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Assessing and managing the relationship between urban growth and greening goals for sustainable urban development. An innovative methodological approach.

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Abstract

As part of the transformation and qualifying processes of cities and territories, considering the challenges posed by climate change and the ecological transition in progress, the need to define new methods for sustainable urban planning capable of analyzing, evaluating, and managing the complex relationship between urban growth and greening processes to guarantee adequate levels of urban liveability and sustainability has emerged in an increasingly evident way.

The thesis deals with the complex relationship between urban growth and urban greening processes. Precisely, after the analysis of the state-of-the-art on the topics of urban growth, compact and dispersed, and greening processes, such as urban green areas, ecosystem services, and nature-based solutions, and the innovative methods and tools employed in urban planning to pursue this purpose, an innovative methodological approach based on innovative information technologies, such as artificial intelligence models and remote sensing techniques, and advanced geospatial analysis techniques, also shared via the web, for assessing and managing urban growth and greening processes is defined.

The proposed methodological approach is applied to specific case studies, demonstrating that planners can employ this approach to make informed decisions regarding evaluating and managing urban growth and greening processes to make these processes truly sustainable.

The analyses and experiments led within the thesis bring out the need for flexible, innovative, and integrated urban planning approaches that appropriately direct the urban and territorial planning decision-making processes for achieving sustainable and liveable development.

Nell'ambito dei processi di trasformazione e di qualificazione delle città e dei territori, alla luce delle sfide poste dal cambiamento climatico e dalla transizione ecologica in atto, emerge, in maniera sempre più chiara ed evidente, la necessità di definire nuovi metodi per la pianificazione urbana sostenibile capaci di analizzare, valutare e gestire la complessa relazione tra i processi di crescita e di inverdimento urbano al fine di garantire adeguati livelli di vivibilità e di sostenibilità urbana.

Il lavoro di tesi esplora la complessa relazione tra i processi di sviluppo e di inverdimento urbano. Nello specifico, dopo un'attenta revisione della letteratura riguardante i concetti di sviluppo e inverdimento urbano, nonché degli strumenti e dei metodi innovativi impiegati nella pianificazione urbana per perseguire tali obiettivi, viene proposto un nuovo approccio metodologico. Questo nuovo approccio metodologico si basa sull'utilizzo di tecnologie dell'informazione innovative e su avanzate tecniche di analisi geospaziale, anche fruibili via web, per una pianificazione e gestione più efficace dei processi di sviluppo e inverdimento urbano.

L'approccio metodologico proposto è applicato su specifici casi di studio e i risultati ottenuti dimostrano come tale approccio possa essere effettivamente utile ai pianificatori per prendere decisioni informate riguardo la valutazione e la gestione dei processi di sviluppo e di inverdimento urbano affinché questi possano essere effettivamente sostenibili nel tempo.

Le analisi e le sperimentazioni condotte all'interno della tesi fanno emergere la necessità di approcci flessibili, innovativi e integrati che sappiano indirizzare opportunamente le decisioni relative alla pianificazione urbana e territoriale per il perseguimento degli obiettivi di sostenibilità.

Introduction

1. Problem statement

Around 50% of the world's population resides in urban areas, serving as central hubs for economic activities, employment, and overall economic progress. Projections indicate that by 2050, urban areas will accommodate approximately 75% of the global population. Consequently, the future growth patterns of cities can raise intricate socio-economic and environmental challenges that need to be appropriately handled. Such challenges include unsustainable development trends which negatively affect carbon emissions, air and water quality, and waste control.

The unprecedented urbanization phenomena and the increasing environmental awareness have demonstrated that the intricate connection between urban growth and the pursuit of green objectives has become a crucial focus for urban planning research and practice. With cities persistently growing and transforming, it is imperative to comprehend the complex interdependencies between urban growth patterns and ecological sustainability. This understanding is essential for fostering harmonious, resilient, and enjoyable urban environments. In recent years, the need for urbanization and urban growth to deal with environmental challenges has reached significant consideration within the scientific community. The investigation and harmonization of these two objectives have inevitably become one of the most critical challenges of the 21st century.

Specifically, creating a balance between urban growth patterns, land take containment, climate adaptation, and availability of urban green areas and their related benefits is a challenge that impacts the urban dwellers' quality of life, economic performance, and the social cohesion of cities. Promoting social, economic, and land use growth while safeguarding the ongoing provision of resources and environmental benefits of natural systems in urban areas has become a great challenge for urban planners and decision-makers. This ambition aligns with the goals of the New Urban Agenda. It offers a pathway to realize the Sustainable Development Goals (SDGs), focusing on Goal 11, which seeks to raise inclusivity, safety, resilience, and sustainability in cities and human settlements. Moreover, the principles of green growth hold significant relevance in the context of the post-COVID-19 recovery efforts.

The interplay between urban growth and greening goals has been known since the end of the twentieth century. According to Naess (1997), for example, two sustainable urban development models contrast with each other: models that support the development processes of dense and compact cities to avoid negative impacts of dispersed urban growth and models focused on the development of green cities, a type of urban structure more open and permeable in which coexist the combination of buildings and green areas.

Even if the existence of such a complex relationship is known, observation and studies on the ongoing tensions between urban growth processes – both compact and dispersed – and the imperative to push the advantages afforded by green spaces within city limits are still limited. Moreover, as urban systems rapidly expand globally, comprehending their spatial evolution and implications for sustainable development remains complex and contentious. A robust conceptualization and empirical evidence are essential to understanding the spatial dynamics of urban systems and their effects and impacts. The physical growth of cities manifests in diverse spatial patterns, often resulting in urban sprawl driven by various factors and causing multidimensional adverse impacts on the economy, society, and ecology. It is crucial to consider the impacts of urban growth processes on natural areas at larger scales and the neighborhood and household levels to pursue measured and well-qualified planning policies to guarantee urban sustainability.

This objective can be pursued only by implementing a well-calibrated set of planning policies and strategies to manage potential conflicts and generate positive interaction between urban growth and greening goals to pursue sustainability and liveability. At the same time, the definition of planning policies and strategies relies on the definition of effective and efficient decision support tools to monitor, assess, quantify, and update such processes.

2. Research questions and objectives

Urban areas' growth patterns generally assume two forms: compact or dispersed. However, within the scientific literature, it has been demonstrated that both negatively impact the natural ecosystem of urban systems. While a compact city may lose urban green areas due to densification interventions, urban sprawl determines a loss of urban green spaces in the urban area outskirts due to the suburbanization phenomenon.

Understanding the relationship between urban growth, both compact and dispersed, and greening to support sustainable urban planning is complex. This complex relationship between compact and dispersed urban growth has been investigated in many ways within the scientific literature. However, it emerged that understanding this complex relationship to support sustainable urban planning requires specific techniques and tools, which must be innovative and flexible. In this context, innovative technologies and spatial analysis techniques have become imperative. Following these assumptions, the research project addressed in this study intends to answer the following research questions:

- How can innovative technologies, such as artificial intelligence techniques and geospatial analysis, contribute to a better understanding urban growth patterns and implementing urban greening planning policies?
- How can these methods support urban planners and decision-makers in managing the complex relationship between these two policies and, therefore, define sustainable urban growth and greening policies?
- How can information about urban growth and greening policies be shared with different stakeholders and make them accessible and consultable?

3. Structure of the thesis

This thesis follows the following structure to answer these research questions and pursue the defined research objective.

First, in Chapter 1, the analysis of the new and consolidated practices on urban growth and greening goals is performed. Indeed, despite the concepts of urban growth, the greening of the city, and the management of their complex relationship to achieve sustainable urban development are widely spreading within the scientific and public discourse, these concepts are not deeply and fully understood. Therefore, these concepts have been clarified in Chapter 1. The theoretical foundation on urban growth patterns of cities, both compact and dispersed, is analyzed, emphasizing concepts, definitions, and main characteristics of such kinds of city planning policies and development patterns. Then, the main concepts related to the policies of greening the city are defined. Indeed, in this case, while the idea of greening the city is currently spreading in the scientific and public discourse, it is unclear what introducing nature in the city means and which concepts are used in planning and designing urban green areas within the context of sustainable urban planning. In Chapter 1, therefore, the most relevant concepts for urban greening planning policies, such as urban green areas, ecosystem services, and nature-based solutions, are presented and analyzed. Finally, after introducing the complex relationship between urban growth and urban greening, the methods, tools, and decision support systems defined and employed to manage this relationship are presented and investigated.

Using innovative methods and tools based on Information and Communication Technology, especially remote sensing technologies and innovative spatial analysis techniques, is imperative to support and manage the relationship between urban growth and greening. In this regard, valuable methods are represented by innovative artificial intelligence techniques, geographic information systems (GIS) for spatial analysis, and web-based geographic information systems (WebGIS). Artificial intelligence techniques consent to analyze large volumes of data, including demographic information, traffic patterns, energy consumption, and more, through tools and techniques that can enhance city development's efficiency, sustainability, and overall effectiveness and make informed decisions. GIS consents to having a large amount of data and automatized analysis computation. Both these technologies can be integrated into an innovative discipline, which is widely recognized as Geospatial Artificial Intelligence (GeoAI), which can also be used via the web and integrated within WebGIS. In Chapter 2, these three technologies and their main characteristics are presented and analyzed, emphasizing GeoAI applications and WebGIS development for sustainable urban planning. Specifically, in the first part of Chapter 2, the advantages of the combined use of artificial intelligence and geographic information systems techniques are presented, while in the second part, a systematic literature review of the GeoAI applications for sustainable urban planning is performed. To date, a general recognition of the role of artificial intelligence and its application combined with geospatial techniques in the urban planning scientific and technical sector is lacking and, therefore, a systematic literature review of the state of the art about artificial intelligence and geographic information systems applications in the urban planning context is performed. Following that review, a general analysis of the role of web-GIS within the urban planning field is also conducted. Moreover, focusing on Italian WebGIS platforms, an in-depth analysis of those WebGIS is also carried out.

Despite the common understanding that innovative methods and analysis could support policymakers in managing urban growth and greening goals sustainably, approaches and techniques are not fully defined and not applied to make informed urban plans and strategies. The development and operationalization of such analysis are still far from being developed and used. Therefore, following these needs, Chapter 3 presents a comprehensive operational approach to managing urban growth and greening policies towards sustainable urban development. The proposed framework consists of three subsequent steps: (i) the identification of urban and greening changes over time to assess, evaluate, and monitor the changes in these two planning policies during an observation period and the analysis of their co-relation with population dynamics towards urban sustainability; (ii) the development of a multi-criteria decision support system to identify, assess and quantify the potential of urban areas to undergo for dense urban growth processes and greening interventions; (iii) the development of a Web-GIS platform prototype to visualize, manage and update such information by stakeholders, who, for many reasons, could be interested in that analysis about urban and greening development.

Chapter 4 describes the results of applying the proposed approach to case studies. Specifically, the analysis of urban and greening changes and their co-relation with population dynamics towards urban sustainability over time is tested by selecting Matera (Basilicata, Italy) as a case study. The multi-criteria framework to assess the potential of urban areas for densification and/or greening interventions is tested in a union of municipalities located in the Emilia Romagna region (Italy), which is Terre d'Argine and encompasses four municipalities: Campogalliano, Carpi, Novi di Modena and Soliera. The WebGIS platform prototype and its functionalities are tested through the applications above as the primary goal of the proposed WebGIS prototype is to support sustainable urban planning and, specifically, sustainable use of land.

Finally, the author presents the conclusions, the recommendations, and the further developments of this research work.

1. New and consolidated practices to assess the relationship between urban growth and greening goals

1. Urban growth and greening goals: concepts and definitions

Urban areas are growing very fast worldwide due to the urbanization process. Population growth projections suggest that more than two-thirds of the world's population is expected to live in cities by 2050, with a marked increase from today's level of 55 percent (United Nations, 2019). This rapid urban development and the need for climate change adaptation represent a great challenge for urban planning. Therefore, spatial planning approaches and frameworks are needed to cope with urban growth's environmental, social, and economic effects.

Urban growth is a complex process. Its main drivers are population growth, increased motorization rates, and income capacity, such as Gross Domestic Product (GDP) (Haase et al., 2013). The urban growth process of cities depends on historical and contextual factors and can assume different spatial patterns, mainly identified as compact and dispersed development.

Dispersed development indicates the unplanned expansion of urban areas into surrounding rural or undeveloped land (Burchfield et al., 2006). It often leads to low-density development on vacant land and greenfield sites, causing adverse economic, social, and environmental effects (European Environment Agency, 2016). Scientists and policymakers recognize the need to manage dispersed urban growth processes and their adverse consequences by promoting compact urban development through urban densification interventions. This latter urban growth pattern generally involves increasing the population density within existing urban areas to promote more efficient land use.

In urban research and practice, it is widely recognized that both compact and dispersed urban growth processes (Jenks, 2000; Holden & Norland, 2005; Westerink et al., 2012) represent a threat to the provision of green and natural areas putting pressure on urban natural ecosystems (Nuissl et al., 2009; Gupta et al., 2012; Haaland & van Den Bosch, 2015; Elmqvist et al., 2018; Wolff & Haase, 2019). Indeed, while urban sprawl produces scattered low-density development without urban green areas, implementing densification and re-utilization interventions produces a loss of urban green areas. In this context, spatial planning approaches to handle urban growth's effects on urban green areas (UGAs) must balance preserving and enhancing green spaces.

Urban green areas (UGAs) are the natural areas in urban environments and include parks, open spaces, green squares, residential gardens, and urban forests. UGAs are essential in cities as they provide a wide range of ecosystem services that contribute to the well-being of humans and the environment. Ecosystem services offered by UGAs include air quality improvement, temperature regulation, stormwater management, biodiversity support, physical and mental health benefits, noise reduction, socialization, educational and cultural value, and economic benefits. Therefore, the planning and management of UGAs to preserve and enhance these ecosystem services are essential in creating sustainable, livable, and resilient urban areas.

Over the past decade, there has been a growing recognition in urban planning of the imperative to effectively manage the interplay between urban growth and the pursuit of greening goals. This acknowledgment has also been driven by the necessity to adopt planning strategies to realize the United Nations' vision of making *"cities and human settlements inclusive, safe, resilient, and sustainable"* (United Nations, 2015). Consequently, sustainable urban development has gained prominence in this urban research and practice field (Hansen et al., 2019). Generally, the roots of sustainability in urban planning literature can be traced back to the 1970s when the concept began to emerge. Despite being somewhat radical initially, the 1987 World Commission on Environment and Development's Our Common Future (WCED, 1987), also known as the "Brundtland Report", played a pivotal role in mainstreaming sustainability. Therefore, the concept of sustainability has been integrated into urban planning theory, advocating for promoting the urban growth process while guaranteeing urban livability.

The issue under extensive discussion, examination, and resolution pertains to the prevalent conflicts between the imperative of limiting soil consumption by limiting urban dispersion, advocating for compact cities, and ensuring high levels of livability of the built environment through the preservation of existing green spaces and the establishment of new ones. This discourse has gained increased attention in recent years due to the challenges posed also by climate change. The imperative to address urban sprawl and its diverse negative consequences by advocating for compact urban development and urban reutilization has been widely recognized in urban science and policymaking. However, ensuring a high quality of life for urban residents requires comprehensive perspectives on the types of compact development to promote, particularly concerning urban green spaces within densification processes.

Although there is a general understanding of the need to balance urban growth with environmental protection to guarantee urban sustainability and livability, the concepts and definitions involved in managing the interplay between these two kinds of planning policies are poorly understood. Furthermore, the scientific discourse and debate on methods, tools, and frameworks in managing such interplay has never been defined.

Therefore, within this Chapter, the author aims to illustrate the new and consolidated practices existing within the current urban research and practice to assess the relationship between urban growth and greening goals. Before exploring the tools and frameworks available within the scientific literature to analyze and manage the complex relationship between these two kinds of planning policies, the author defined the two main patterns of urban growth processes (compact and dispersed) and clarified what greening goals mean. First, the definitions, concepts, and characteristics of compact and dispersed urban development are defined. Then, the author introduced the main concepts and definitions of greening goals, such as green areas, ecosystem services, and nature-based solutions. Finally, the scientific literature on tools and frameworks to manage and assess the complex relationship between these two kinds of development within urban research and practice has been investigated.

1.1. Urban growth processes: compact versus dispersed

Urban growth has become an unavoidable process driven by the social and economic development of urban areas. The urban growth process evolves and assumes different spatial patterns and forms depending on cities' historical and ecological background. Specifically, two main urban growth patterns can be identified: compact and dispersed.

Dispersed urban growth processes refer to a complex phenomenon usually associated with low-density suburban development and dispersed urban structure (Galster et al., 2001; Song & Knaap, 2004). The scattered pattern of urban growth and expansion determined by the sprawling of cities determined severe environmental and social impacts on urban areas and natural ecosystems. The sprawling of cities, notably, increased traffic congestion and transportation costs, promoted social segregation and determined the loss of biodiversity and natural ecosystems (Inostroza et al., 2013; Artmann et al., 2019).

Specifically, Burton (2000) pointed out that urban sprawl is connected to increased car dependency within the emerging urban peripheries. Furthermore, along with the forest cover alteration due to urban sprawl (Miller, 2012), this latter also determined substantial communal and social costs associated with low-density development (Deal and Schunk, 2004) as well as informal urban development (Inostroza, 2017).

Urban sprawl, as the dominant form of urban growth in the developing world era, has been criticized for its adverse impact on the environment, society, and economy (Newman & Kenworthy, 1989; Jenks et al., 1996; Ewing, 1997; de Roo & Miller, 2000; Burton, 2000; Breheny, 1992; Elkin et al., 1991). This happened also because there was increasing attention to sustainability as a globally significant issue. This allowed for a new planning paradigm, the compact and dense development of cities, considered a sustainable response to urban sprawl.

Before deepening the various definitions of compact cities within the urban research and practice field, it is essential to understand and define the roots of this concept.

The compact city concept as the primary strategy to avoid urban sprawl's social, economic, and environmental problems and achieve sustainable urban development was born in the 1990s. Before this date, the term was not fully developed as a planning concept. Indeed, in the 1930s, it was just a response to urban expansion and the need to preserve the environment and agricultural land (O'Toole, 2009). This is demonstrated by the fact that the compact city term was coined in 1973 by two mathematical scientists, George Dantzig and Thomas L. Saaty, in their book *Compact City: A Plan for a Livable Urban Environment*.

Focusing on the compact city as a multidimensional strategy for achieving sustainable urban development gained support through various policy frameworks and urban agendas promoted from 1990 onwards. One notable example is Agenda 21, introduced by the United Nations Conference on Environment and Development in 1992. It underscored the importance of adopting a more efficient and compact urban form to diminish resource consumption, advocate environmental principles, and enhance resilience to the impacts of climate change. Additionally, the United Nations Framework Convention on Climate Change (UNFCCC) acknowledged the potential of compact cities to mitigate greenhouse gas emissions. This recognition stems from their capacity to reduce dependence on private vehicles, promote energy-efficient buildings, and facilitate the utilization of renewable energy sources in urban areas.

The growing interest in the compact city concept determined a wide array of definitions, making it impossible to have a standard definition for this urban form. For example, Dantzig and Saaty (1973) first defined that a compact city is characterized by a highly dense and low car-dependent urban form, clearly identified and distinguished by the surrounding areas, high diversity of land uses, and social equity and self-sufficiency. According to Newman and Kenworthy (1989), compact cities have more intensive land use, centralized activities, and higher densities. Elkin and McLaren (1991) describe the compact city development process as intensifying the use of space in the city with higher residential densities and centralization. Breheny (1992) emphasized that *"compact cities have high density and mixed-use, with growth encouraged within the existing urban boundaries"*. According to Thomas and Cousins (1996), the main characteristics of a compact city are compactness, pedestrian, bicycle, public transport accessibility, and high respect for wildlife. For Churchman (1999), a compact city is characterized by high residential density, the principle of centrality, diversified land use, and a well-defined area that limits development outside of this area. Specifically, the characteristics that, according to the author, define it are the high density, decline in population density, built environment, of homes, the use of diversified soil, understood as the varied and copious offer of services and equipment distributed horizontally than vertically, and, finally, the intensity, understood as the increase in population, as well as the development of new density in correspondence with the nodes or sub-centers. Neuman (2005) pointed out that a compact city is characterized by 14 characteristics, including high residential and employment density, the diversified use of soil, the proximity of soil uses, the contiguous urban development, the high waterproofing of the soil and the high degree of accessibility and road connectivity, both internal and external. Daneshpour and Shakibamanesh (2011) described a compact city as *"a city that mixes shared civic spaces with concentrated arrangements of structures"*. The Organization for Economic Cooperation and Development (OECD, 2012) defines the main characteristics of compact cities, such as dense and compact development, public transport systems, and accessibility to local services and jobs.

In general, a compact city is characterized by high density, a high functional mix, with high availability and good accessibility to services and equipment, as well as by the presence of an efficient public transport service and the possibility of moving by foot or bike. In addition to these characteristics, the growing attention to environmental and energy effects has enriched the definition of compact cities.

Along with the massive research in the scientific literature, many policies and strategies related to compact cities have developed since the 1990s onwards to reduce the use of private cars and minimize the loss of rural areas. In addition to these environmental benefits, compact cities are characterized by social benefits, such as easy accessibility to urban services by guaranteeing equity and distributional justice. According to Williams et al. (1996), thanks to these characteristics, the compact city can be considered a stimulating and lively environment capable of stimulating social and economic interactions. The compact city is more energy-efficient and less polluting than other urban development strategies and, therefore, is considered an efficient strategy for contrasting urban sprawl (Abdullahi et al., 2015; Chang & Chen, 2016; Dempsey, 2010).
The policies and strategies developed over the years are also accompanied by much research on identifying the main characteristics of compact cities. Specifically, many authors developed different frameworks and methods to measure the compactness of urban areas. From these frameworks, it is also possible to identify the main themes and characteristics of the compact city concept. They often include factors related to the urban form, accessibility, and transportation system. Table 1.1 summarizes the main indicators in the most important framework developed worldwide.

