International conference: **“ICCSA 2021 - International Conference on Computational Science and Applications”**. *Cagliari (Italy).*
- “Urbing_phd”, *Salerno (Italy)*

2022

- International conference**: “ICCSA 2021 - International Conference on Computational Science and Applications”**. *Malaga (Spain).*
- International conference **“NMP - 2020: New Metropolitan Perspectives.”** On-line conference.
- **“**Urbing phd”, *Salerno (Italy).*
- XIII Giornata Internazionale di Studi INU/13°Inu International Study Day*, Naples (Italy)*

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Google Scholar
Number of published documents: 25
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