Table 1.1. Summarization of the main compact city indicators developed in the scientific literature.

Author/s	Aims and scope of the study	Dimensions	Indicators
Burton (2002)	Measure urban compactness by developing a large set of urban compactness indicators	Density	Density of population
			Density of built form
			Density of subcentres
			Density of housing
		Mix of use	Provision of facilities
			Horizontal mix of uses
			Vertical mix of uses
		Intensification	Increase in population
			Increase in development
			Increase in density of new development
			Increase in density of sub-centres
Song and Knaap (2004)	Measure of urban form	Street Design and Circulation Systems	Int_Connectivity
			Blocks_Peri
			Blocks
			Length_Cul-De-Sac

			Ext_Connectivity
		Density	Lot_Size
			SFDU_Density
			Floor_Space
		Land Use Mix	Mix_Actual
			Mix_Zoned
		Accessibility	Com_Dis
			Bus_Dis
			Park_Dis
		Pedestrian Access	Ped_Com
			Ped_Transit
OECD (2012)	Define policies of compact city	Dense and proximate development patterns	Population and urban land growth
			Population density on urban land
			Retrofitting existing urban land
			Intensive use of buildings
			Housing form
			Trip distance
			Urban land cover
		Urban areas linked by public transport systems	Trips using public transport
			Proximity to public transport
		Accessibility to local services and jobs	Matching jobs and homes
			Matching local services and homes
			Proximity to local services
			Trips on foot and by bicycle
		Environmental	Public spaces and green areas
			Transport energy use
			Residential energy use
		Social	Affordability
		Economic	Public service
Kotharkar et al. (2014)	Measure compact urban form	Density	Gross population density & Average (built up area) density
			Land use spilt up
			Average land consumption per person
		Density distribution/dispersion	Density profile
			Population by distance to the center of gravity or CBD
			Density gradient
		Transportation network	Mode share
			Average trip length
			Road network density
			Congestion index
			Walkability index
		Accessibility	Public transport Accessibility
			Service Accessibility Index

		Shape Performance	Dispersion Index
		Mixed Use Land Composition	Land use split up
			Ratio of residential to non-residential use
			Ratio of built to open area
Shi et al. (2016)	Assess effects of a compact city on urban resources and environment	High density	Compactness index
			Population density of built-up area
			Proportion of built-up area in total urban area
		Traffic Accessibility	Number of buses per 10000 people
			Road area per capita
		Mixed Land Use	Shannon's diversity index
Nadeem et al. (2021)	Scale the potential of compact city development	Landscape Ecology	Land Use and Land Cover
			Saturation level
		Density	Gross population density
			Built-up area density
			Land use split up
			Average land consumption per person
		Density Distribution	Density profile
			Population through distance to CBD
		Transportation Network	Mode share
			Average trip length
			Road network density
			Congestion index
		Accessibility	Service accessibility
			Public transport accessibility
		Shape performance	Dispersion index
		Mixed-Use Land Consumption	Ratio of residential to non-residential use
			The ratio of built-up to open area

Compact city indicators encompass the physical and spatial attributes that define a compact city and are utilized for assessing the effectiveness of compact city policies (Burton, 2002; Lee et al., 2015; OECD, 2012). Various researchers have discussed multiple compact city indicators, with variations based on individual perspectives and the characteristics of cities designed around this concept. Dantzig and Saaty (1973) introduced composite indicators like urban forms, spatial features, and social functions. Similarly, Lee et al. (2015), and the OECD (2012) have formulated compact city indices incorporating factors ranging from density, and urban form to public transport usage, and proximity to services.

Therefore, compact development is considered the opposite of dispersed development. Urban planners, administrators, and policymakers push to encourage and promote compact development patterns. However, both compact and dispersed development patterns are found to be responsible for UGAs' loss and their services and functions' deterioration. In general, urban growth processes may lead to the elimination or deterioration of existing green spaces in ways that are challenging to reverse. The reduction and degradation of urban green areas can contribute to health issues, compounding the impact of other adverse factors in the urban environment, such as inequalities, air pollution, noise, and scarce physical activity. Urban planners need to better plan and manage such complex interplay between these policies to mitigate health risks and promote the health benefits of urban living.

1.2. Greening goals: urban green areas, ecosystem services, and nature-based solutions

The strategic introduction and maintenance of vegetation, green spaces, and natural elements within urban environments, defined in this study as urban greening, plays a crucial role in mitigating the adverse effects of urbanization, known as urban environmental challenges (Pan et al., 2021), and developing more sustainable and livable cities.

As highlighted by the new urban ecology research field, there is an urgent need to overcome the classical divide between natural and urban ecosystems through specific urban planning actions. In this context, as Niemelä (1999) stated, natural areas are an integral part of the urban environment and, therefore, must be protected and promoted.

UGAs are a range of forests, parks, trees, green allotments, and cemeteries (Breuste et al., 2013). The most common definition of UGAs used by European studies is the one proposed by the European Urban Atlas (European Commission, 2011). According to it, the UGAs are identified in the Urban Atlas code 14100. They include public green areas used predominantly for recreation, such as gardens, zoos, parks, and suburban natural areas and forests, or green areas bordered by urban areas managed or used for recreational purposes. In policy terms, it is essential to focus on UGAs that are open to the public. Therefore, in a more general way, they can be defined as all parks and green areas that are publicly accessible and usable by citizens and provide multiple benefits.

The importance of UGA planning and management for improving urban environment quality of life is widely supported both by the scientific literature (Artmann et al., 2019; Andersson et al., 2014; Niemelä, 2014) and by the policies that, at various levels, have been promoted over time. Specifically, Target 11.7 of the 11-th Sustainable Development Goals set by the United Nations (2015) defines that *"by 2030, it is necessary to provide universal access to safe, inclusive and accessible, green and public spaces, in particular for women and children, older persons and persons with disabilities"*.

UGAs benefit urban dwellers (Pauleit, 2003) and wildlife (Goddard et al., 2010). Specifically, UGAs provide different environmental benefits, which include air filtration (Jim & Chen, 2008), urban cooling (Aram et al., 2019), noise reduction (Tashakor et al., 2023; Dzhambov & Dimitrova, 2014), energy consumption reduction (Zhu et al., 2022; Simpson, 2002), carbon storage (Ariluoma et al., 2021; Sun et al., 2019) and rainwater infiltration (Técher & Berthier, 2023; Huang et al., 2023). UGAs contribute to mitigating climate change (Nero et al., 2017) and have essential ecological functions (Mell, 2009).

Besides these environmental benefits, UGAs improve urban residents' physical and mental health (Kabisch et al., 2016). UGAs contribute to improving mental health by reducing stress and promoting relaxation. These spaces promote physical health improvements through active and passive activities, such as experiencing nature, meeting other people, doing sports, and walking. These spaces stimulate physical activity by reducing obesity, improving the immune system, significantly reducing external noise and exposure to air pollution, and improving sleep (WHO, 2016).

In the scientific literature, the multiple direct and indirect benefits supplied by UGAs are conceptualized as ecosystem services (ES). This concept was introduced in 1997 by Costanza et al. to raise awareness for biodiversity, ecosystem preservation, and conservation (Birkhofer et al., 2015) and for the human benefits derived from their functions.

The ES concept received recognition among policymakers with the publication of the Millennium Ecosystem Assessment (MEA) (2005) by the United Nations. The MEA study defines ESs as "*the ecological characteristics, functions, or processes that directly or indirectly contribute to human wellbeing: the benefits people derive from functioning ecosystems"*. ESs considered in the MEA study are shown in Figure 1.1.

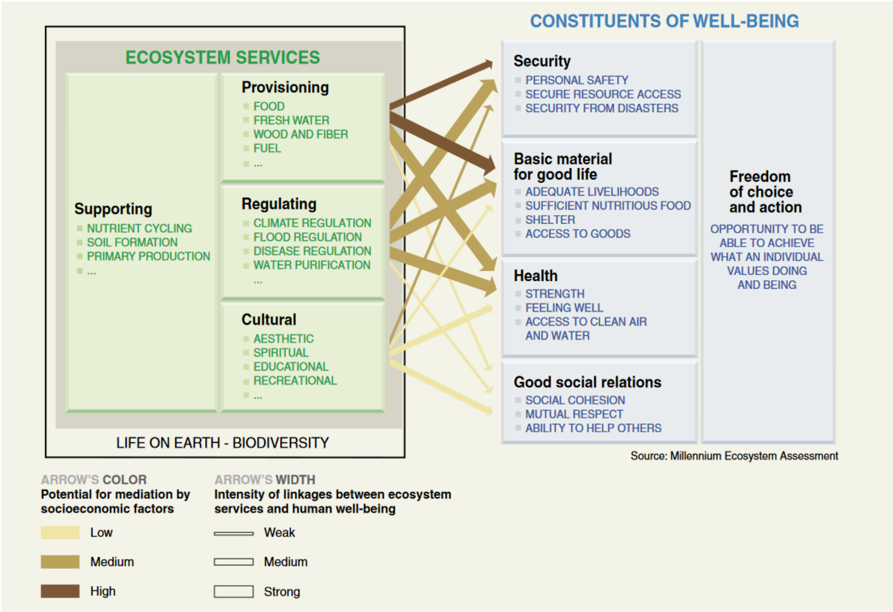


Figure 1.1. ES framework developed by MEA (2005).

They include supporting ecosystem services (ecosystem functions underlying other ecosystem services, e.g., primary production, soil formation); provisioning services (products obtained from ecosystems, e.g., food, fiber, and water), regulating services (benefits obtained from the regulation of ecosystem processes, e.g., climate regulation, flood regulation) and cultural services (non-material benefits people obtain from ecosystems, e.g., recreational, aesthetic, and spiritual benefit). The MA analyzed the influence of ES changes on human well-being, highlighting an “anthropogenic” approach to this concept, according to which people are an integral part of ecosystems. The key result of this study is that currently, 60 percent of the ecosystem services evaluated are degraded or used in an unsustainable way due to human changes in ecosystems that happened rapidly and extensively.

Another global initiative is represented by the Economics of Ecosystems and Biodiversity (2010), which is focused on "making the values of nature visible." Its main objective is to integrate the economic value of ecosystem services in the decision-making process at all levels. The ecosystem services recognized by the TEEB global initiative are shown in Figure 1.2. They comprise provisioning, regulating, habitat, and cultural ecosystem services.

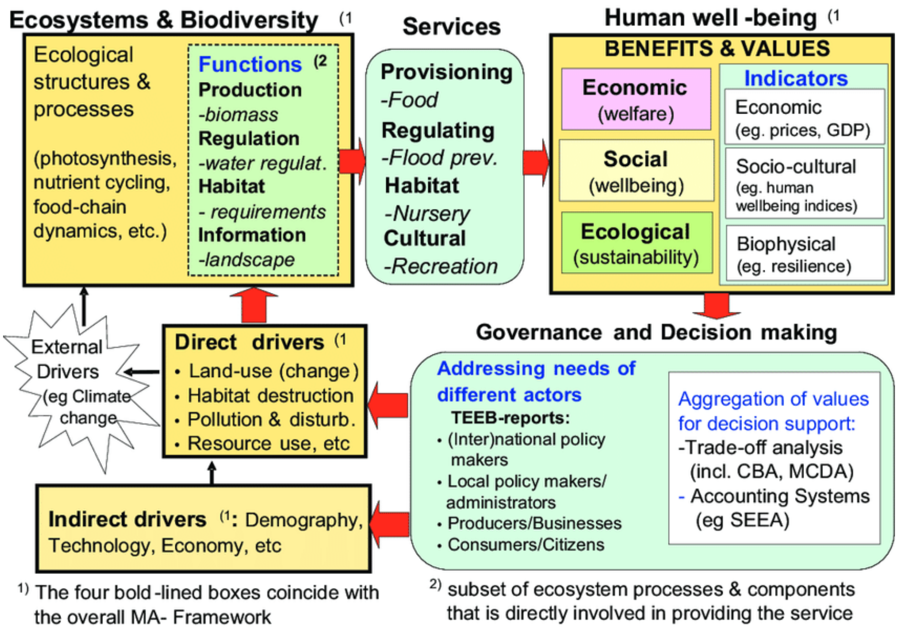


Figure 1.2. ES framework developed by TEEB (2010).

Another classification frame of reference for ESs delivered by UGAs is the Common International Classification of Ecosystem Services (CICES) for Integrated Environmental and Economic Accounting, which is proposed by the European Environment Agency (Figure 1.3). This framework attempted to synthesize the different MA and TEEB classification systems developed to date. For this reason, it has become an essential reference framework within the ES research area. Unlike the MA and TEEB classification, CICES merges supporting/habitat services with regulating services into a new category identified as "regulating and maintenance services" (Haines-Young & Potschin, 2018).

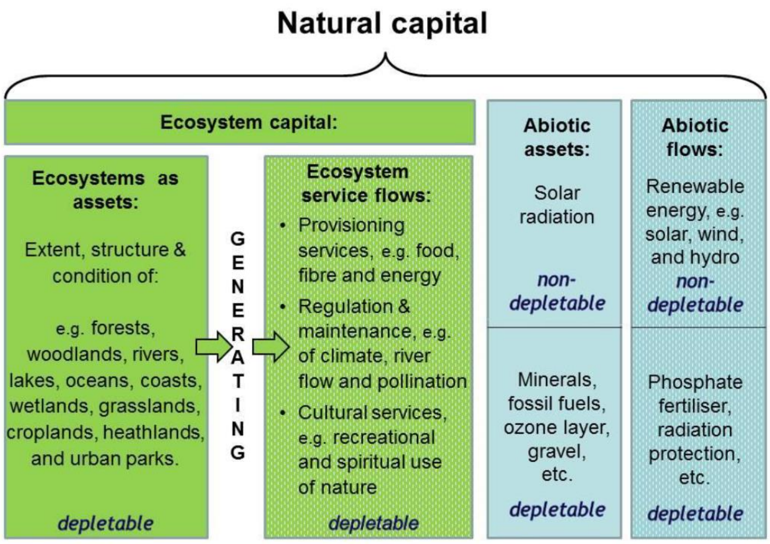


Figure 1.3. ES framework developed by Haines-Young and Potschin (2018).

Various global policy initiatives acknowledge the significance of ES, making their mapping and assessment a priority for all European Union (EU) Member States after adopting the EU 2020 Strategy on Biodiversity. The objective of the Strategy is to break biodiversity loss and ecosystem service degradation in the EU by 2020, with efforts to restore them as much as possible. To enhance understanding of ecosystems and their services in the EU, Member States were called to conduct mapping and assessment of ecosystems and their services within national territories by 2014, including their economic value. In the strategy context, 'mapping' involves spatially defining ecosystems, quantifying their condition, and enumerating the services they provide. On the other hand, 'evaluation' refers to translating this scientific evidence into understandable information for policymakers and the decision-making process (Maes et al., 2016; Maes et al., 2012).

From that moment, research on ESs about the definition and implementation of ESs methodological framework for spatial planning practices has been developed meaningfully (Gómez-Baggethun & Barton, 2013; Geneletti et al., 2020; Vignoli et al., 2021). They provided an overview of the most relevant urban ESs, identifying and measuring their value in urban planning management and decision-making with different methodologies and frameworks.

Although the importance of green areas in urban environments has been widely recognized, the research within the scientific literature has demonstrated how the urbanization process and, therefore, the conversion of natural areas into semi-natural, semi-artificial, and artificial areas represent a significant threat to the provision of ESs (Peng et al., 2017; Song & Deng, 2017; Cao et a., 2021). The lack of ES supply has been found in compact cities, as Larondelle and Lauf (2016) demonstrated. Within their study, the authors, through the supply and demand of urban ESs assessment, detected that the most dense and compact structures are characterized by negative balance for almost every urban ES. These results align with what Jim (2013) discussed, who emphasized that compact cities are generally less green and, therefore, need for cities to be compact and green. Also, Larondelle et al. (2014), after mapping regulating ES across European cities, noticed that the compact city concept should be redefined to promote enough green spaces.

In general, the regulation of urban growth processes and the solutions to the negative impacts of urban growth on natural areas related to the protection, enhancement, and promotion of green and natural spaces in an urban environment are of great importance. Nature-inspired solutions for addressing the multiple environmental, social, and economic challenges associated with the loss of ESs due to urban growth processes are represented by nature-based solutions (NBSs).

The NBS concept is the latest addition to the urban greening lexicon (Nesshöveret al., 2017), as it was first introduced in 2012 by the International Union for Conservation of Nature (IUCN). However, European countries adopted the NBS concept in 2015, when the European Commission established an expert group focused on Nature-Based Solutions and the Revitalization of Urban Environments (European Commission, 2015) to create a dedicated funding stream within the Horizon 2020 funding program. In that context, the European Commission (2016) stated that "*NBSs are solutions inspired and supported by nature, which are cost-effective, simultaneously provide environmental, social and economic benefits and help build resilience. Such solutions bring more, and more diverse, nature and natural features and processes into cities, landscapes, and seascapes, through locally adapted, resource-efficient and systemic interventions".*

Similarly, the IUCN defines NBS as *"actions to protect, sustainably manage and restore (create) natural or modified ecosystems that address societal challenges (including urban ones) effectively and adaptively, simultaneously providing human well-being and biodiversity benefits"* (Cohen-Shacham et al., 2016).

Building on this definition, therefore, NBSs are supposed to be the most suitable nature-inspired solution for addressing the challenges associated with rapid urbanization and urban growth processes, such as ecosystem services degradation, including urban heat island effects and flooding, as well as weakened human health and wellbeing (Tzoulas et al., 2007; Demuzere et al., 2014). For these reasons, they should be part of the planning processes, as Pan et al. (2021) revealed in their study.

To facilitate the implementation of the NBSs in the urban planning research and practice for addressing the challenges related to urban growth processes, Almenar et al. (2021), building on Eggermont et al. (2015) and (Cohen-Shacham et al., 2016), proposed three main types of NBSs, as shown in Figure 1.4.

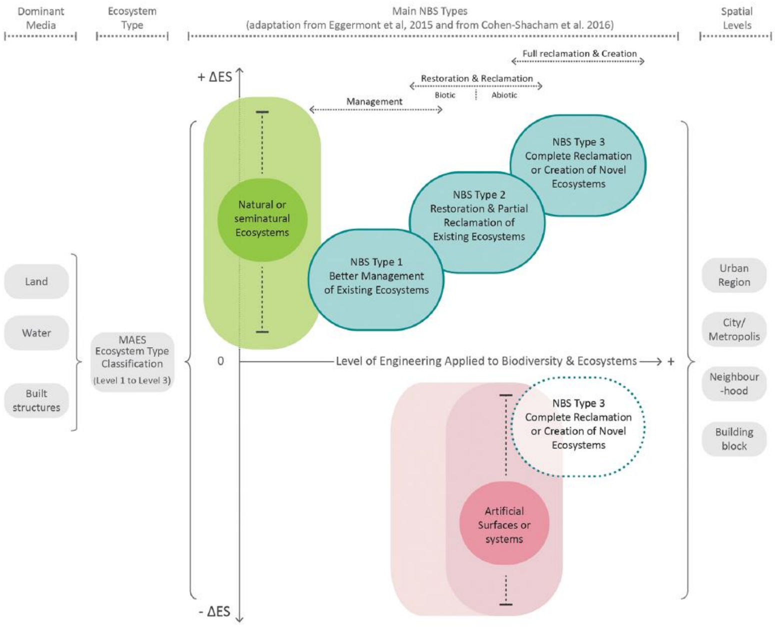


Figure 1.4. Conceptualization of NBS types according to Almenar et al. (2021).

The NBS Type 1 comprises solutions enabling improved utilization and management of current natural and naturalistic ecosystems, excluding physical alterations. NBS Type 2 encompasses solutions and processes designed for ecosystem restoration, further categorized into reclamation and restoration. NBS Type 3 involves the creation of new ecosystems, encompassing solutions that entail extensive (a large portion of the area) and intensive (high degree) modifications of existing ecosystems. An example would be transforming a heavily artificialized urban green area into a highly naturalized one.

The NBS Type 1 and 2 correspond mainly to ecosystem-based adaptation for protecting, managing, and restoring spatial structures (Geneletti & Zardo, 2016), while NBS Type 3 refers only to urban case studies. The most frequently studied NBS Type, 3 per type of media, are green roofs, green walls, woodland-like structures, urban grasslands and meadows, urban scrubland and heathland, horticultural gardens, vegetated filter strips, swales, constructed wetlands, natural(ised) wetlands, natural(ised) ponds, and bioretention basins.

Although the NBS concept is broad and its innovation an intrinsic part, the usefulness of employing such solutions for addressing urban challenges is recognized. However, it is still needed to be proved in urban planning practice.

2. Frameworks and tools to manage the "complex" relationship between urban growth and greening goals

The complex relationship between urban growth and greening goals was already discussed by De Roo (2000) and Neuman (2005). It involves contending with the conflicting goals of mitigating adverse effects arising from urban growth while simultaneously enhancing environmental well-being and alleviating societal inequities such as insufficient green spaces.

Evaluating and overseeing the interplay between urban growth and greening objectives requires employing various frameworks, tools, and methods. Frameworks are organized processes that specifically compare various policy or project alternatives. Although the analytical techniques for comparison are not predetermined, tools encompass specific analytical methods such as multi-criteria analysis, indices and indicators, and cost-benefit analysis, which are employed to facilitate this comparison (Gasparatos, 2010). Over time, different frameworks and tools have been provided to address the complex relationship between urban growth and greening goals and define proper urban planning strategies to address that issue.

Consolidated frameworks to manage this interplay are represented by the Strategic Environmental Assessment (SEA) and Environmental Impact Assessment (EIA). They have been formally implemented in the European context through the EU Directives 2001/42/EC and 85/337/EEC to define established procedures for evaluating policies and projects that significantly impact the environment. Indeed, conducting comprehensive SEAs to evaluate the potential social, economic, and environmental consequences of urban growth planning strategies and greening improvement is more effective than EIAs or other project sustainability assessment tools, such as BREEAM Communities, LEED Neighborhoods (Conticelli et al., 2020). The need to integrate green quality issues in the early stages of the urban growth planning process through effective and comprehensive SEAs is also emphasized in the study conducted by Khoshkar et al. (2018). In their study, the authors tried to enhance understanding of the current green space management practices in two municipalities undergoing densification in Stockholm, Sweden. Through interviews with municipal planners, among the other challenges identified, such as the site-specific conditions for densification projects, conflicting interests among involved and affected stakeholders, and issues related to green quality management, they also found the limited utilization of environment assessment tools, including SEAs.

Within the scientific literature, different conceptual tools based on criteria exist to help decision-makers manage and assess the interplay between urban growth – compact and dispersed – and greening goals. Among them, Artmann et al. (2019), for instance, developed a systematic conceptual framework to balance the two aspects of smart, compact cities and smart green cities. The proposed indicator-based framework (Figure 1.5) is based on four dimensions: 1) smart environment of compact and green cities, 2) smart multifunctionality of compact and green cities (economic, social, environmental), 3) smart government for compact and green cities and 4) smart governance for compact and green cities. Each pillar comprises 12 factors defined by 39 indicators for smart compact cities and 44 for smart green cities, respectively.

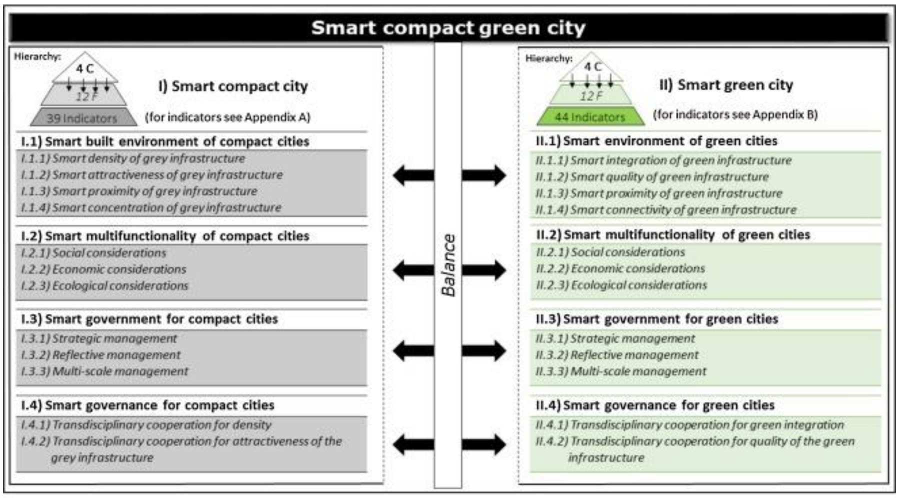


Figure 1.5. Smart compact green city framework developed by Artmann et al. (2019).

Some of the indicators defined within this study were implemented as a part of the German Monitor of Settlement and Open Space Development (IOER monitor) since 2010 (Krüger et al., 2013). The proposed framework aims to support researchers and practitioners in developing visions of how existing or future cities can approach smart-compact-green cities to support sustainable development processes. However, this framework was only proposed theoretically without any information about the analysis and testing of the method in a case study.

Some other studies employed GIS and spatial analysis tools to map urban growth patterns and identify areas suitable for urban development while guaranteeing urban livability and sustainability through greening protection and enhancement. To this aim, spatial analysis helps assess the proximity of green spaces to urban centers and ensures optimal distribution (Jim, 2004; Uy & Nakagoshi, 2008; Li et al., 2018; Ustaoglu & Aydınoglu, 2020).

In many studies, the relationship between urban growth and greening goals has also been analyzed by employing remote sensing data and land use land cover classification methods to monitor changes in land cover and vegetation over time. It provides valuable information on urban growth patterns, the extent of green spaces, and the impacts of urban growth processes on green spaces (Wellmann et al., 2020). Since understanding how urban green spaces evolve in response to both urbanization and greening policies is pivotal in steering sustainable urban development, Zhou et al. (2011), for instance, utilized comprehensive methodologies to depict the evolving trends and intensities of green spaces in Kunming, China, spanning from 1992 to 2009. The analysis involved integrated approaches incorporating concentric and directional landscape analyses, along with landscape metrics, to derive spatial variations in the pattern of green spaces. Furthermore, building on the idea that it is necessary to conduct a comprehensive analysis that considers both spatial and temporal aspects when examining the trends in urban growth and greening goals (Jin et al., 2020; Zulian et al., 2020), Wellmann et al. (2020), introduced a practical concept that contrasts changes in population density (either shrinkage or growth) with vegetation density (sealing or greening) over time to explore the interplay between compact, dispersed and green cities. These evolving patterns are attributed to various land use classes and individual urban development projects, allowing us to quantify trends and pathways for urban greenery in a growing city. Using a Landsat remote sensing time series, the authors mapped the progression in vegetation density over 30 years, represented as subpixel fractions. The city under study, Berlin (Germany), has evolved into a city experiencing simultaneous gains in both vegetation (greening) and population (growth) in recent years. In conclusion, the authors argued that accurately measuring various spatial processes involving urban growth and vegetation cover is crucial for unraveling urban transformations and shaping future sustainable urban forms. In line with this study, Balikçi et al. (2022) investigated the interplay between a compact and a green city by assessing the influence of these two policies on land-use change in two case studies: Amsterdam and Brussels. These two case studies were selected because of their similar urban growth and different urban planning policies and governance structures. The applied research method to analyze the dilemma between compact urban and green areas development was based on two steps: 1) developing geospatial analysis using census data and satellite imageries and 2) performing an analysis of urban planning policy documents and interviews with policymakers. The geospatial analysis involved a remote sensing process of identification of greenspace and not-greenspace from satellite and aerial imageries. The authors applied a process of supervised land-use classification using ArcGIS software. The output of the land-use classification was then integrated into the statistical census data to determine and analyze changes in urban green space and density over time. In addition to the spatiotemporal analysis of urban green areas and density changes, the authors conducted an urban planning policy analysis and policymakers' interviews in urban planning and green space development. The results of these analyses confirmed what was assessed across global contexts about the fact that densification processes put pressure on urban green spaces (Haaland & van den Bosch, 2015).

Many frameworks and tools have been developed to manage and assess the interplay between urban growth and greening development. SEAs represent traditional urban planning frameworks that need to be better integrated with specific social, economic, and environmental aspects to be more effective in defining proper planning strategies. Other tools that can be employed to assess this interplay and define proper planning policies are multi-criteria decision support systems or spatial multi-criteria analysis. Moreover, remote sensing technologies and innovative methods, such as artificial intelligence, employed to detect and monitor changes in land use over time can provide a comprehensive understanding of urban growth dynamics and help identify potential locations for greening initiatives. However, the potential of all these three kinds of methods and tools has not yet been fully exploited for urban growth and greening relationship assessment and management.

2. *The role of innovative methodologies and tools for sustainable urban planning and management*

1. Innovative methodologies to support sustainable urban planning. A systematic literature review on the combined use of Artificial Intelligence and Geographic Information Systems

Intelligent tools and systems, such as Information and Communication Technologies (ICT), have transformed various sectors, including finance, healthcare, services, and goods provision. ICT refers to using digital technologies to collect, store, process, and communicate information, representing powerful tools for supporting sustainable urban planning and management (Park & Yoo, 2023).

The recent advancement in ICT has accelerated the implementation and application of newly disruptive technologies, such as artificial intelligence (AI). These technologies are valuable in urban planning as data science capabilities make decision-making processes expeditious, particularly in handling vast urban data sets, thereby promoting sustainability. Over the past few years, there has been a growing interest in AI technology applications for urban planning decision-making, and the prospects for AI in this context are exceedingly promising (Schwab, 2016). Indeed, the use of these technologies is gaining particular attention in urban planning areas as it can provide valuable insights into urban dynamics, such as land use patterns, transportation networks, energy consumption, and environmental quality, as well as support decision-making processes by providing real-time data, predictive models, and scenario analysis.

AI is a computer science field that focuses on developing intelligent agents capable of accomplishing tasks autonomously without human intervention (Ongsulee, 2017).

Over the years, the AI field has evolved through machine learning studies based on the definition of innovative algorithms able to make data-driven predictions and decisions (Bahvsar et al., 2017). Machine learning is the intersection of computer science and statistics, the heart of intelligence and data science. ML is also known as Statistical Learning (SL) or Artificial Learning (AL). Mitchell et al. (1997) defined a machine learning program as *"a computer program that learns from experience E concerning a certain class of tasks T and performance measure P, if its performance on tasks in T, as measured by P, improves with experience E"*.

The most used machine learning algorithms are grouped into two categories: supervised and unsupervised machine learning methods.

Supervised machine learning algorithms are trained using labeled elements, an input for which the output is known. In this case, the algorithm receives inputs corresponding to the correct outputs. In this case, the algorithm learns by comparing the actual and correct outputs to find any errors. The most common supervised machine learning methods are classification, regression, prediction, and gradient boosting, which use patterns to predict the label's values on additional unlabeled data. Supervised algorithms, therefore, are typically used to predict likely future events based on historical data. The most known supervised machine learning algorithms are linear regression, logistic regression, Naïve Bayes classifier, Support Vector Machine, and random forest.

Unsupervised machine learning methods are employed when historical data are unavailable as they explore data and try to find a structure within. Indeed, in unsupervised machine learning models, only the input data is available, and no corresponding output variables (Barlow, 1989). Unsupervised models aim to model the underlying structure or distribution of the input data to learn more. Popular techniques are self-organizing maps, nearest-neighbor mapping, k-means clustering, and singular value decomposition. These models are grouped into clustering or association.

Clustering models aim to group similar data points into clusters without predefined labels. They are unsupervised ML models as they try to discover characteristic patterns or structures in the data. Examples of these models are K-Means (Krishna & Murty, 1999), EM algorithms (Moon, 1996), Gaussian mixture models (Han et al., 2021), and graph clustering (Schaffer, 2007).

Association models serve to identify interesting relationships or patterns within large datasets. It is commonly used in market basket analysis to find associations between items purchased by customers. However, it has various applications, including understanding human behavior and urban planning. Association models mainly employed are the Apriori Algorithm (Wei et al.,

2009) and the Class Association Rule (CAR) Algorithm (Nguyen et al., 2013).

The study of machine learning algorithms and artificial neural networks containing hidden layers is known as deep learning (deep structured learning, hierarchical learning, or deep machine learning). This field of study is based on learning data representations and has determined a profound revolution in machine learning.

The structure of deep learning algorithms (Figure 2.1) simulates human neural networks, and their origin can be traced back to Frank Rosenblatt's creation of perceptrons in 1957 (Rosenblatt, 1958). The simplest deep learning algorithms are characterized by two neurons, one that receives an input signal and one that sends an output signal. Between these two neurons, there are many layers so that the algorithm can use multiple processing layers made of multiple linear and non-linear transformations.

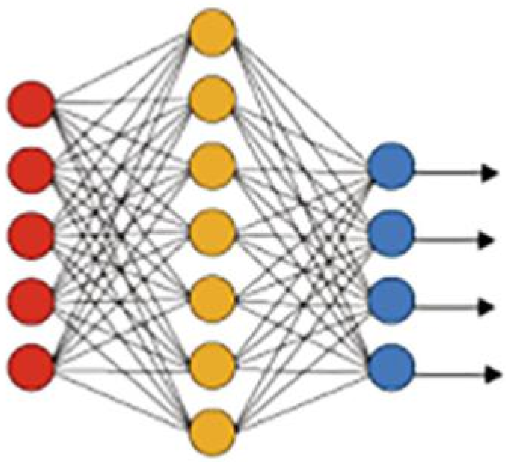


Figure 2.1. Deep learning algorithms' structure.

Deep learning methods perform better in object recognition tasks than machine learning algorithms (Voulodimos et al., 2018). Indeed, various deep learning architectures, such as deep neural networks, convolutional deep neural networks, deep belief networks, and recurrent neural networks, have been widely applied in many computer vision tasks, such as automatic speech recognition, natural language processing, audio recognition, and bioinformatics.

The ANN algorithm generally learns using a direct-acting neural network formed by a back-propagation algorithm. In this operation, the neuron is primarily a mathematical operator that performs a weighted sum followed by a non-linear function. The particularity of this function is that it must be limited, continuous, and differentiable. The most used are the sigmoid functions because the forms of the derivatives of its inverse functions are elementary to calculate, which improves the algorithm's performance. The working principle of the ANNs is shown in Figure 2.2 and better detailed in (Thayse et al., 1988; Wang, 2003).

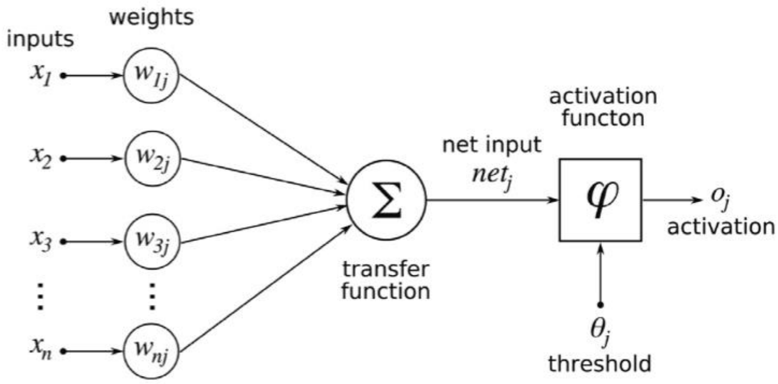


Figure 2.2. Artificial neural network algorithms working principle.

Artificial neural networks have some limitations related to the number of parameters they employ. Convolutional Neural Networks (CNNs) were introduced to mitigate the parameter burden (Guo et al., 2017). The strategy behind parameter reduction in CNNs relies on three fundamental concepts: sparse interaction, parameter sharing, and representation. By reducing the connections between layers, CNNs enhance scalability and streamline the training process for complex neural networks. CNNs have multiple layers of perceptrons designed to preprocess limited amounts of data (Kuo, 2016). The utility of CNNs presents a wide array of applications, including image and video recognition, recommendation systems, and natural language processing, as evidenced by the studies conducted by LeCun et al. (1995) and Matsugu et al. (2003). Furthermore, CNNs have proven their efficacy in various urban modeling projects, such as flood prediction (Guo et al., 2021), climate modeling (Middel et al., 2018), and analyzing street mobility (Middel et al., 2019). Furthermore, CNNs were valuable in developing deep convolutional networks and other more efficient approaches for tackling intricate problems.

Cities and territories planning, designing, and managing can be revolutionized with AI technologies and geographic information systems (GIS) integration. It would enhance decision-making processes, optimize resource allocation, and improve urban sustainability. Indeed, the potentialities of AI technologies and GIS are employed in many urban planning applications. The increasing interest in this topic recently led to the emergence of a new research area defined as Geographic Artificial Intelligence (GeoAI), which refers to the application of AI techniques to geospatial data and GIS (Scheider & Richter, 2023; Liu & Biljecki, 2022). As it combines the capabilities of AI techniques with GIS, this tool consents to solve complex spatial problems and, therefore, gain helpful insight into various wicked urban planning problems.

On the one hand, AI algorithm implementation consents to processing vast amounts of geospatial data, such as satellite imagery, sensor data, and social media feeds, to extract valuable information about urban and territorial environments. On the other hand, GIS tools allow the analysis of these data and elaborate maps, graphs, and interactive dashboards, making complex data more accessible and understandable and allowing planners to make informed decisions about urban and territorial systems. The combination of these technologies is essential for sustainable urban planning and development.

Therefore, the overview of the AI-GIS application by date within the scientific literature is of great importance to the state-of-the-art application towards urban and territorial sustainability.

An overview of the main application of AI technologies within the urban and territorial planning field is decisive in assessing the main relevant application of AI technologies for urban planning. Many researchers have conducted systematic and non-systematic literature reviews on this topic.

In their research, Sanchez et al. (2023) drew results from a literature review about AI applications in urban planning and from a survey of American Planning Association (APA) members whose aim was to assess the experiences and perspectives of urban planning about AI technologies application for professional activities. The results of this study revealed that urban planning, both in research and practice, is at the early stages of AI adoption and that researchers and professionals must collaborate to accelerate the adoption of such technologies in this research and practice field. The review of the state of the art regarding AI applications in the urban planning field in this study represents an initial exploration of how research is going on within this field. Koutra and Ioakimidis (2023) reviewed the literature on ML methods and urban modeling applications to identify gaps and significant constraints related to this research area and to define its future directions. Wu and Silva (2010) examined the application based on AI in urban planning for land use and land cover dynamics analysis. Jha et al. (2021) reviewed artificial intelligence and machine learning techniques in smart city development and urban planning applications. Yigitcanlar et al.

(2020) aimed to gain insights into enhancing general comprehension of AI potential in advancing smart city development through a systematic review of the existing literature. Son et al. (2023) reviewed AI technology applications in urban planning areas and analyzed how AI technologies support smart and sustainable development processes. Allam and Dhunny (2019) assessed the potentialities of AI applications in smart city concept planning and implementation.

The previous work on reviewing the scientific literature about AI application in sustainable urban planning demonstrates that most analyze and assess the AI-based approaches and technologies employed to implement smart city concepts and dimensions of sustainable development. None of them reviewed the scientific literature on applications based on the integration of AI and GIS and how they can contribute to sustainable urban and territorial development.

As the integration of AI and GIS represents a valuable reference within urban studies, a comprehensive analysis of the scientific literature in this field is of great significance. Reviewing this topic can help identify the existing knowledge and applications proposed by researchers to date and define future research developments of AI-GIS integration in urban planning toward sustainability.

To this end, a review of the AI-GIS-based applications to support sustainable urban planning is conducted here. This review is systematically performed as, from a methodological perspective, it follows the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) protocol.

This systematic literature review wants to address the following research questions: (i) What are the urban planning areas where AI-GIS technologies are integrated? (ii) How can AI and GIS integration support urban planning towards sustainability?

Therefore, this Chapter's main objective is to conduct a systematic literature review of the application of AI and GIS in sustainable urban planning and management. The primary purposes of this study are (1) to provide a comprehensive overview of the existing research on this topic, including the different applications of AI and GIS; (2) to identify the main limitations and the gaps in the current knowledge, (3) identifying the key methods adopted in urban planning and management by comparing documents, (4) drawing a future outlook in the application of AI and GIS in urban planning and management processes. The scope of this Chapter includes studies that have used AI and GIS for urban planning and management, focusing on sustainability. This systematic literature review is valuable for researchers, practitioners, and policymakers interested in applying AI and GIS for sustainable urban planning and management.

1.1. The process of systematic literature review

The main purpose of this work is to enable a comprehensive analysis of the existing literature on the application of Artificial Intelligence and GIS in sustainable urban planning and management. This systematic literature review follows the PRISMA statement, published for the first time in 2009 and revised in 2020 by Denyer and Tranfield.

PRISMA methodology was designed to help systematic reviewers develop the research question and the related literature search according to the guidelines proposed by Denyer and Tranfield (2009). PRISMA methodology is a helpful guideline for the critical development of systematic reviews. This methodology optimizes identifying bibliographic databases representing the main tendencies and approaches adopted into the analyzed research field. The main phases of the PRISMA methodology are identification, screening, eligibility, and inclusion of studies. The summary of the PRISMA methodology is presented with a flow chart that shows the number of bibliographic records initially identified by the search query and subsequently included in this study (Figure 2.3).

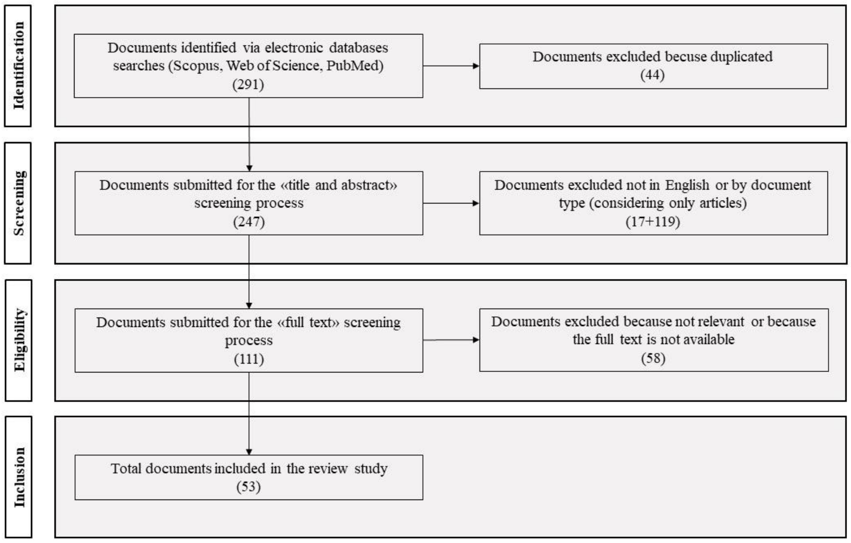


Figure 2.3. Literature screening process following the PRISMA framework (Liberati et al., 2009; Carlucci et al., 2020).

1.1.1. The identification of studies

The first step of the proposed methodology consists of constructing the research question using the CIMO logic (Denyer et al., 2008) (Table 2.1). The acronym CIMO stands for Context, Intervention, Mechanism, and Output. The posed research question is: “How do we employ (M) Artificial Intelligence and Geographic Information Systems (GIS) (I) for sustainable urban (C) planning and management (O)?”.

The next step consists of developing a comprehensive list of keywords for each CIMO term and building a research query using the Boolean operators AND, OR, and NOT. According to the CIMO standards, the query employed to search articles in the three databases is the following: ("urban area*" OR "cit*" OR "urban context*") AND ("artificial intelligence" OR “ai” OR "deep learning" or “dl” OR "machine learning" or “ML”) AND ("geographic information system*" OR "GIS") AND ("employ*" OR "appl*" OR "use*" OR "implement*" OR "utiliz*") AND ("sustainable development" OR "urban planning" OR "sustainable urban planning" OR "urban management" OR "smart cit*").

This search query is executed in the Scopus, Web of Science, and PubMed databases by generating 291 papers from 2003 to 2023, which were considered eligible for further detailed analysis. First, the papers simultaneously presented in at least two of the three databases considered were identified and excluded from the total of documents retrieved from the research. Then, based on the screening phase of the PRISMA methodology, further analysis of these documents was done. Exclusion criteria are applied by screening the titles and abstracts of the identified documents to limit the search to published and in-press journal articles written in English.

Subsequently, the author conducted a comprehensive analysis of the documents. Only studies pertinent to the research scope and possessing complete texts are considered suitable for examination. During this phase, the analysis involves evaluating the available full text of eligible documents and considering the quality and consistency assessments of the research. Documents that do not align with the research question, lack relevance, contain insufficient data, or exhibit overlaps are excluded from the final database. After the bibliographic database definition, the bibliometric analysis revealed connections between topics, patterns within publication metadata, and the evolution of themes.

Table 2.1. The CIMO logic for studying the employment of AI and GIS in sustainable urban planning and management.

Context (C)	Intervention (I)	Mechanism (M)	Outcomes (O)
urban area	artificial intelligence	employment	sustainable development
city	geographic information systems	application	urban planning
urban context	machine learning	use	sustainable urban planning
	deep learning	implementation	urban management
		utilization	smart cities

1.1.2. The bibliometric analysis

The bibliometric analysis is led by employing Bibliometrix (Aria & Cuccurullo, 2017) and identifying relationships between authors, topics, patterns, and thematic evolution.

The bibliometric analyses performed within this work include collaboration network, keyword occurrence, and co-word analyses.

The collaboration network examines authors' productivity, affiliations, and countries through a map. It focuses on the breakdown of scientific production by country and the collaborative efforts between authors affiliated with each country. If individuals with affiliations in different countries author a document, it is recognized as a collaboration.

The keyword occurrence analysis consents to examine the frequency and the distribution of keywords in the documents. The goal is to quantify and analyze the prevalence of keywords in the analyzed documents to gain insights into patterns, trends, or themes in the dataset. Keyword occurrence analysis helps uncover significant terms, track changes over time, identify prevalent themes, and better understand the content under investigation.

A co-word analysis is a methodological approach that examines and identifies the relationships between terms or concepts based on their co-occurrence within a body of scholarly literature. This analysis aims to uncover patterns of association and thematic connections among words or terms used in the documents under review. By exploring how certain words tend to appear together, researchers can gain insights into the underlying structure of knowledge, key themes, and the interrelationships between concepts within the field of study. Co-word analysis reveals the intellectual structure and trends in a specific research domain, providing a systematic and quantitative means of understanding the relationships among terms and the evolution of ideas over time.

1.2. The results from the systematic literature review

1.2.1. The results from the bibliometric analysis

The collected bibliographic data comprises 53 documents from 38 sources, covering 21 years from 2012 to date. A total of 215 authors contributed to these documents. Each document has 4.4 co-authors and has been cited 20.53 times on average. The annual growth rate of documents is 19.53%. These statistics highlight an initial growing interest in the AI-GIS integration topic in the urban planning field.

The interest in AI-GIS integration in urban planning tasks and the scientific production of this topic is increasing nowadays (Figure 2.4). It should be noted that many collected documents have been published from 2017 onwards, as demonstrated by the annual scientific production of documents over time. As a result, this systematic literature review can be viewed as an evaluation of the most recent existing applications of AI-GIS in urban planning.

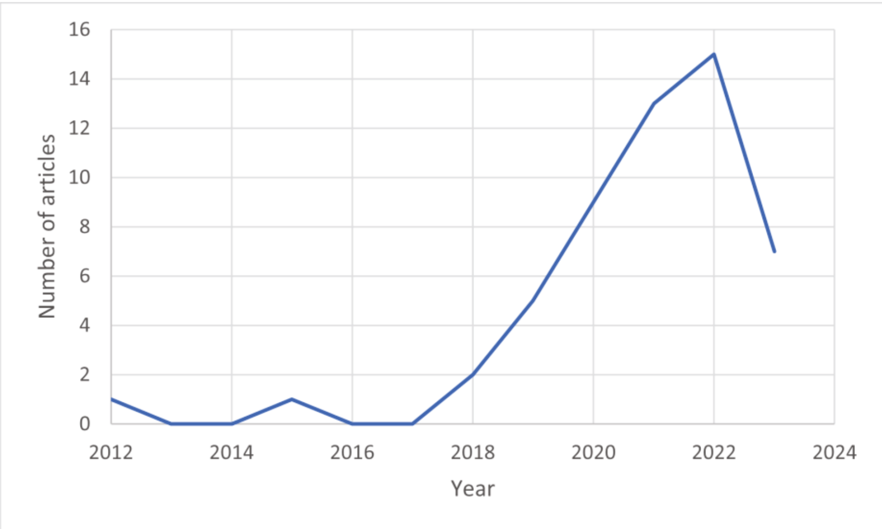


Figure 2.4. Annual scientific production over time.

The chronological development of published documents by their sources shows that Sustainability, along with Remote Sensing journals, has been the most prolific publisher of research on AI-GIS applications for sustainable urban planning in recent years. Following closely behind are the Building and Environment, International Journal of Disaster Risk Reduction, and

International Journal of Geographical Information journals, as illustrated in Table 2.2.

Table 2.2. Number of articles published per source.

Sources	Articles
SUSTAINABILITY (SWITZERLAND)	5
REMOTE SENSING	4
BUILDING AND ENVIRONMENT	3
INTERNATIONAL JOURNAL OF DISASTER RISK REDUCTION	3
COMPUTERS, ENVIRONMENT AND URBAN SYSTEMS	2
ENVIRONMENTAL MONITORING AND ASSESSMENT	2
INTERNATIONAL JOURNAL OF GEOGRAPHICAL INFORMATION SCIENCE	2
SENSORS	2
ADVANCES IN ENGINEERING SOFTWARE	1
AI AND SOCIETY	1
APPLIED GEOMATICS	1
COMPLEXITY	1
ENERGY AND BUILDINGS	1
ENVIRONMENTAL EARTH SCIENCES	1
FRONTIERS IN EARTH SCIENCE	1
FUTURE GENERATION COMPUTER SYSTEMS	1
GEOCARTO INTERNATIONAL	1
GEOJOURNAL	1
HABITAT INTERNATIONAL	1
IEEE ACCESS	1
IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING	1
INTERNATIONAL JOURNAL OF APPLIED EARTH OBSERVATION AND GEOINFORMATION	1
INTERNATIONAL JOURNAL OF ENVIRONMENTAL RESEARCH AND PUBLIC HEALTH	1
INTERNATIONAL JOURNAL OF GEOINFORMATICS	1
ISPRS INTERNATIONAL JOURNAL OF GEO-INFORMATION	1
JOURNAL OF ENVIRONMENTAL MANAGEMENT	1
JOURNAL OF HYDROLOGY	1
JOURNAL OF THE INDIAN SOCIETY OF REMOTE SENSING	1
KOREAN JOURNAL OF REMOTE SENSING	1
LAND	1
MODELING EARTH SYSTEMS AND ENVIRONMENT	1
REMOTE SENSING OF ENVIRONMENT	1
SCIENCE OF THE TOTAL ENVIRONMENT	1
TRANSPORTATION RESEARCH PART C: EMERGING TECHNOLOGIES	1
TRANSPORTATION RESEARCH PART D: TRANSPORT AND ENVIRONMENT	1
URBAN CLIMATE	1

URBAN FORESTRY AND URBAN GREENING	1
WATER (SWITZERLAND)	1

Looking at the country's production (Figure 2.5), China leads the way. India, Iran, Italy, and the United States of America follow it.

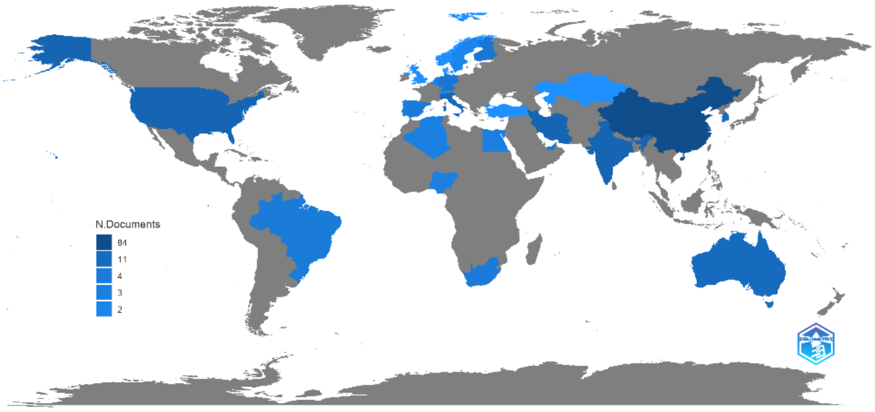


Figure 2.5. Country production map.

Regarding collaboration (Table 2.3), Iran is the most collaborative country, with eight collaborations. It is followed by the United States of America, which has six collaborations with other countries, while China has four. In general, European countries have internal collaborations; in some cases, they collaborate with countries from all over the world.

Table 2.3. Collaboration network.

From	To	Frequency
CHINA	USA	3
IRAN	FINLAND	2
IRAN	KOREA	2
KOREA	AUSTRALIA	2
BRAZIL	NETHERLANDS	1
BRAZIL	SPAIN	1
CHINA	DENMARK	1
CHINA	GERMANY	1
CHINA	LUXEMBOURG	1
FINLAND	NORWAY	1
FINLAND	SWEDEN	1
GERMANY	NETHERLANDS	1
INDIA	IRAN	1
INDIA	KOREA	1

IRAN	GERMANY	1
IRAN	NETHERLANDS	1
IRAN	NORWAY	1
IRAN	SWEDEN	1
IRAN	TURKEY	1
IRAN	USA	1
KOREA	FINLAND	1
SOUTH AFRICA	NIGERIA	1
SPAIN	KAZAKHSTAN	1
SWEDEN	NORWAY	1
SWITZERLAND	UNITED KINGDOM	1
UNITED ARAB EMIRATES	KAZAKHSTAN	1
UNITED ARAB EMIRATES	SPAIN	1
USA	FINLAND	1
USA	HONG KONG	1
USA	LUXEMBOURG	1
USA	NORWAY	1
USA	SWEDEN	1

The keywords used by the authors within the analyzed scientific works are 214. Their occurrence is assessed through the word cloud shown in Figure 2.6. It effectively illustrates the prevalence of terms associated with AI-GIS integration for sustainable urban planning topics, establishing a ranking list. The top five terms identified include "geographic information systems" (19 occurrences), "machine learning" (16), "remote sensing" (8), "artificial neural networks" (6), and "deep learning" (6), aligning with the keywords search.

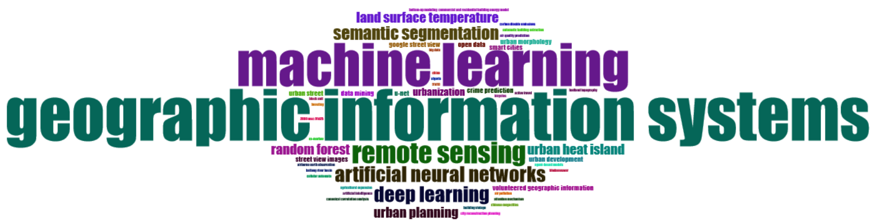


Figure 2.6. Authors' keyword occurrence related to AI-GIS integration for sustainable urban planning.

From these results, additional analyses are conducted to methodically delineate the bibliographic database: the three-field plot and the cooccurrence network map. These analytical approaches play a crucial role in scientifically elucidating research trends and revealing the interconnections among the emerging themes derived from the state of the art.

The three field plots illustrate the frequency of connections (represented by the size of the boxes) and the intensity of these connections (indicated by the size of the connecting lines).

The first three-field plot shown in Figure 2.7 focuses on the connections between the most common words found in abstracts (left field), authors' keywords (middle field), and scientific journals (right field). The predominant terms used in the abstracts highlight the main concepts related to the research question, such as "urban" and "model". Within the middle field of the author's keywords, the foundational concepts shaping the research issue are presented, encompassing elements such as “geographic information systems”, “machine learning”, “remote sensing”, artificial neural networks”, and “urban planning”. Finally, the main sources are shown. From this analysis, for example, emerges that generic authors' keywords on the topic such as “geographic information systems” and “machine learning” encompass every term in the abstract and are employed in all the most representative sources. Specific keywords, referring to particular and explicit applications, encompassing “remote sensing”, “artificial neural networks”, “urban planning”, “urbanization”, and so on, even if they are connected to most of the main words employed in the abstract, they are employed in specific sources, such as Sustainability, Remote Sensing, Geocarto International, and Environmental Monitoring and Assessment.

This analysis offers valuable insights to researchers new to the field, assisting them in identifying the most appropriate journals for publishing their studies.

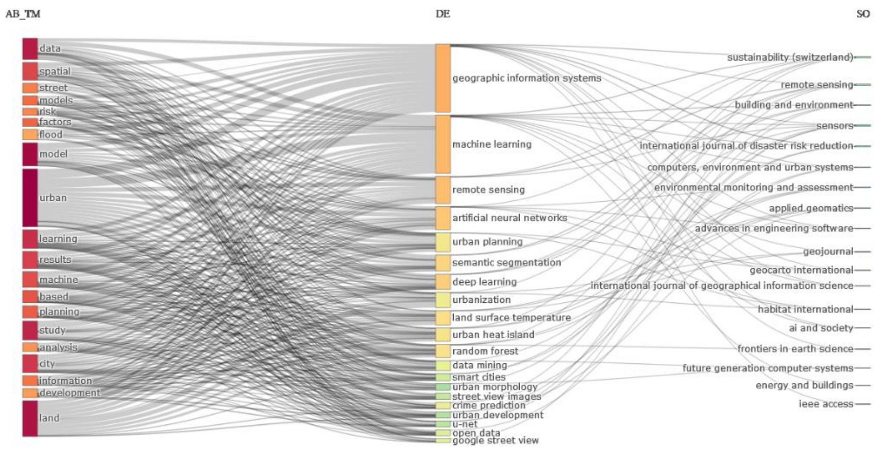


Figure 2.7. Relationship between words in the abstract (left), keywords (middle), and the journal sources (right).

The second three-field plot shown in Figure 2.8 focuses on the connections between the affiliations (left field), authors’ keywords (middle field), and scientific journals (right field). The affiliations that contributed used the main keywords for research on this topic are the University of Calabria, the Shangai University of Engineering Science, the University of Oulu, and the Tongji University. The authors’ keywords mainly used by scientists from the University of Calabria include geographic information systems, remote sensing, semantic segmentation, deep learning, and urban development. Researchers from the Shangai University of Engineering Science referred mainly to machine learning, semantic segmentation, urban development, urban morphology, and street view images. Analysis of connections between affiliations, authors’ keywords, and sources provides valuable information about the scientific interest of the research group from worldwide affiliations and the preferred source for those topics.

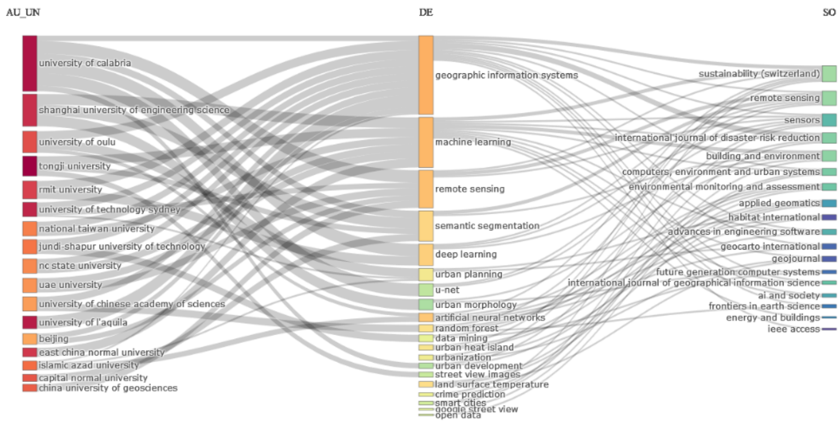


Figure 2.8. Relationship between affiliations (left), keywords (middle), and the journal sources (right).

The third three-field plot depicted in Figure 2.9 shows the relationship between countries (left), journal sources (middle), and keywords (right). This diagram helps to analyze the countries mainly contributing to specific sources and the main themes addressed in these sources. The results show that Building and Environment, Sustainability, and Remote Sensing are the most relevant sources. The main research contributors of the Building and Environment journal are from China, the United States of America, and Hong Kong. The main keywords employed in these works are related to machine learning, semantic segmentation, deep learning, urban morphology, and Google Street View. Considering scientific works on the topic published in the Sustainability journal, the authors are mainly from China and Korea, and the keywords employed are geographic information systems, machine learning, artificial neural networks, remote sensing, urban heat island, urbanization, and crime prediction. Scientific works published in the Remote Sensing journal are from China, Italy, Germany, and Belgium. The main keywords employed by the authors from these works deal with geographic information systems, random forests, remote sensing, deep learning, and semantic segmentation. This analysis depicts the main research topics and the countries contributing to each scientific source. It is of great significance for defining a scientific background and the related topics of each relevant source.

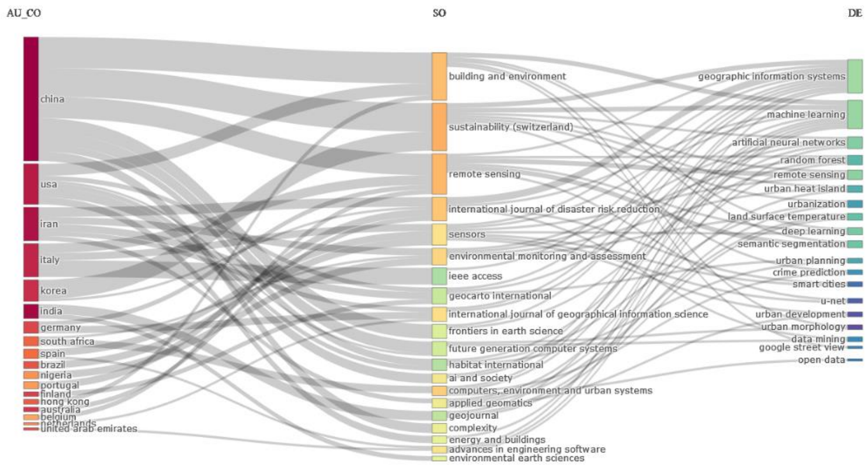


Figure 2.9. Relationship between countries (left), journal sources (middle), and keywords (right).

Illustrated in Figure 2.10, the co-occurrence network displays the clusters of authors' keywords, identified through the Walktrap clustering algorithm with 50 nodes and normalization of relationships based on association strength (Aria and Cuccurullo, 2017).

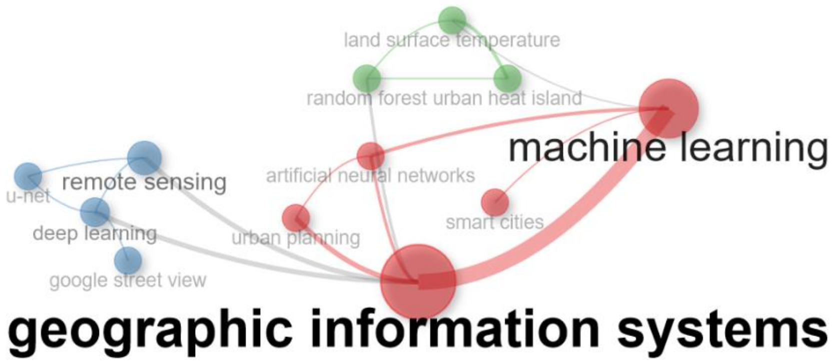


Figure 2.10. Co-occurrence network of authors' keywords.

The central cluster is the red one, which encompasses the strong relationship between the key terms of the research topic, "machine learning" and "geographic information systems". This cluster includes the main applications and models applied, namely "urban planning", "artificial neural networks", and "smart cities". The second cluster (in green), starting from "geographic information systems" and "machine learning" keywords, includes a specific machine learning method, such as "random forest", and is related to defined applications aimed at investigating "land surface temperature" and "urban heat island". The blue cluster connects "geographic information systems" with "remote sensing" and "deep learning" referring, then, to AI-GIS integration applications based on the use of remote sensing techniques and deep learning methods, such as the "u-net" model, for image processing, like "google street view" images included in this cluster. The identified clusters are united and mostly connected, suggesting that the analyzed research topics are increasingly being investigated by researchers.

1.2.2. The results from the document analysis

After the bibliometric analysis, the publications were clustered through a full-text analysis of each publication, assigning them the best-fitting category. From the full-text screening of each publication, the author identified different research areas of AI-GIS applications for sustainable urban planning. The identified areas are (i) AI-GIS integration for disaster management planning, (ii) AI-GIS integration for land use land cover and urban features detection, (iii) AI-GIS integration for land use land cover change prediction, (iv) AI-GIS integration for environmental quality assessment, and (v) AI-GIS integration for spatial planning tasks. Table 2.4

shows the identified key research area, associated keywords, and the number of articles.

Table 2.4. Key themes and their characteristics identified through the systematic literature review.

Research area	Related authors' keywords	Number of articles
AI-GIS integration for disaster management planning	geographic information systems; machine learning; urban planning; artificial intelligence; artificial neural networks; deep learning; crime; risk assessment; resilience planning; vulnerability; urban flooding; susceptibility map; sustainable development; natural disaster; remote sensing; hazard; landslide	13
AI-GIS integration for land use land cover and urban features detection	deep learning; machine learning; remote sensing; semantic segmentation; volunteered geographic information; airborne earth observation; convolutional neural networks; geographic information systems; detection; google street view; greening development; ground-based pictures; high-resolution satellite data; information extraction; instance segmentation; land use characterization; roofscape; smart cities; social sensing; spatial analysis; street canyon; street trees; u-net; ultrahigh spatial resolution; urban areas; urban development; urban functional zones mapping; urban street; view factor; visual geometry group	9
AI-GIS integration for land use land cover change prediction	geographic information systems; remote sensing; agricultural expansion; artificial neural networks; CA-Markov; cellular automata; classification accuracy; informal settlement development; land change modeler; land cover change; land transformation model; land use management; land use/cover change; machine learning; multi-layer perceptron network;	6

	multiple land use transitions; object-based image analysis; radial basis function network; random forest; spatial accuracy assessment; urban change; urban growth prediction; urban planning; urban sprawl; urbanization	
AI-GIS integration for environmental quality assessment	machine learning; land surface temperature; urban heat island; artificial neural networks; geographic information systems; random forest; urbanization; active travel; air pollution; air quality prediction; carbon dioxide emissions; deep learning; digital twins; energy consumption; extreme gradient boost; remote sensing; geographic information systems technology; geographic object-based image analysis; geospatial technology; google earth engine; heat vulnerability index; high-density urban blocks; land use land cover; low impact development; mobile monitoring; NDVI; noise prediction; pollutant concentration; prediction; remote sensing; scenario planning; semantic segmentation; shapley additive explanation; sky view factor; spatio-temporal features; sponge city; support vector machine	13
AI-GIS integration for spatial planning tasks	geographic information systems; machine learning; deep learning; remote sensing; street view images; artificial neural networks; big data; block unit; data-informed urban design; data mining; google street view; greenway planning; high-resolution urban grids; industrial ecology; interactive analytics; landscape structure; material flow analysis; mobile lidar; multi-sourced urban data; open data; OpenStreetMap; principal component analysis (PCA); random forest; roof greening; semantic segmentation; sensitivity analysis; spatial distribution; spatial planning; suitability evaluation; urban fabric;	12

	urban morphology; urban planning; urban quality of life; urban street; urban studies; visual comfort; visual quality; walkability	

Moving from this general analysis, the author identified the aim, relevance, technologies, and findings of all these studies divided into key research areas. These results are shown in Table 2.5 and analyzed in the following subsections.

Table 2.5. Summarization of the main characteristics of the reviewed articles.

Thematic	Reference	Title	Year	Source	Aim	Study area	Data	AI model	AI usage	GIS software	GIS usage	Accuracy measure	AI-GIS level of integration	Main findings
AI-GIS integration for disaster management planning	Hamid et al. (2023)	Landslide susceptibility mapping using GIS-based statistical and machine learning modeling in the city of Sidi Abdellah, Northern Algeria	2023	Modeling Earth Systems and Environment	To assess and compare the landslide susceptibility maps by applying GIS-based statistical and machine learning models	City of Sidi Abdellah and surrounding areas (Northern Algeria)	Geospatial data, satellite imageries, aerial photographs	Logistic regression	Landslide susceptibility modeling and mapping	ArcGIS	Data collection and development of a spatial database; spatial landslide susceptibility assessment	ROC curve parameters: AUC, Sensitivity, Specificity	Good	The statistical and machine learning models provided satisfactory results and depicted a high accuracy level for landslide susceptibility mapping
	Darabi et al. (2019)	Urban flood risk mapping using the GARP and QUEST models: A comparative study of machine learning techniques	2019	Journal of Hydrology	To predict and validate the flood hazard map by two models, GARP and QUEST; and produce a flooding vulnerability map using Fuzzy Analytical Network Process (FANP)	Sari City (Iran)	Geospatial data	Genetic Algorithm Rule-Set Production (GARP), Quick Unbiased Efficient Statistical Tree (QUEST)	To produce flood hazard maps	ArcGIS	Driving factors collection and assessment; development of maps based on AI models' results	AUC-ROC value and Kappa statistic	Good	Machine learning techniques can be applied to urban flood zoning.
	Rizeei et al. (2019)	Allocation of emergency response centres in response to pluvial flooding-prone demand points using integrated multiple layer perceptron and maximum coverage location problem models	2019	International Journal of Disaster Risk Reduction	To assess the current situation of ERCs in terms of PF-prone demand points	Damansara City (Peninsular Malaysia)	Geospatial data, satellite imageries	MLP	Pluvial flood-prone urban areas identification	Not defined	Data weighting, interpolation, data mining, and qualitative technique	Correlation coefficient; Mean absolute error, ROC curve; RMSE; Relative absolute error; Root relative squared error	Fine	Combining an ML model for PF identification with location-allocation models in a GIS framework is an approach for disaster managers to enhance the precision of expanding the spatial layout of ERCs.
	Motta et al. (2021)	A mixed approach for urban flood prediction using Machine Learning and GIS	2021	International Journal of Disaster Risk Reduction	To develop a flood prediction system using a combination of ML classifiers along with GIS techniques to be used as an effective tool for urban management and resilience planning	Lisbon (Portugal)	Geospatial data	Logistic Regression, Support Vector Machine, Gaussian Naive-Bayes, Random Forest, K-Nearest Neighbours, Multi-Layer Perceptron	Flood prediction	ArcGIS Pro	Geospatial analysis and statistics; flood spatial cluster identification	Accuracy, Area Under Curve (AUC), Recall, F1 and Matthews Correlation Coefficient (MCC)	Good	Integrating ML and GIS makes it feasible to identify the pivotal factors and conditions contributing to a flooding scenario, even when working with a restricted dataset.
	Eini et al. (2020)	Hazard and vulnerability in urban flood risk mapping: Machine learning techniques and considering the role of urban districts	2020	International Journal of Disaster Risk Reduction	To produce a flood risk map by combining flood hazard and vulnerability maps	Kermanshah City (Iran)	Geospatial data	Maximum Entropy (MaxEnt) and Genetic Algorithm Rule-Set Production (GARP)	Flood hazard maps generation	ArcGIS	Data collection and analysis; ML output gridding and mapping	AUC-ROC and Kappa performance indices	Good	ML methods deliver consistent results for areas where data access is challenging.

	Zhou et al. (2022)	Risk Assessment of Debris Flow in a Mountain-Basin Area, Western China	2022	Remote Sensing	To assess the hazard of debris flow based on artificial intelligence methods	Bailong River Basin (China)	Topographic data, remote sensing images, geological, disaster, rainfall, soil, and socio-economic data	AdaBoost, Gradient Tree Boosting (GDBT), Bagging, Random Forest, Extra Trees, Gaussian Process, Logistic Regression (LR), Passive Aggressive, Ridge, Stochastic Gradient Descent (SGD), Perceptron, Gaussian Naive Bayes, Bernoulli Naive Bayes, Nearest Neighbours, VC, Linear SVC, Nu-SVC, decision Tree, Extra Tree, Linear Discriminant, Quadratic Discriminant, XGBoost, MLP	Debris flow hazard assessment.	ArcGIS	Data collection and analysis; Debris flow disaster area delineation	Accuracy	Good	The study is innovative to a certain extent, enriching the theoretical methods of geological disaster risk management and providing a scientific reference for the effective prevention and control of BRB debris flow disasters.
	Francini et al. (2022)	A Deep Learning-Based Method for the Semi-Automatic Identification of Built-Up Areas within Risk Zones Using Aerial Imagery and Multi-Source GIS Data: An Application for Landslide Risk	2022	Remote Sensing	To propose a deep learning approach to map buildings that fall into risk areas	Cetraro, Petrizzi, and San Vito sullo Ionio Municipalities (Southern Italy)	Remote sensing data: “semantic segmentation of aerial imagery” for training and validation, orthoimages for testing	U-Net	Buildings classification and segmentatio	QGIS	Representation of U-Net output, identification of buildings at landslide risk	Precision, Recall, and F1-Score	Good	The results show that the proposed methodology can detect and predict buildings that fall into landslide risk zones, with an appreciable transferability capability
	Wang et al. (2020)	Comparison of Random Forest Model and Frequency Ratio Model for Landslide Susceptibility Mapping (LSM) in Yunyang County (Chongqing, China)	2020	International Journal of Environmental Research and Public Health	To compare the random forest (RF) model and the frequency ratio (FR) model for landslide susceptibility mapping (LSM)	Yunyang Country	Historical records; satellite images; and extensive field surveys, geospatial data	RF	Landslide susceptibility simulation	ArcGIS	Conditioning factors assessment and mapping; LSM mapping	Accuracy, Precision, Sensitivity, Specificity, AUC	Good	The study provided a theoretical basis for application of machine learning techniques (e.g., RF) in landslide prevention; mitigation; and urban planning; so as to deliver an adequate response to the increasing demand for effective and low-cost tools in landslide susceptibility assessments

	Darabi et al. (2022)	Development of a novel hybrid multi-boosting neural network model for spatial prediction of urban flood	2021	Geocarto International	To develop a new hybridized machine learning algorithm for urban flood susceptibility mapping, named MultiB-MLPNN, using a multi-boosting technique and MLPNN.	Amol City (Iran)	Flood imventory maps, geospatial data of driving factors, rasters and vectors	The performance of the hybridized model was compared with that of the standard MLPNN and two benchmark models–a regression-based model (boosted regression tree or BRT) and a robust machine learning model (random forest or RF).	These four models were applied for flood susceptibility mapping in Amol City in Iran.	Not defined	Not defined	AUC, Sensitivity, Specificity, Accuracy, True Skill Statistic, Matthews Correlation Coefficient (MCC), Misclassification Rate (MR)	Bad	The hybridized MultiB-MLPNN model is thus useful for generating realistic flood susceptibility maps for data-scarce urban areas. The maps can be used to develop risk-reduction measures to protect urban areas from devastating floods, particularly where available data are insufficient to support physically based hydrological or hydraulic models
	Mudassir et al. (2021)	Toward Effective Response to Natural Disasters: A Data Science Approach	2021	IEEE Access	To propose a data science-based methodology able to cope with different post-disaster emergencies	L'Aquila (Abruzzo, Italy)	Geographical data; census tract data	Double DeepQ-Learning Network (DDQN)	To define alternative reconstruction plans	Not defined	Not defined	Not defined	Bad	The proposed framework, incorporating automated assistance for evacuation and post-disaster reconstruction planning, could assist decision makers in addressing natural disasters
	Kim et al. (2021)	Theft Prediction Model Based on Spatial Clustering to Reflect Spatial Characteristics of Adjacent Lands	2021	Sustainability	To predict crime in the microscopic range through grid-level analysis	Dongjak-gu (Seoul, South Korea)	Geographical data; land characteristics data	RF	To build a crime prediction model and then compared each mode	Not defined	Divide the target area into a grid of 100×100 m cells, driving factors assessment	F1-Score	Bad	Reflecting spatial continuity to predict crime was effective in enhancing the model's performance
	Saha et al. (2021)	Optimization modelling to establish false measures implemented with ex-situ plant species to control gully erosion in a monsoon-dominated region with novel in-situ measurements	2021	Journal of Environmental Management	To assess the gully erosion susceptibility (GES) mapping and optimization of land use planning	Garhbeta-I C. D. Block (India)	Satellite images, geographical data as driving factors for gully erosion	RF, BRT, Ecogeography based optimization (EBO)	To model gully erosion susceptibility (GES)	ArcGIS	Pre-processing satellite images, statistical analysis and conditioning factors preparation; classification of the output of susceptibility map	AUC, accuracy, precision, kappa	Good	The outcomes of GES mapping through ML algorithms should be helpful for administrators, decision-makers, and planners to avoid this kind of devastating erosional problems through proper land use planning and suitable measurements.
	Rosés et al. (2021)	A data-driven agent-based simulation to predict crime	2021	Computers, Environment and Urban Systems	To simulate crime at a high resolution using various large-	New York City	Complaint data (i.e. crime data), census tract and	Not defined	To study the impact of data-driven decision-	Not defined	Not defined	Predictive Accuracy Index (PAI), RMSE, AUC	-	The resulting ABM for crime utilizing a data-driven approach

		patterns in an urban environment			scale data layers and integrating machine learning at individual agent level to process the data layers		street segment data, LBSN data, taxi trip data, weather data, land use information, population density, points of interest, calls for service (i.e. 311 calls), public transportation stops, tree census data, and school locations		making on the outcome of crime simulation through different steps					integrating ML to inform agent behaviour model can be used by practitioners engaging in crime prevention as a tool to predict street segments at higher risk for future robberies.
AI – GIS integration for land use land cover and urban features detection	Silva et al. (2023)	Active actions in the extraction of urban objects for information quality and knowledge recommendation with machine learning	2023	Sensors	To provide an initial response to the need for mapping zones in cities.	Brazilian city of Itajaí (SC)	Multifinality Technical Cadastre, the CBERS-4 and CBERS-4A satellite images	OneR, NaiveBayes, J48, IBk, Hoeffding Tree algorithms, Region-based Convolutional Neural Network (R-CNN) and the YOLO algorithm	The elements recognized and classified are vegetation zones, exposed soil zones, asphalt, and buildings within an urban and rural area.	QGIS	Use of deep learning techniques for object detection in GIS images and GIS detection.	Kappa agreement coefficient.	Bad	The authors proved the applicability of the extraction of knowledge with the integration of data collected from Cadastral geoportal. Furthermore, the authors tested different Weka classifiers, such as OneR, IBk, NaiveBayes, and J48, giving for each one a performance evaluation.
	Pandey et al. (2021)	Integration of texture and spectral response with ai techniques for buildings footprint identification using high-resolution satellite images	2021	Journal of the Indian Society of Remote Sensing	To improve the efficiency of feature detection for identifying small houses using high-resolution satellite data.	Mumbai city of Maharashtra state (India)	Worldview-3 high-resolution satellite image of Mumbai city	VGG-16 (Visual Geometry Group) conventional neural network (CNN) model	Feature detection for identifying small houses using high-resolution satellite data.	Not defined	Not defined	Precision, Recall, F1 score, FPR, MR, ER, AC and IoU	Bad	Results indicates that the integration of Single-shot multibox detector (SSD) technique with spectral response and signature performs well in detection of houses in high-density region.
	Srivastava et al. (2019)	Understanding urban landuse from the above and ground perspectives: A deep learning, multimodal solution	2019	Remote Sensing of Environment	To automate the mapping of land use at the urban-object level, utilizing a deep learning approach that incorporates data from multiple sources or modalities.	Île-de-France (France)	OSM to obtain a collection of urban objects with associated land use categories; Google Street View API to obtain the ground-based pictures corresponding to each urban object; Google Maps Static API to obtain the top-view image of each urban-object	VGG-16 and the Variable Input Siamese Convolutional Neural Network (VIS-CNN)	To extract specific urban features from images.	Not defined	Not defined	Overall Accuracy (OA); Average Accuracy (AA)	Bad	The inclusion of complementary visual information from each modality significantly enhanced the model's accuracy across various classes. The proposed multimodal CNN model demonstrated the capability to predict land use labels for urban objects, even in cases where

														ground-based pictures were unavailable, by identifying the most plausible set of Google Street View (GSV) pictures within the training dataset.
	Fan et al. (2021)	Urban Functional Zone Mapping With a Bibranch Neural Network via Fusing Remote Sensing and Social Sensing Data	2021	IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	To propose a UFZ mapping method using OpenStreetMap-based (sample generation and the bi-branch neural network (BibNet).	Shenzhen City and Hong Kong City (China)	OpenStreetMap data to generate a UFZ dataset using remote sensing and social sensing data and contains high-resolution remote sensing images, POI data, and their UFZ category labels.	BibNet	To map UFZ.	QGIS	To manage OSM polygon vectors.	Overall Accuracy (OA); Kappa statistic	Bad	The experiments verify the high level of efficiency of OSM-based sample generation and the BibNet for UFZ mapping.
	Gong et al. (2018)	Mapping sky, tree, and building view factors of street canyons in a high-density urban environment	2018	Building and Environment	To estimate sky view factor (SVF), tree view factor (TVF), and building view factor (BVF) within densely populated urban environments.	Hong Kong (China)	Google Street View (GSV) images	Pyramid Scene Parsing Network (PSPNet)	To extract street features (sky, trees, and buildings).	Not defined	Not defined	R2	Bad	The proposed approach for examining visual fields within a 3-D street setting is poised to significantly contribute to connecting evidence-based scientific insights with urban climatic research and facilitating informed decision-making in the realms of urban planning and design.
	Hagenauer and Helbich (2012)	Mining urban land-use patterns from volunteered geographic information by means of genetic algorithms and artificial neural networks	2012	International Journal of Geographical Information Science	To address the impact of completeness errors in OpenStreetMap (OSM), this study introduces a methodological framework for predicting urban areas in Europe that are currently unmapped or only partially mapped using OSM.	42 randomly selected Global Monitoring for Environment and Security Urban Atlas (GMESUA) urban regions	GMESUA and OSM data	ANN	To map urban areas in Europe that are currently not mapped or only partially mapped.	Not defined	Not defined	RMSE, R2, Rs	Bad	Predicting urban patterns is feasible when enough OpenStreetMap (OSM) data is available for analysis. For ML models to be effective, it depends on encoding geographical features within the dataset.
	Francini et al. (2023)	Combining Deep Learning and Multi-Source GIS Methods to Analyze Urban and Greening Changes	2023	Sensors	To propose an innovative methodology for the analysis of the urban and greening changes over time by integrating deep learning (DL)	Matera (Italy)	Semantic Segmentation of Aerial Imagery" dataset; natural color orthoimages covering the case study area with those	U-Net	To classify and segment buildings and vegetation areas from the natural color orthoimage of the study area.	QGIS	To import and vectorize the output of the U-Net model; to assess the accuracy of the U-Net model prediction; to assess changes	Precision, Recall, F1-Score	Good	The U-Net model demonstrated good predictions for both built-up areas and vegetation polygons. The proposed methodology

					technologies to classify and segment the built-up area and the vegetation cover from satellite and aerial images and geographic information system (GIS) techniques.		retrieved from the National Synthesis Database (DBSN)				in urban and greening			offers a reliable estimation of the development of built-up areas and vegetation over the analyzed period. The constraints posed by various orthoimages served as an opportunity to assess the methodology's capability in swiftly and accurately predicting changes in built-up areas and vegetation cover. Overcoming this limitation would be facilitated by having a homogeneous, up-to-date, and openly accessible database of natural orthoimages.
	Van den Broeck and Goedemé (2022)	Combining Deep Semantic Edge and Object Segmentation for Large-Scale Roof-Part Polygon Extraction from Ultrahigh-Resolution Aerial Imagery	2022	Remote Sensing	To define a completely automated end-to-end process designed to extract extensive continuous polygon maps of roof parts from ultra-high-resolution (UHR) aerial imagery.	Three municipalities within Flanders: Brugge, Jabbeke, and Lokeren (Belgium)	Aerial RGB orthophoto with ultrahigh resolution of 0.03 m; a digital elevation model (DEM) of 0.25 m; Polygon labels delineating all distinct roof parts within the three considered regions, stored as GeoJSON files.	Fully Convolutional Network (FCN)	To predict semantic roof edges and objects.	Not defined	To map roof extraction.	Panoptic Quality (PQ); Recognition Quality (RQ) and the Segmentation Quality (SQ)	Bad	Ultra-high-resolution (UHR) optical imagery could present a viable alternative to the traditionally employed LiDAR data for the given task. When coupled with human validation, this methodology offers automated assistance for the thorough and efficient mapping of roofscapes.
	Chen at al. (2022)	A self-attention based global feature enhancing network for semantic segmentation of large-scale urban street-level point clouds	2022	International Journal of Applied Earth Observation and Geoinformation	To propose a novel deep learning framework of point cloud semantic segmentation for large-scale urban street.	-	The datasets include Semantic3D, and vehicular MLS point cloud collected by SSW® vehicular laser modeling and measurement system developed by Beijing Geo-Vision Information Technology Co. ltd. and	The entire network architecture includes a down-sampling network layer, a global feature self-attention encoding mod-ule, a weighted semantic mapping module, and an up-sampling network layer.	For point cloud semantic segmentation of large-scale urban street scenes.	Not defined	Not defined	Intersection over Union (IoU), mean Intersection over Union (mIoU) and Overall Accuracy (OA).	Bad	The introduced GFSAE and WSM enhance the semantic segmentation of point clouds within expansive urban street scenes. The proposed model's effectiveness is demonstrated through comparison with other state-of-the-art methods.

							Capital Normal University.							
AI-GIS integration for land use land cover change prediction	Wang et al. (2018)	Predicting multiple land use transitions under rapid urbanization and implications for land management and urban planning: The case of Zhanggong District in central China	2018	Habitat International	This paper presents a new model integrating geographic information systems (GIS) with artificial neural networks (ANNs) to predict multiple transitions among land use types and urban subclasses	Zhanggong District of Ganzhou city (China)	Satellite images, geospatial predictors data	ANNs algorithm	To predict the land use change	Not defined	Map gridding, predictiors assessment, AI model output mapping	Error map, error percentage	Fine	Land use management and urban planning will benefit from these kind of predictive models
	Shawul and Chakma (2019)	Spatiotemporal detection of land use/land cover change in the large basin using integrated approaches of remote sensing and GIS in the Upper Awash basin, Ethiopia	2019	Environmental Earth Sciences	To analyze the historical and future modelled LULC changes using multi-temporal Landsat images	Upper Awash River Basin (Ethiopia)	Reference data, GPS data location, geospatial data, socioeconomic data, Landsat imageries	MLP	To model multiple land use transition	ArcGIS	Post-classification smoothing and generalization of the classified LULC map, future LULC modeling and mapping	user's accuracy, producer's accuracy, overall accuracy, and the Kappa coefficient for LULC classification (which is not performed using AI techiques)	Fine	The use of remote sensing and GIS technology consents to understand the dynamics of LULC change at different spati-otemporal scales
	Saharkhiz et al. (2020)	Land Use Feature Extraction and Sprawl Development Prediction from Quickbird Satellite Imagery Using Dempster-Shafer and Land Transformation Model	2020	Korean Journal of Remote Sensing	To simulate LULC changes, including residential sprawl expansion, via a change detection procedure	Karbala city (Iraq)	Satellite images	ANN	Land use modelling	Not defined	Not defined	Percent Correct Metric (for LULC prediction)	Bad	This study successfully extracts the LULC, detect the changes, and predicts the urban expansion in Karbala city.
	Cilliers et al. (2021)	A framework for modelling spatio-temporal informal settlement growth prediction	2021	Computers, Environment and Urban Systems	To predict future spatio-temporal informal settlement population growth	Ekurhuleni Metropolitan Municipality (South Africa)	spatial data, data related to informal settlements, spatial attributes	Random forest, kNN, Decision tree, Logistic regression, Naive Bayes, Support vector machine	To identify the driving factors that significantly influence the location and formation of an informal settlement to model this phenomenon	Not defned	Categorise data, discretise investigated area, generate features, visualize results	AUC, Accuracy, F1-Score	Fine	The framework based on GIS, ML and CA can be involved in practical applications within a developing area.
	Shafizadeh-Moghadam et al. (2015)	Performance analysis of radial basis function networks and multi-layer perceptron networks in modeling urban change: a case study	2015	International Journal of Geographical Information Science	The aim of this study is to investigate two ML techniques for modelling urban change.	Mumbai, India	aerial imageries, data from OSM, spatial data as urban growth predictors	Radial basis function network (RBFN) and multi-layer perceptron (MLP)	modeling urban change	ArcGIS	assess urban growth driving factors,	figure of merit (FoM), overall accuracy (OA), producer accuracy (PA), and average spatial distance deviation (ASDD)	Good	ANN-based models can learn essential characteristics of urban change dynamics. Spatial accuracy of the employed models may vary depending on characteristics of geographical regions and the role of master plans and

														policy makers. ANN are not capable of quantifying and separating the effect of urban change driving forces in an explicit way.
	Zhang et al. (2023)	A Random Forest-Based CA-Markov Model to Examine the Dynamics of Land Use/Cover Change Aided with Remote Sensing and GIS	2023	Remote Sensing	To design and apply a machine learning-based CA-Markov model to gain insights into the dynamics of LULC within a coastal watershed.	Minjiang River Watershed (China)	Landsat images of the study area; high-resolution images from Google Earth, GIS data, and information collected during field trips; topographical data; OSM data; socioeconomic and population data.	Iterative Self Organizing Data Analysis Technique Algorithm (ISODATA); RF-CA-Markov Model	ISODATA to classify LULC; RF-CA-Markov Model to simulate LULC based on the probability of occurrence, neighborhood influence, and transition probability. RF to assess the relationship between land use and driving factors; CA-Markov to simulate land use dynamics.	Not defined	To assess driving factors; to visualize LULC prediction.	Overall Accuracy; Area Under Curve	Fine	The presented approach quantifies Land Use and Land Cover Change (LUCC) within evolving environmental conditions and can function as a valuable tool for promoting sustainable watershed management.
AI-GIS integration for environmental quality assessment	Tashakor et al. (2023)	Noise pollution prediction and seasonal comparison in urban parks using a coupled GIS- artificial neural network model	2023	Environmental Monitoring and Assessment	To develop a combined GIS-artificial neural network (ANN) model to predict the spatio-temporal contribution of low-width parks to noise pollution mitigation.	Isfahan City (Iran)	Data from noise measurement stations, transport infrastructure data, vegetation parameter from satellite imageries, digital surface mode, building layer	MLP	To investigate the importance and association of land surface characteristics with noise levels measured at the stations and to produce the noise level map of the region in summer and winter.	ArcGIS	Layer with data production, variables assessment, map production	Sum of Square Errors (SSE)	Good	Machine learning models might provide promising implications for decision-making in data-limited contexts. It also provides scenario-based prediction outcomes to inform urban managers of the choices they must make regarding the soundscape of the city.
	McCarty et al. (2021)	Machine Learning Simulation of Land Cover Impact on Surface Urban Heat Island Surrounding Park Areas	2021	Sustainability	To investigate how different LULC classifications impact the LST and park cooling effect.	Dallas (Texas)	LULC data, Landsat 8 satellite imges, park location and polygons	XGBoost	To study the relationship between chosen factors, the park cooling intensity and land surface temperatures.	ArcGIS	Data assessment and layer creatin, park buffers,	Not defined	Good	The use of ML is a viable method to study the impact of different factors, with us focusing on LULC classification, LST and PCI, two factors found to correlate with UHI. It allows for quicker analyses over larger areas of studies.
	Huang et al. (2022)	Effect of urban morphology on air pollution distribution in high-density	2022	Building and Environment	To investigate the morphological factors that contribute to air pollution's spatial	Huangpu District, Shanghai (China)	Data from monitoring atmospheric particulates stations, spatial	Deeplab V3+ (CNN); linear regression, regression trees, support vector	Deeplab V3+ (CNN) for semantic image segmentation to calculate morphological	ArcGIS	Data collection, data assessment	MSE (Mean Square Error) R2 (R-square coefficient of determination)	Fine	ML has the potential to be used together with CFD as a tool for the evaluation of

		urban blocks based on mobile monitoring and machine learning			distribution using mobile monitoring data		geographic data from OSM	machine (SVM) regression, ensemble trees, Gaussian process regression, and neural networks	indicators; linear regression, regression trees, support vector machine (SVM) regression, ensemble trees, Gaussian process regression, and neural networks, to train and predict the spatial distribution of pollutants.					contaminant distribution in the design process. For this task, standard ML models have better interpretability and require less data, computational resource and storage capacity than DL model.
	Sameh et al. (2022)	Automated Mapping of Urban Heat Island to Predict Land Surface Temperature and Land use/cover Change Using Machine Learning Algorithms: Mansoura City	2022	International Journal of Geoinformatics	To investigate the impact of LULC class changes on LST based on the distribution of UHI spot map	Mansoura city (Egypt)	Landsat TM 5 data up to 2013 and afterward Landsat OLI 8 data for 1991, 2001, 2011 and 2021;	SVM, CA-ANN	SVM for LULC classification, CA-ANN for LULC and LST maps prediction for 2031	ArcGIS, QGIS	ArcGIS: LULC classification import, estimation of LULC indices, LST maps derivation QGIS: LULC and LST prediction maps using MOLUSCE (CA-ANN) QGIS plugin	kappa statistics, overall accuracy, user accuracy, and producer accuracy for LULC classification through SVM; Kappa for LULC and LST prediction through CA-ANN (MOLUSCE QGIS plugin)	Good	This study will be helpful to politicians, policymakers, government representatives, and urban planners in Mansoura city, who will be able to utilize the study's financing for future planning and decision-making
	Das et al. (2021)	Spatio-temporal pattern of land use and land cover and its effects on land surface temperature using remote sensing and GIS techniques: a case study of Bhubaneswar city, Eastern India (1991–2021)	2021	GeoJournal	To assess the impact of LULC dynamics on urban LST for 30 years	Bhubaneswar City (India)	Multi-temporal Landsat remotely sensed data, with data covering the period from 1991 to 2021, Multispectral bands of TM/ETM/OLI images	SVM	Detection and classification of LULC changes during the study periods (1991, 2001, 2012, and 2021)	Not defined	Not defined	Overall accuracy, user's accuracy, producer's accuracy, Kappa	Bad	Policymakers should be worried about future urban expansion and develop a comprehensive plan for environmentally friendly constriction and green building to reduce the urban microclimate warming effect. Urban Green Spaces (UGS) can help in improving the overall urban life and sustainable environment.
	Liu et al. (2022)	Spatio-temporal prediction and factor identification of urban air quality using support vector machine	2022	Urban Climate	To predict air quality of unknown space and time	Northern Air Basin of Taiwan (China)	AQI and meteorological parameters, spatial features data	SVM	Temporal prediction and spatial inference performing	ArcGIS	Spatial data processing and gridding	Root Mean Square Error (RMSE) and the coefficient of determination (R2)	Fine	The use of SVM and GIS for air quality predictions for unknown time and space achieved accurate results and helped in processing complex spatial data.
	Park and Yang (2020)	GIS-Enabled Digital Twin System for Sustainable	2020	Sustainability	To develop a structural schematic of a GIS-enabled	Jeonju city (South Korea)	Data on monthly electricity usage, city gas consumption,	SVM; backpropagation neural network (BPNN)	SVM to predict spatial trends of carbon emissions;	ArcGIS	Data gathering, data processing, data visualization	Accuracy	Fine	Geo-AI enabled Digital Twin systems are valuable for

		Evaluation of Carbon Emissions: A Case Study of Jeonju City, South Korea			Digital Twin system for the sustainable evaluation of carbon emissions		monthly household waste, number of cars in the city		BPNN to investigate the most influencing factor on carbon emission.					information or subjects relevant to sustainable urban planning and management, such as carbon emissions evaluation.
	Fashae et al. (2020)	Land use/land cover change and land surface temperature of Ibadan and environs, Nigeria	2020	Environmental Monitoring and Assessment	Use remote sensing technique and geographical information system (GIS) to analyse the relationship between changing land use/land cover and land surface temperature.	Ibadan City (Nigeria)	Landsat series TM, ETM+, and OLI satellite images of December 1984, December 2002, and January 2019; annual pentad millimetre rainfall data of 1984, 2002, and 2019	RF	To classify land use land cover	Not defined	Not defined	Not defined	Bad	The study confirms the potential application of GIS and remote sensing for detecting urban growth as well as relates growth impact to LST, thereby suggesting that fitting strategies will be important for the sustainable management of the urban areas
	Khorrami et al. (2021)	Evaluation of the environmental impacts of urbanization from the viewpoint of increased skin temperatures: a case study from Istanbul, Turkey	2021	Applied Geomatics	To explore the degree of urbanization that Istanbul has undergone over the past few decades and its effects on the severity of the urban heat island (UHI) phenomenon, as well as the ecological implications in relation to reduced thermal comfort.	Istanbul (Turkey)	Population data from the Turkish Statistical Institute (TSI), and remotely sensed imageries of Landsat satellite series TM5 and ETM+7	RF	LULC mapping	Not defined	Not defined	Confusion matrices; area-weighted accuracy; class-specific accuracies	Bad	The authors recommend that decision-makers incorporate the findings of this study into their policymaking for urban planning and development in Istanbul. They also advise taking appropriate measures to address the adverse environmental effects of elevated skin temperatures, particularly in the downtown area, which experiences the most significant impact from the severe urban heat island (UHI) phenomenon in Istanbul.
	Amiri et al. (2023)	Investigating the application of a commercial and residential energy consumption prediction model for urban Planning scenarios with Machine Learning and Shapley	2023	Energy and Buildings	To predict energy consumption in both commercial and residential buildings and enhance municipal scenario planning by offering a more detailed spatial perspective on	Philadelphia (US)	Socioeconomic and demographic data; household-level and commercial buildings energy consumption	Extreme Gradient Boosting (XGBoost)	To predict building energy use for residential and commercial buildings	QGIS	Scenario modeling	R2, Meand and Median Absolute Error	Fine	In addition to showcasing innovative applications of ML and statistical methods in scenario planning, this research also strives to offer a wide range of tools to support municipal

		Additive explanation methods			future energy usage									planning efforts and a comprehensive map highlighting areas of interest for future research in energy modelling.
	Deng et al. (2022)	Risk Assessment and Prediction of Air Pollution Disasters in Four Chinese Regions	2022	Sustainability	To assess the regional patterns of air pollution disaster risk in heavily industrialized and economically developed urban areas for promoting sustainable development at the regional level	Liaoning Province, Beijing, Shanghai, and Guangdong Province (China)	Data on regional economic and social development; data about residents' health status; meteorological data; annual average of air pollutants emissions	PCA-GA-BP Neural Network	To evaluate the regional disaster risk	Not defined	Air pollution disaster risk mapping	Mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE)	Fine	The results confirmed that machine learning could serve as a viable approach for assessing air pollution disaster risk to a significant degree.
	Sun et al. (2021)	A human-centred assessment framework to prioritise heat mitigation efforts for active travel at city scale	2021	Science of The Total Environment	To introduce a novel approach for policymakers to identify optimal resource allocation for heat mitigation, aiming to achieve the most effective results for communities.	City of Greater Bendigo (CoGB), Victoria, Australia	Google street view images; Landsat satellite images; environmental factors; census demographics data	pix2pix algorithm	To segment GSV panoramas into landscape type pixel and derive the tree shade information in street canyons	ArcGIS	To collect and process data from multiple sources; to compute street landscape metrics; to assess the three components of heat vulnerability indicators; to calculate the route thermal comfort level and neighbourhood heat vulnerability index, and finally to identify the least thermally comfort streets.	Not defined	Good	This method can enhance the targeted allocation of limited resources in heat mitigation strategies.
	Randall et al. (2019)	Geographic Object Based Image Analysis of WorldView-3 Imagery for Urban Hydrologic Modelling at the Catchment Scale	2019	Water	To create a Geographic Object-Based Image Analysis (GEOBIA) approach that can effectively classify land cover types crucial for evaluating runoff volume and implementing Low Impact Development (LID) strategies on a significant geographical scale.	Upper Qing Catchment study area in Beijing (China)	Panchromatic and 8 band multispectral imagery from the WorldView-3 satellite; digital surface model (DSM) and digital terrain model (DTM);	"Classifier" algorithm in eCognition using Bayes classifier	For automated LULC classification	Not defned	Not defined	Confusion matrices; overall accuracy; producer's accuracy; kappa index	Bad	The outcomes of the land cover classification underscore the constraints of automated classification using satellite imagery as the sole data source and underscore the significance of incorporating supplementary information and additional criteria to enhance classification precision.
AI-GIS integration for	Yu et al. (2020)	Spatial Pattern Characteristics	2020	Complexity	To assess the efficiency of	Jilin Province (China)	Landsat remote sensing image,	Support vector machine	To examine the predominant	ArcGIS	DEM assessment	Not defined	Bad	This study introduces the

spatial planning tasks		and Influencing Factors of Green Use Efficiency of Urban Construction Land in Jilin Province			green space utilization on urban construction land (GUEUCL) over time.		DEM, environmental pollution, and socioeconomic data.		factors influencing GUEUCL.					novel concept of GUEUCL, employing the Pollution Load Index as an unconventional metric for urban construction land evaluation. Utilizing a SVM regression model, the research establishes an influential factor index system. The findings contribute to the improvement of green land utilization in Jilin Province, addressing challenges in human-land relations, providing an academic basis for formulating green development policies in the land sector, and offering insights applicable to similar regions worldwide.
	Akylbekov et al. (2022)	ML models and neural networks for analyzing 3D data spatial planning tasks: Example of Khasansky urban district of the Russian Federation	2022	Advances in Engineering Software	To monitor and evaluate territorial rating and suitability for civil engineering activities.	Khasansky urban district (Russia)	OS; climate data from Copernicus	NN, MLP	To identify slope and to define suitability areas.	ArcGIS	To handle geographic data and visualize them	Not defined	Fine	The application of AI and cloud-based services was utilized to analyze 3D terrain images, ensuring the alignment with sustainable development goals.
	Xu et al. (2020)	Accurate Suitability Evaluation of Large-Scale Roof Greening Based on RS and GIS Methods	2020	Sustainability	To evaluate the suitability of roof greening for buildings in cities.	Xiamen Island (China)	High-spatial-resolution remote sensing data; data on land uses and buildings from municipal bureau; air pollution data; precipitation data; population data	D-LinkNet (a deep learning algorithm)	For building roof extraction	ArcGIS	Roof buildings segmentation binarization and vectorization; suitability criteria spatialization; results mapping	Intersection over union (IOU) and pixel accuracy (PA)	Good	The proposed framework in this paper enables the rapid assessment of roof greening suitability across extensive areas. Relevant government departments and urban designers can utilize the ranked evaluation results of building roofs across the entire area for informed roof greening planning and implementation based on budget considerations.

	Tang et al. (2020)	A data-informed analytical approach to human-scale greenway planning: Integrating multi-sourced urban data with machine learning algorithms	2020	Urban Forestry & Urban Greening	This study proposes a data-informed approach to planning urban greenway networks using a combination of classical urban design theories, multi-sourced urban data, and machine learning algorithms	Maoming City (China)	Location based services data; point of interest data; street network data; street network data; data about buildings; street view images	SegNet; SVM	SegNet for extracting street greenery from street view images: SVM for classifying high or low values of street greenery index based	ArcGIS	To process data; to generate greenway networks;	Not defined	Good	The proposed approach attempts to consider human-scale considerations at the city-wide level in gen-erating greenway networks. Addi-tionally, it extends the methodological frontiers of greenway planning by integrating traditional urban design principles with contemporary urban data and innovative techniques.
	Ito & Biljecki (2021)	Assessing bikeability with street view imagery and computer vision	2021	Transportation Research Part C: Emerging Technologies	To investigate, with experiments at a fine spatial scale and across multiple geographies, the use of street view imagery (SVI) and computer vision (CV) to assess bikeability comprehensively.	Singapore and Tokyo (China)	Street View Imagery (SVI), surveys, OpenStreetMap (OSM), Land Use (LU), Digital Elevation Model (DEM), and Air Quality Index (AQI)	In-Place Activated BatchNorm model; GluonCV's model with a YOLOv3 model pre-trained on Pascal VOC dataset with Darknet53	In-Place Activated BatchNorm model for detecting the scenery along bike lanes; GluonCV's model with a YOLOv3 model pre-trained on Pascal VOC dataset with Darknet53 for vehicles detection	Not defined	Not defined	Median absolute deviation method	-	This study demonstrated the effectiveness of utilizing computer vision (CV) techniques and street view imagery (SVI) for evaluating bikeability both within and across cities. The paper details the development and implementation of a bikeability index, employing SVI and CV, with calculations performed at a fine spatial scale and aggregated to the city level. It underscores that this index, at a minimum, supplements conventional tools widely used in this research domain.
	Yagoub et al. (2022)	Extraction of Urban Quality of Life Indicators Using Remote Sensing and Machine Learning: The Case of Al Ain City, United Arab Emirates (UAE)	2022	ISPRS International Journal of Geo-Information	To generate a map illustrating the urban quality of life index for Al Ain city in the United Arab Emirates (UAE).	Al Ain city (UAE)	Sentinel 2A and Sentinel 5P satellite images from August 2021, obtained from the European Space Agency (ESA) through GEE (Google Earth Engine); Landsat TM satellite images from August 2021, obtained from the United States Geological Survey (USGS) through GEE;	Random Forest (RF)	To categorize satellite imagery and produce a Land Use and Land Cover (LULC) map.	QGIS	Urban quality of life indicators assessment and mapping; UQoL mapping	Overll Accuracy; Kappa statistic.	Good	The findings offer a general overview of urban quality of life, illustrating the potential value of this study for policymakers in urban planning and socioeconomic departments.

							Shuttle radar topography mission (SRTM) digital elevation from USGS; (4) GIS vector maps of Al Ain (hospitals, schools, parks, and roads) obtained from Al Ain Town Planning Department.							
	He & He (2023)	Using open data and deep learning to explore walkability in Shenzhen, China	2023	Transportation Research Part D: Transport and Environment	To present an enhanced walkability framework that measures walkability based on four key pedestrian requirements: safety, convenience, continuity, and attractiveness.	Shenzhen (China)	SVIs, social media, government open data, Points of Interest (POI), and OSM data.	Video Propagation and Label Relaxation (VPLR); Fast Segmentation Convolutional Neural Network (Fast-SCNN); DeepLabV3; ResNeSt.	Multiple semantic segmentation models to extract street features (traffic lights, sidewalks, etc.)	Not defined	Not defined	Accuracy	Bad	This study presents a case analysis of walkability within a fast-growing megacity in a developing nation, introducing an improved framework that assesses walkability through four essential pedestrian criteria: safety, convenience, continuity, and attractiveness. Leveraging multisource open data and diverse deep-learning methods, the research simultaneously extracts mesoscale and microscale built-environment features. The outcomes of this investigation unveil significant insights and offer initial recommendations for enhancing walkability in urban environments.
	Li et al. (2020)	Data analytics of urban fabric metrics for smart cities	2020	Future Generation Computer Systems	To analyze urban fabric through advanced computational methods, establishing a set of morphological indices for urban blocks to estimate their overall	Hankou riverside area in Wuhan (China)	Geometric data of urban blocks with building footprints and selecting predefined morphological indexes.	K-means algorithm	Classification and clustering of block units.	ArcGIS	To assess, visualize and map morphological indexes; classification results loading and mapping.	Not defined	Good	The research offers a precise foundation and technical assistance for refining urban construction, providing a scientific basis and accurate technical support

					characteristics and fine distinctions.									for optimizing urban planning.
	Shao et al. (2023)	Assessing and Comparing the Visual Comfort of Streets across Four Chinese Megacities Using AI-Based Image Analysis and the Perceptive Evaluation Method	2023	Land	To compare the visual comfort of streets across four Chinese megacities, each characterized by distinct geographical features.	Beijing, Shenzhen, Shanghai and Guangzhou (China)	Street view image data used obtained in 2019 from the Baidu open-sourced map application program interface through Python programming software.	DeepLab V3+ (deep learning model); Hierarchical cluster (unsupervised machine learning model)	DeepLab V3+ to assess street features proportion; Hierarchical cluster to classify streets according to their characteristics.	Not defined	To visualize the spatial distribution of street comfort and its influential indicators using kernel density analysis.	Not defined	Fine	By combining objective image analysis with subjective visual comfort assessment, this study introduces a more robust and efficient method for large-scale street evaluation research, expanding the scope of human perceptual studies in public spaces at the city level. The identified influencing mechanisms on street visual comfort not only offer practical insights for enhancing street design but also underscore the importance of tailoring design solutions to local characteristics and development.
	Wu et al. (2021)	Mapping fine-scale visual quality distribution inside urban streets using mobile LiDAR data	2021	Building and Environment	To introduce a novel method for assessing the visual quality within urban streets by leveraging mobile LiDAR point clouds.	Two study areas within the center of Yinzhou District of Ningbo City (China)	Mobile LiDAR data	Gradient Boosting classifier; RF	Gradient Boosting classifier to extract semantic information of urban streets; RF to associate the computed values of key elements for the 377 sample sites with their respective visual quality scores.	Not defined	Not defined	User's accuracy (UA), producer's accuracy (PA), overall accuracy (OA), and Kappa coefficient (KA).	Bad	The proposed approach enabled a quantitative examination of the spatial pattern of visual quality in urban streets, revealing that areas with higher visual quality scores tend to exhibit elevated sky view factor, green space factor, motorization rate, and vehicle occurrence rate.
	Freitas et al. (2023)	Characterizing the perception of urban spaces from visual analytics of street-level imagery	2023	AI & Society	Leveraging machine learning and computer vision methodologies along with an innovative interactive visualization tool to offer a street-level analysis of urban environments, encompassing	Raleigh (North Carolina)	GSV images	YOLOv3; t-SNE	YOLOv3 to build the base image feature; t-SNE for visualizing high-dimensional datasets without human training.	Not defined	Not defined	Not defined	Not valuable	Using such AI models is promising and adds a tool to the human analyst's toolbox.

					factors such as safety and maintenance in urban neighborhoods.								
	Mao et al. (2022)	Quantifying spatiotemporal dynamics of urban building and material metabolism by combining a random forest model and GIS-based material flow analysis	2022	Frontiers in Earth Science	To create a city-level building dataset, with a focus on estimating building vintage using a Random Forest (RF) model that incorporates both individual and neighborhood-level morphological and geospatial features, and to characterize material metabolism by employing a Geographic Information System (GIS)-based Material Flow Analysis (MFA) model.	Shenzhen (China)	Geolocation, footprint, and height of buildings was in Shenzhen based on the digital maps generated by Beijing CityDNA Technology Company.	RF	To estimate the vintage of buildings.	Not defined	To quantify material stocks and flows based the MFA model; to map spatiotemporal patterns of buildings and materials at the 500x500 m of spatial resolution	The area under the curve (AUC) and the 1:1 line between the predicted and in-situ data.	Fine	The RF model's success consented to analyze the evolution of urban material metabolism over time and space by informing decision-makers in urban renewal planning. The spatiotemporal patterns of in-use material stocks and potential Construction and Demolition Waste (CDW) generation serve as benchmarks for environmental risk assessment. It also offers insights into potential secondary resources, facilitating a shift towards environmentally friendly and sustainable practices in urban renewal.

1.2.2.1. AI-GIS integration for disaster management planning

The systematic literature review shows that many scientific articles deal with AI-GIS applications for disaster management planning. Disaster management planning deals with the role of urban planning around the disaster management process, which consists of four stages: (1) reduction, (2) preparedness, (3) response, and (4) recovery (Alexander 2002, 2005, 2013). In this field, urban planning investigates the consequences of different natural hazards impacts in cities and surrounding areas. Since the early stages of their impacts, addressing these challenges is crucial to ensure the sustainable development of cities and their resilience.

Integrating AI with GIS can significantly enhance disaster management planning by providing better data analysis, predictive capabilities, and decision support. According to the findings of this study, there are many ways AI-GIS integration can be used in disaster management planning.

They include applications of AI-GIS for data collection and analysis, such as Francini et al. (2022), which proposed a deep learning approach to analyze remote sensing and satellite imagery and detect buildings in at-risk areas. This application can help monitor urban features in at-risk areas and define preventive disaster management planning policies.

Many applications found through this systematic literature review regard predictive modeling, namely the application of artificial intelligence models and algorithms combined with GIS tools for analyzing historical data and environmental factors to predict the likelihood of disasters occurring in specific areas. Within this research area, some authors combined artificial intelligence models and GIS techniques to assess landslide susceptibility maps (Hamid et al., 2023; Wang et al., 2020), to assess debris flow hazard (Zhou et al., 2022), and to model gully erosion susceptibility (Saha et al., 2021). Others applied and combined these algorithms and techniques for analyzing and predicting flood hazards (Darabi et al., 2019; Eini et al., 2020; Motta et al., 2021; Darabi et al., 2022). Kim et al. (2021) and Rosés et al. (2021) focused on social hazards by predicting and simulating crime patterns at a high-resolution level. In the first study, an RF model was applied to build a crime prediction model, while in the second, the employment of artificial intelligence is not defined. Neither of these studies defines the use of GIS tools and the integration with AI algorithms. Each paper highlighted how AI models can forecast the impact of disasters, enabling better preparedness and how GIS helps to visualize and analyze these results.

Integrating AI with GIS can also be an effective tool for emergency response center allocation (Rizeei et al., 2019). Specifically, this study is an example of how AI can optimize resource allocation by analyzing spatial data to determine the most effective deployment of emergency response teams and supplies. At the same time, GIS can help to visualize and analyze the geographic distribution of resources and demand to identify gaps in coverage.

Evacuation planning represents another field of AI-GIS for disaster management planning (Mudassir et al., 2021). For this purpose, GIS can be used to create evacuation route maps, and AI can provide real-time updates on traffic conditions and other factors affecting the safety of evacuees. In this context, AI models can predict evacuation needs and help plan for shelter capacity based on forecasted disaster impact.

Each reviewed paper highlighted that integrating AI and GIS is valuable in boosting disaster management planning strategies (Abid et al., 2021) because it can save lives and reduce the economic impact of disasters by providing timely and data-driven insights. However, it is essential to ensure that data quality, privacy, and ethical considerations are considered when implementing such systems and to involve stakeholders from various domains in the planning and implementation process.

1.2.2.2. AI-GIS integration for land use land cover and urban features detection

Ten papers deal with AI-GIS integration for land use, land cover, and urban feature detection. The interest in integrating AI technologies with GIS techniques for LULC and urban and territorial feature detection has increased as it can provide accurate, efficient, and timely information about urban and territorial environments. This information is essential for many urban and territorial planning applications, as well as for environmental monitoring.

From the performed systematic literature review, it has emerged that many applications deal with detecting specific urban objects and that most employ only AI models without integrating GIS techniques. Urban object detection via AI models consents to identifying and locating specific urban features within satellite and aerial imagery, such as buildings, roads, bridges, streetlights, and vegetation. GIS consents to geo-reference and display the detected urban features for further analysis and decision-making. However, GIS software and usage are not defined within the reviewed studies about urban object detection.

For instance, Srivastava et al. (2019) utilized a deep learning approach, a multimodal Convolution Neural Networks (CNNs) model, to extract specific urban features from the above and ground perspectives employing Google Street View and Google Maps Static images, while Gong et al. (2018) employed a semantic segmentation model, the Pyramid Scene Parsing

Network (PSPNet), to extract street features (sky, trees, and buildings), which are valuable information for microclimatic studies. Another example of AI usage for urban object detection is the scientific work developed by Chen et al. (2022), in which the authors propose a novel deep learning framework of point cloud semantic segmentation for large-scale urban street scenes and compare the obtained results with other known deep learning models.

In the context of AI-GIS integration for urban object detection, Pandey et al. (2021) and Van den Broeck and Goedemé (2022) used the VGG-16 (Visual Geometry Group) conventional neural network (CNN) model and Fully Convolutional Network (FCN) to predict building footprint and roof from high-resolution satellite data, respectively. Also, the GIS software and usage are not defined.

Some applications deal with the integrated usage of AI and GIS for land use land cover detection from image classification. Specifically, AI algorithms are trained and validated to classify aerial or satellite images into various land use land cover categories, such as residential, commercial, industrial, agricultural, forests, water bodies, etc. The classified images can be imported into GIS software to create detailed land use land cover maps with a specific spatial resolution. Land use land cover detection via AI algorithms can be extended over a period by comparing land use land cover from historical and current satellite or aerial imageries to detect changes in land use land cover over time. In this kind of AI application, GIS techniques can be used to visualize and analyze change detection results to understand the dynamics of urban and territorial development. These applications are crucial for monitoring urban expansion and environmental changes.

In this context, Silva et al. (2022) used deep learning techniques and classifiers to recognize and classify specific zones, such as vegetation, exposed soil, asphalt, and buildings, within an urban and rural area. In this study, even if the authors employed the QGIS software for image detection, the integration of AI and GIS is not fully explored. On the contrary, Francini et al. (2023) emphasized the integration of AI and GIS for urban and greening cover detection. In this study, the authors employed a tested and validated deep learning model, the U-Net, to classify and segment built-up area and vegetation land use classes over a specific period. The GIS software, which, in this case, is the open-source QGIS software, is integrated with the deep learning model as they used it for vectorization and urban and greening change assessment and visualization.

Other applications were focused on Urban Functional Zone (UFZ) mapping using labeled data from OpenStreetMap through a bi-branch neural network (BibNet) (Fan et al., 2021). Another work on AI-GIS integration for

LULC and urban object detection deals with urban areas' mapping in Europe to mitigate the effect of completeness errors in OSM. In doing that, a machine learning approach consisting of artificial neural networks and a genetic algorithm to reduce the number of attributes is applied.

As a result, many applications of integrating AI and GIS for land use, land cover, and urban feature detection exist. All provide valuable insights for sustainable urban development, disaster management, and natural resource management. As demonstrated by the analyzed studies, training AI models with high-quality and up-to-date data and validating their accuracy through ground truth data are recommended. Additionally, the integration should consider data privacy and ethical considerations, especially when dealing with high-resolution imagery and geospatial data.

1.2.2.3. AI-GIS integration for land use land cover change prediction

In the era of rapid urbanization, there is an increasing concern about the effects of urban growth on environmental resources, climate, and biodiversity (Huang et al., 2020). Therefore, it becomes imperative to think about new models for modeling and predicting patterns of urban change for urban and territorial planners and decision-makers.

Many models exist to assess future land use land cover transformations, characterized by five steps: data collection, calibration, simulation, validation, and prediction (Gaur & Singh, 2023). The data collection consists of obtaining data about the historical LULC transformation and the LULC driving factors. LULC data come from orthoimages, satellite imagery processed and elaborated through the application of image classification techniques, both traditional and innovative. Driving factors data represent biophysical, socio-economic, and institutional factors responsible for the LULC changes over time. The calibration phase is needed to parameterize the model, starting from LULC data and driving factors. This latter is then applied to simulate future changes by generating the transition probability maps. The model validation phase estimates the model accuracy in predicting the LULC changes by comparing the LULC prediction with the LULC data available at a specific time. After checking the model prediction accuracy and validation, the last stage of LULC modeling consists of predicting future LULC.

These models can predict LULC changes covering a period of twenty or thirty years and encompass a wide range of models, including statistical, such as logistic regression (Huu et al., 2022), generalized additive models (Brown et al., 2002), and Markov chains (Kumar et al., 2014; Zhang et al., 2011; Singh et al., 2022), cellular automata (CA) (Al-Darwish et al., 2018; Feng &

Qi, 2018), and agent-based models (Arsanjani et al., 2013; Zhang et al., 2015; Li et al., 2020). Hybrid models also integrate several methods, such as CA-Markov (Maurya et al., 2023; Hamad et al., 2018) models.

In the last decades, artificial intelligence has been employed for LULC prediction through artificial neural networks (ANNs), also in an integrated way with other models, such as CA-ANN models.

The findings of the systematic literature review showed that integrating artificial intelligence with geographic information systems for LULC change prediction represents a valuable tool for understanding and planning environmental, urban, and rural changes.

Wang et al. (2018), for example, integrated GIS and ANNs to predict LULC changes over time, while Shawul and Chakma (2019) and Shafizadeh-Moghadam et al. (2015) modeled future LULC changes using multi-temporal Landsat images by integrating a machine learning models with the ArcGIS tool. ANNs and GIS were also employed for simulating residential sprawl expansion (Saharkhiz et al., 2020). Different machine learning models, such as Random Forest, kNN, Decision tree, Logistic regression, Naive Bayes, Support vector machine, and GIS tools, were also employed in an integrated way to predict future spatio-temporal informal settlement growth (Cilliers et al., 2021). Zhang et al. (2023) designed and implemented an RF-based Cellular Automata-Markov (CA-Markov) model to acquire insights into the dynamics of Land Use and Land Cover (LULC) within a coastal watershed.

In all the reviewed studies, AI-based machine learning models or ANNs are trained to predict LULC changes and, in general, urban growth processes based on historical data and a variety of driving factors, while GIS tools for preparing the geospatial data to input these models, visualization of LULC historical data and future predictions.

The critical result of reviewing AI-GIS applications for land use land cover change prediction is that AI models provide a more realistic understanding of potential LULC changes because they ensure data integration from multiple sources, including satellite imagery, environmental data, socio-economic factors, and policy information. GIS tools consent to handle this integration better. Moreover, the potential of integrating such methods and techniques is that their use could also be effective for scenario-based analysis, which is very important for planners and decision-makers for interactive planning. Using scenario-based analysis for future LULC changes by employing AI and GIS can model the effects of zoning changes, conservation programs, and infrastructure development, helping decision-makers understand the spatial implications of policies and their effects and assess the potential outcomes of different development paths. The integration of AI-GIS for LULC change prediction could also be integrated with information from stakeholders by engaging communities and incorporating local perspectives into change prediction models. Furthermore, models can be validated and calibrated using real-time data and feedback to improve prediction accuracy. At the same time, GIS can integrate real-time data and support the ongoing refinement of predictive models.

It can be a powerful tool for sustainable land management, urban planning, and environmental conservation by synthesizing and integrating AI and GIS for land use and land cover change prediction. It enables decision-makers to make informed choices by providing insights into potential future scenarios. However, it is essential to continually update and validate these models with real-world data to improve their accuracy and reliability.

1.2.2.4. AI-GIS integration for environmental quality assessment

Based on the research results, AI has been effectively integrated with GIS to tackle numerous typical environmental management issues. Noise pollution, air quality monitoring, and land surface temperature assessment are some issues addressed within applications of AI-GIS integration for environmental quality assessment.

Noise pollution assessment, for example, is addressed in the study developed by Tashakor et al. (2023), where a combined GIS-artificial neural network (ANN) model to predict the spatio-temporal contribution of low-width parks to noise pollution mitigation is defined. Specifically, the authors integrated an MLP model to explore the significance and correlation between land surface characteristics and the noise levels recorded at the stations, aiming to generate seasonal noise level maps for the region in both summer and winter and an ArcGIS system for map production and variable assessment.

Land Surface Temperature assessment applications are most addressed. Many applications within the reviewed articles, indeed, deal with the assessment of urban microclimate conditions. For example, McCarty et al. (2021) examined the influence of various Land Use and Land Cover (LULC) classifications on Land Surface Temperature (LST) and the cooling effect of parks by integrating machine learning and GIS techniques. In this study, the authors employed ArcGIS software for variables assessment, definition, and mapping; an ML model, such as XGBoost, is trained to examine the correlation between selected factors, cooling intensity in parks, and land surface temperatures. Sameh et al. (2022) evaluated the impact of LULC class changes on Land Surface Temperature based on the Urban Heat Island spot map distribution. In this study, the integration of AI-GIS for urban heat island analysis has been explored. Specifically, the authors tested a machine learning model, the SVM, for LULC classification and a CA-ANN for LULC and LST map prediction for 2031. These AI methods are integrated with many GIS software: ArcGIS for LULC classification import, estimation of LULC indices, and LST maps derivation, while QGIS is employed for LULC and LST prediction maps through the MOLUSCE plugin, which is based on a CA-ANN model. Sun et al. (2021) proposed an innovative method for policymakers to determine the optimal allocation of resources for heat mitigation to maximize effectiveness and benefits for communities based on a deep learning model and ArcGIS source.

Some studies aimed at analyzing spatiotemporal patterns of LULC changes and their effect on urban land surface temperature by integrating machine learning models and GIS techniques. Das et al. (2021), for instance, assessed the impact of LULC dynamics on LST in Bhubaneswar City, Eastern India, for 30 years (1991–2021) using Landsat data (TM, ETM +, and OLI/TIRS) and ML algorithms as SVM model was used for LULC detection and classification. Fashae et al. (2020) also aimed to analyze the relationship between changing LULC and LST using machine learning models, remote sensing techniques, and GIS. Khorrami et al. (2021) also explored the degree of urbanization that Istanbul has undergone over the past few decades, its effects on the severity of the urban heat island (UHI) phenomenon, and the ecological implications of reduced thermal comfort. To achieve this aim, they employed an RF model for LULC mapping.

Some AI-GIS applications for environmental quality assessment regard air quality monitoring and assessment, in which AI models are used to process data from various sources, such as air quality sensors, meteorological data, and satellite imagery, to predict air pollution levels and identify pollution sources, while GIS techniques to map and visualize real-time air quality data and help identify areas with air quality issues.

Huang et al. (2022) investigated the morphological factors that contribute to the spatial distribution of air pollution using mobile monitoring data and machine learning algorithms. Within their methodology, the authors first identified specific indicators of urban morphology using semantic segmentation and deep learning from street-view images and then compared the performance of six machine learning algorithms in predicting the spatial variability of pollutants. The GIS software employed in this study was ArcGIS, which was used for data collection and analysis. Liu et al. (2022) combined ML algorithms and GIS to predict air quality at a detailed resolution. They employed a machine learning model, the SVM, to predict air quality using ArcGIS software for spatial data processing, analysis, and mapping.

Some studies were also focused on specific pollutant assessment and monitoring, such as Park and Yang (2020), which developed a structural schematic of a GIS-enabled Digital Twin system for the sustainable evaluation of carbon emissions. In this study, the authors employed an SVM model to predict spatial trends of carbon emissions and BPNN to investigate the most influencing factors on carbon emission in combination with ArcGIS software for data gathering, processing, and visualization. Others focused on examining air pollution disaster risk trends in areas characterized by extensive industrialization and economic development, intending to advance sustainable development on a regional scale by employing a PCA-GA-BP Neural Network (Deng et al., 2022).

Energy is another important aspect of ensuring environmental quality addressed within the reviewed study. Monitoring energy consumption is a crucial aspect of urban planning, as it helps identify opportunities for efficiency improvements, informs sustainable development strategies, and contributes to environmental conservation. Some studies under systematic literature review are energy-related (Amiri et al., 2023). In their study, the authors predicted energy consumption in commercial and residential buildings through scenario analysis by integrating machine learning models, such as XGBoos for building energy prediction and QGIS software for scenario modeling.

Another study by Randall et al. (2019) focused on water runoff assessment and control by creating a Geographic Object-Based Image Analysis (GEOBIA) approach to classify land cover types, evaluate runoff volume, and implement Low Impact Development (LID) strategies on a significant geographical scale.

Each paper highlighted how integrating AI with GIS is valuable for assessing environmental quality. By combining AI and GIS, decision-makers and policymakers can analyze and monitor various environmental parameters, detect trends, and make informed environmental management and protection decisions.

1.2.2.5. AI-GIS integration for spatial planning tasks

Technological advancements should support urban planning in effective decision-making processes to develop sustainable and livable cities. The applications of AI-GIS integration for spatial planning tasks and planning decision-making processes are increasing.

Areas of AI-GIS applications for spatial planning tasks cover urban planning suitability analysis, bike-ability and walkability analysis, data-driven approaches for land use planning, urban quality of life assessment, analysis of urban fabric, comparing and assessment of visual comfort of streets, and quantification of building metabolism.

AI usage for land use planning aims to analyze historical land use data, environmental factors, and demographics, while GIS mapping and analysis facilitate informed decisions by planners and policymakers. For example, in the study developed by Yu et al. (2020), a machine learning model, the SVM model, was employed to assess the main factors associated with the effective utilization of resources in current natural, economic, technological, and social conditions, in combination with GIS techniques. Some studies focused on applying machine learning models and neural networks combined with ArcGIS technology to assess and rate the suitability of different planning policies. Some examples are for civil engineering activities (Akylbekov et al., 2022), while others are for green infrastructure strategies planning, such as green roofs (Xu et al., 2020) and greenways (Tang et al., 2020). In the first study, the authors monitored and evaluated territorial rating and suitability for civil engineering activities by integrating machine learning techniques to generate geo-topographical data and GIS software to handle and visualize data. In the second study, a deep learning algorithm is tested for extracting building roofs, while the GIS technique is used for roof greening suitability analysis. The third study employs deep and machine learning models for street greenery extraction from street view images and index classification, respectively. This latter is performed by considering stakeholders' perceptions and feedback.

Some methodologies are based on the AI-GIS integration for spatial planning tasks aimed at assessing sustainable modes of transport, such as walkability and bike-ability, because they play a valuable role in promoting sustainable, healthy, and environmentally friendly urban areas. To this end, for example, Ito & Biljecki (2021) comprehensively assessed bike-ability through the application of deep learning models on street view imageries, while He & He (2023) proposed a framework based on deep learning and GIS technologies to evaluate walkability based on four pedestrian requirements: safety, convenience, continuity, and attractiveness.

Within the applications of AI-GIS integration for spatial planning is a methodology for urban quality of life assessment developed by Yagoub et al. (2022) by combining machine learning models and GIS source technologies. In this study, the authors developed an urban quality of life map. The machine learning model, namely RF, served to categorize satellite imagery and develop land use and cover maps, while QGIS software was used for urban quality of life assessment and mapping.

Some other approaches are based on urban metrics analysis for classifying and defining urban blocks based on their specific characteristics (Li et al., 2020). In this case, unsupervised machine learning models are used for urban blocks clustering and classification according to their morphological indexes.

Increasing attention is also paid to the assessment of urban street perception. To this aim, for example, Shao et al. (2023) compared the visual comfort of streets employing a deep learning model, the DeepLab V3+, to assess street feature segments and a machine learning model, the hierarchical cluster, to classify streets according to their characteristics in combination with GIS technology for the spatial distribution of street comfort and its influential indicators using kernel density analysis. Wu et al. (2021) defined a novel method for assessing the visual quality within urban streets by leveraging mobile LiDAR point clouds, in which machine learning techniques are employed to extract semantic information from urban streets, and a random forest algorithm to associate the computed values of elements for the 377 sample sites with their respective visual quality scores. Finally, Freitas et al. (2023) utilized machine learning and computer vision approaches, coupled with an advanced interactive visualization tool, to provide a detailed analysis of urban environments at the street level. This analysis includes considerations of factors like safety and maintenance in urban neighborhoods.

Combining AI and GIS technologies is also tested for measuring the spatiotemporal dynamics of urban building and material metabolism by integrating a random forest model with GIS-based material flow analysis, as done by Mao et al. (2022).

Integrating AI and GIS in spatial planning tasks provides a data-driven approach to making more informed and efficient land use, infrastructure, and environmental management decisions. It allows planners, policymakers, and stakeholders to visualize and analyze spatial data and to understand decision implications. It is crucial to ensure data quality and consider ethical and privacy concerns when using AI-GIS integration in spatial planning tasks, especially when dealing with sensitive location-based data.

1.3. The main research findings

This systematic literature review demonstrated that AI-GIS integration is applied to various urban planning areas. The increasing amount of urban big data to process and manage and the multiple urban planning phenomena to assess have consequently led to this growing interest in this topic.

This systematic literature review revealed that the leading urban planning research areas where AI-GIS integration is most prolific are disaster management planning, environmental quality assessment, and generic spatial planning tasks. The interest in this topic is followed by greater attention on the combined use of AI and GIS for land use land cover: at first for land use land cover and, generally, for urban features mapping and then for land use land cover prediction.

The systematic literature review of studies on the AI-GIS integration for disaster management planning reveals that the combined application of these two technologies represents a valuable instrument for dealing with cities' planning and management during hazardous events. In disaster management planning applications, AI is applied mainly for hazard modeling and mapping, elements or features in at-risk locations and identification, reconstruction plan definition, risk prediction, and data-driven simulation. Therefore, GeoAI applications in this field can support urban planning in the disaster management process, disaster policy creation, emergency rescue operations, and response. In these applications, both machine learning and deep learning models are applied by demonstrating, through different accuracy measures, a good level of accuracy. Many analyzed studies employed ArcGIS, while few used open-source QGIS software for GIS technology concerns. The level of integration between AI and GIS technologies was mainly considered good, except for some cases where the level of integration was poor. This was due to the authors' unclear definition of the integrated methodology. In some cases, the GIS technology employed and its use was not defined.

The findings from the review of the articles related to the AI-GIS integration for land use land cover and urban features detection showed that all these applications are of valuable importance for land use control and development. In these studies, the most employed AI technique was deep learning models, which perform better in object recognition. Indeed, in all the analyzed studies, deep learning models were applied for image classification and segmentation to contour land use land cover or specific urban objects. In a few studies, the software GIS employed was clearly defined, which, in most cases, coincides with the open-source QGIS software. However, the level of integration between AI and GIS was not so profoundly reached. It is correlated with the application of AI for image processing in most cases. Therefore, the integration between these two kinds of technologies must be further analyzed in this field.

Regarding AI-GIS integration for land use and land cover prediction, the study revealed that combining these technologies is essential for this application. They can assist decision-makers and planners in the planning of tomorrow's cities. Except for a few cases, the level of integration of AI and GIS was acceptable as the two technologies were put in a relationship for constructing practical decision support tools.

Also, for environmental quality assessment, the systematic literature review revealed that different studies have been developed for this purpose and different domains of environmental quality, including noise pollution, air pollution, energy consumption assessment, urban heat island, and land surface assessment. The level of integration between AI and GIS was generally acceptable. Also, in this case, it was mainly because the authors did not define the GIS software use and its purpose. The AI models generally employed in studies related to environmental quality assessment are machine learning and deep learning models. They are mainly employed to assess and investigate environmental quality elements or to assist in this assessment.

AI-GIS integration for spatial planning tasks, which, from the performed systematic literature review, includes land use suitability analysis and sustainable transportation systems assessment, also revealed a great domain of innovative GeoAI field of methodology applications and development. Like the other research domains, in this case, the integration level was generally fine. The AI algorithms employed for this research area are different, ranging from supervised and unsupervised to deep learning models, considering the specific application of these algorithms.

As a result, reaching a great level of integration between AI and GIS technologies was difficult in every urban domain identified in this study. This suggests that many applications must be developed to investigate and strengthen this integration. Within the analyzed studies, few reached a significant level of integration because integrating AI models with GIS techniques needs specific and defined skills and knowledge.

In summary, the main research findings drawn from this study are that the combined use of innovative AI models with GIS represents a prolific field of study within the urban planning context. It consents to manage urban data efficiently by developing strong, reliable, and robust methods for specific urban planning purposes.

The results revealed that this topic is being investigated within the scientific community and that the integration between AI and GIS technologies must be further analyzed to be strengthened. This task is of great significance for making these technologies effective. Making the integration simple and reliable would, in turn, facilitate using these models and technologies in urban planning practices. Therefore, much must be done to integrate these two technologies better and apply them in decision-making processes.

GeoAI applications analyzed in this systematic literature review represent the most recent methodologies of technological advancement combined with GIS systems within various topics of the analyzed research field.

From the conducted analysis, it emerged that GeoAI for sustainable urban planning purposes is a research field of growing interest within the scientific community, demonstrating that the use of artificial intelligence models is also increasing in the urban planning domain.

Furthermore, GeoAI represents an exciting research field for urban planning as urban planning is characterized by big urban data derived from fixed and mobile sensors and ultra-high-resolution images from satellites and unmanned aerial vehicles.

From the performed systematic literature review, it emerged also that GeoAI applications can be performed by involving people's perceptions and feedback in the modeling phase. This is significant for decision-making as specific analysis, like scenario modeling, can be performed considering stakeholders' considerations; therefore, planning is more effective and efficient.

The main challenge that GeoAI applications had to tackle is related to the scarcity of data. Indeed, artificial intelligence models work well if they are trained and validated with a large amount of data. The more they train, the more they are efficient, and their accuracy increases in regression and semantic segmentation.

In conclusion, the conducted study wants to provide a theoretical basis for GeoAI applications for sustainable urban planning, which identifies the main research domain where this kind of technology has been developed and tested. Starting from these results, this study wanted to summarize the main key characteristics and shortcomings of this study to open the floor to new research ideas and development. In this context, this study aims to be the first analysis of the existing research on this new topic, making the development of new research possible. Moreover, as implementing this kind of technology is not addressed in the urban planning practice, more can be done to bridge the gap between research and practice on applying GeoAI systems for various urban planning domains.

2. Innovative tools to manage sustainable urban planning: web-based Geographic Information Systems (WebGIS)

Another essential task in sustainable urban planning is managing a large quantity of spatial data and visualizing and disseminating them in a valuable way. The recent technological developments of Information Technology (IT) tools and sensors, as well as the evolution of the methodologies based on the use of satellite Earth observation technology and remote sensing, have led to an ever-growing increase in the availability of large quantities of geospatial data (Goodchild, 2012; Goodchild et al., 2012; Goodchild, 2018). However, as previously said, the most significant challenge is the dataset organization and management in a systematic and logical configuration to interact with end users effectively and efficiently.

Over the last decade, integrating information technologies and Geographic Information Systems (GIS) has led to Web-GIS, also known as web-based GIS. These applications have gained high popularity since they enable multi-user visualization, processing, and spatial analysis without installing any specific software and using the internet (Simão et al., 2009).

Web-GIS platforms have been considered the best solution for allowing users to access, read, and share spatial data and geo-information and ensure efficient urban data management. These systems' great advantage relies on their ability to access and manage data by providing a spatial data overview. Furthermore, employing GIS tools and functions through the combination of data and geospatial analysis techniques allows the creation of thematic maps via the web, which can properly support the decision-making process (Sejati et al., 2020).

WebGIS, therefore, plays a crucial role in sustainable urban planning as it represents a platform for integrating, analyzing, and visualizing spatial data from different sources. WebGIS lets urban planners integrate various spatial data, including demographic information, land use and land cover data, transportation networks, and environmental data, and permits the visualization of this data through maps and interactive dashboards by providing a comprehensive understanding of the urban environment. Furthermore, WebGIS facilitates collaboration among various stakeholders, such as government agencies, community groups, and businesses. In the planning process, it provides a common platform for sharing and accessing spatial information, fostering better communication and collaboration.

As a spatially informed decision-making platform, WebGIS is a powerful tool that enhances urban planning and management's efficiency, effectiveness, and sustainability. It supports collaboration, data-driven insights, and community engagement, contributing to creating more sustainable cities.

2.1. The general aspects of WebGIS

Web-GIS platforms are based on the integration between GIS and the internet and, therefore, incorporate the advantages of both technologies. Indeed, the main strength of these technologies is the ability to process georeferenced spatial data by employing GIS geoprocessing functions and tools through a browser and not by downloading geospatial data on a device and processing them locally.

Web-GIS tools are generally based on a client/server architecture. The client architecture consents to display geospatial and numerical data tables, to acquire input data from external users, and to boot geospatial tools and functions for spatial data analysis. The server architecture processes the input data and provides the output in different formats, such as vector, raster, or attribute, to the client.

The growing interest in Web-GIS geoportals is demonstrated by some statistics provided by Google, which show how the word geoportal in 2007 was searched for by about 182,000 users (Goodchild et al., 2007), while in 2023 by 8,400,000 users.

Web-GIS platforms, in recent years, have been considered as a link between what can be defined as smart governance and the world of Information and Communication Technology (ICT) (Feltynowski, 2015; Eom et al., 2016; Gil-Garcia et al., 2016; Fietkiewicz et al., 2017). Smart governance represents a government that aims to define strategic lines of action by involving citizens in issues of public importance. The Web-GIS platforms have been widely used as a preventive system for analyzing natural and anthropic risks (Dong et al., 2013; Thiebes et al., 2013; Fago et al., 2014; Ahmed et al., 2018; Capolupo et al., 2021; Francini et al., 2022; Faravelli et al., 2023), urban planning and management purposes (Alicandro et al., 2022; Ostadabbas et al., 2021; Bendib et al., 2016; Ostadabbas et al., 2019; Francini et al., 2023; Michailik & Zwirowicz-Rutkowska, 2023), meteorology (Stefanov, 2021), water and coastal management and control (Randazzo et al., 2021), cultural heritage management and defense (Oxoli et al., 2019; Vacca et al., 2017) and health ambits (Mushonga et al., 2017; Kulawiak et al., 2022).

The technical and functional characteristics of the various online Web-GIS are linked to the objectives and purposes for which they are designed. These platforms are practical tools for studying and analyzing human activities and natural phenomena and are essential for optimizing and managing all decision-making processes (Opdam, 2010).

WebGIS plays a crucial role in making cities and communities more environmentally responsible, socially inclusive, economically viable, and resilient by providing a platform for integrating, analyzing, and visualizing spatial data from multiple sources. WebGIS represents the most suitable decision support system for urban planning practice as it can effectively link and support planning policies and activities.

In Italy, there is not a specific law that fully addresses WebGIS operationalization for urban and territorial planning, except for the State, Regions, and Local Authorities Agreement on the reference cartographic system, known as the GIS agreement, approved on 26/09/1996 and operationalized in 2000, to develop territorial bases covering the entire national territory. Since then, in many regional urbanistic laws, WebGIS, generally known as territorial information systems (SIT), have been defined as tools to arrange and manage urban data for defining general and sectoral planning choices, territorial planning, and project activity that provides services and information to all citizens and can bring together information from public bodies and the scientific community. The implementation of geoportals is defined as strengthening the main criteria of territorial planning, such as subsidiarity, the sustainability of planning choices, the participation of citizens in the definition of territorial governance choices, and the flexibility of territorial planning.

In line with these objectives, regional and local administrations have provided geoportals for consulting, querying, and, in some cases, downloading geographical data in the last three decades. However, these Web-GIS platforms have, in many cases, only viewing and consultation functions but do not allow any spatial data processing. A geoportal developed with interactive tools, under a supervised process, permits end users to work directly on Web-GIS platforms, with the great advantage of having databases that are updated and shared in real time. This vision converges with European strategies, such as the Open-Source Software Strategy 2020 – 2023 (European Commission, 2020), which have an even greater diffusion of open-source technologies inside the public sector and local governments as a primary goal. Given that, in recent years, open-source solutions have reached a very consolidated level of development, and they are primarily employed in many countries and governments of the world (Coetzee et al., 2020; Mobasheri et al., 2020).

2.2. The analysis of the main Italian WebGIS platforms for urban planning processes

The Web-GIS platforms developed by local and administrative authorities have, mainly the purpose of publishing, with the most transparency, geospatial data concerning socio-economic and territorial aspects of a given study area to share this information with the end users. To analyze the functional aspects, it is necessary to explore the type of data they make usable, their degree of harmonization, the standards with which they are designed, and the essential functions they guarantee to end users.

For this purpose, a sample of institutional Web-GIS in Italy is chosen, and their characteristics and functions are examined. Eight regional Web-GIS are considered, selecting geoportals for each Italian geographical area, corresponding to the North, Center, South, and Islands. In particular, the Web-GIS of the following regions is considered:

- Lombardy, Veneto, and Emilia Romagna for Northern Italy;
- Lazio, Tuscany, and Umbria for Central Italy;
- Puglia, Basilicata, and Sicily for Southern and Insular Italy.

From the architectural point of view, the geoportals of Lombardia, Umbria, Basilicata, Puglia, and Sicilia adopt a top-down policy-driven method to define data entry, transfer, maintenance, and delivery processes. Instead, the choice undertaken by the regions of Emilia Romagna, Veneto, Tuscany, and Lazio is to provide a better service, offering both a top-down and bottom-up policies-driven method.

According to available information, the technology chosen for the system architecture is INSPIRE in all the institutional Web-GIS platforms examined. The INSPIRE-based geoportals provide online access to geospatial data and information services supplied by multiple national members and public and private organizations (Bernard et al., 2005).

Policy and standards deal with data management principles, metadata standards, and implementation rules for constructing Web-GIS platforms. These elements relate to the system architecture and interoperability issues, which could be guaranteed by implementing the regulations and standards given by Open Geospatial Consortium (OGC) web services and International Organization for Standardization (ISO) specifications. Indeed, all regional geoportals examined are based on INSPIRE Normative specifications (metadata, network services, interoperability of spatial data sets and services, data and service sharing, monitoring, and reporting) with implementing rules and technical guidelines. In addition, all the platforms are designed following federated Service-Oriented Architecture (SOA).

Some geoportals of the analyzed sample serve large volumes and intensive categories of spatial data and geo-information generated from multiple data providers in Earth science. For example, the Web-GIS of Lombardia region provides various data themes such as cartographies, aerial imageries, landscape constraints, land uses, information from geological studies, agro-forest rural roads, underused areas, reclaimed and contaminated sites, regional hydrographic networks, regional ecological networks, negotiated programming, water protection, hydrogeological structure plan (PAI), regional plans, floods directive, territorial database, seismic classification of municipalities, census of historical buildings, United Nations Educational, Scientific and Cultural Organization (UNESCO) sites and administrative boundaries. The Web-GIS of the Tuscany region also offers the possibility for end users to access various data topics, including several map libraries and geographic open data photo libraries, satellite images, land use and land cover data, hydrogeological constraints, data about cultural heritage and landscapes, building site dating, forest fire risk database, and rural and biological districts. The Veneto Web-GIS offers smaller layers and themes, providing several apps, an aerial photo library, forestry, geo-resources, toponymy, and territory.

On the other hand, considering the web processing and data functions offered by institutional geoportals, Lombardia provides an essential service. Indeed, this regional Web-GIS offers only data information extraction by location service. The same services are provided by Emilia Romagna Web-GIS only for authenticated users. Veneto Geoportal, in addition to essential services, allows users to download multiple layers of the study area.

From examining the institutional Web-GIS, the existing regional Geoportals offer users a limited range of functions. Therefore, the need to provide authorized users with functions that allow a bottom-up participatory planning approach emerges. This need aligns with the present thesis's objectives, which present a Web-GIS platform prototype suitable for more shared urban and territorial planning and management.

3. An innovative methodological approach for assessing the relationship between urban growth and greening goals

1. Methodology overview

Building on the results achieved from the theoretical analysis, within this Chapter, the author proposes an innovative methodological approach to manage urban growth and greening policies sustainably. This methodological approach precisely, consists of the three following phases:

1. The first phase deals with the identification of urban and greening changes over time to assess and evaluate the changes in these two kinds of planning policies during an observation period and the subsequent analysis of the co-relation between urban and greening development with population dynamics by combining RS methodologies, AI technologies, and geospatial techniques;
2. The second phase regards the definition of an indicator-based geospatial tool capable of identifying urban areas most suitable for dense urban growth processes and greening interventions;
3. The third phase consists of developing a WebGIS platform to upload, visualize, and update such information by stakeholders, who, for many reasons, could be interested in that analysis.

Building on this conceptual framework, each phase wants to address specific research gaps within the urban planning field on the defined topics.

The first phase wants to address the gap that few studies have measured in how greening has developed in terms of its complete spatial-temporal configuration with urban growth and population dynamics, especially using RS technologies and innovative AI models (Francini et al., 2022). Such technologies allow accurate information and drastically reduce operational times and costs. Urban growth and greening changes are generally assessed by retrieving data from the LULC maps. Urban and greening information can be retrieved from the Urban Atlas (Montero et al., 2014), OSM, or maps and geo-databases provided by local authorities and public administrations. Nonetheless, comprehensive data concerning buildings and vegetation is not consistently accessible, as detailed LULC maps are frequently unavailable, and when they are, they may come at a cost. Alternative conventional approaches for acquiring urban shapes and vegetation polygons rely on visual interpretation of aerial imagery and manual digitization (Skokanová et al., 2020). These methods, requiring many manual operations, are time-consuming and costly. Furthermore, the scientific literature also lacks studies that co-relate urban and greening changes with population dynamics to analyze how the relationship between urban and green features goes with population changes over time. This analysis could give valuable insights into the urban planning process. As seen in Chapter 3, applying AI-GIS technologies to RS data for LULC mapping at a reasonable spatial resolution has reached considerable attention during the last decade. The integrated use of RS data, GIS, and AI technologies is a valuable system to identify and assess the urban and green cover dynamics as they allow studying patterns of land cover changes at various scales accurately and efficiently (Hassan, 2017; Bhat et al., 2017; Huang et al., 2021). To address these multiple gaps, within this study, the author proposed an innovative approach that, combining innovative RS methodologies, AI technologies, and geospatial techniques, looks at the co-relation between urban growth, green development, and population dynamics assessment over time. First, the urban and greening features are detected with a high level of detail by employing AI models to remotely sensed data (Francini et al., 2023). Next, the co-relation impact between urban and green space transformations and population trends on the urban sustainability level is evaluated. This assessment is performed through a quadrant analysis and quantitative metrics. The co-relation among urban growth, greening changes, and population dynamics is assessed by investigating the mismatch between the presence and the demand of built-up and vegetation cover areas within the research area over time. The demand for these spaces considers population needs and adherence to existing legal standards and requirements.

In the subsequent stage of the proposed methodological framework for examining the relationship between urban growth and green space policies, the objective is to identify the potentiality of urban areas for implementing renowned sustainable urban growth strategies, specifically densification, alongside opportunities for green interventions. This phase addresses the gap within the scientific literature, according to which solving interactions between urban growth and the need to provide UGAs' environmental and social benefits is very challenging. Creating urban areas that are both sustainable and livable (Berke et al., 2006) is a challenging task since densification and greening need capacity and form (Burton et al., 1996) depending on the characteristics of each city, such as geology, urban climate, urban morphology, buildings, mobility, and transportation networks. Knowing the capacity and potential of the territory for densification can avoid too high or too low densities and can help improve sustainability and the quality of urban life. While it is already known that resolving this issue necessitates the initial identification of urban areas most suitable for green space enhancement and densification initiatives, a limited number of research works have focused on assessing the appropriateness of such planning processes. Additionally, a shortage of decision-support tools exists to assist planners and decision-makers in formulating well-balanced densification strategies that promote sustainable development and the urban population's quality of life. To overcome this limitation, the author proposes a decision support tool to optimize sustainable urban densification and urban greening development based on an analysis of the built environment and its characteristics. Specifically, a methodology to assess the urban scale potential for urban densification is defined. It sets criteria to measure and map the potential of the location of densification interventions, providing guidance to urban planners and decision-makers in establishing planning policies based on quantified results and values. The significance of this approach is rooted in its establishment as a versatile method, utilizing data from a GIS database to assess and measure the potential for urban densification and/or greening interventions. Additionally, it aids in generating maps that highlight the specific areas with various densification and/or greening potential.

An innovative WebGIS platform is developed in the third and final phase of the proposed methodological approach to support sustainable urban growth and green planning. This platform allows stakeholders, motivated by various considerations, to upload, visualize, and update geospatial information. Specifically, the development of this WebGIS platform addresses the gap that, as found in Chapter 2, considering the Italian case study, regional and local administrations offer limited functionalities, focusing on data viewing and consultation rather than facilitating spatial data processing. The proposed WebGIS platform, however, distinguishes itself by incorporating interactive tools, enabling end users to engage with the platform directly in a supervised process for real-time updates and data sharing. Acknowledging the maturity and widespread adoption of open-source solutions globally, this platform is developed using open-source technology and designed to collect, manage, process, and visualize geospatial data from diverse sources, contributing to decision-making processes in sustainable urban planning. The proposed WebGIS platform serves as a geo-referenced GIS-based tool, facilitating a bidirectional flow of information among the public, stakeholders, and local authorities. The database is implemented using Quantum GIS software (QGIS), and the entire project is shared on the web through Lizmap. The effectiveness of the Web-GIS platform is demonstrated by uploading, visualizing, and updating information coming from the other two phases of the proposed methodological framework.

The methods employed for each part of the proposed methodological approach are deepened within the following Sections.

2. Assessing the co-relation between urban growth, greening development, and population dynamics

The analysis of urban and greening development over time and the assessment of their co-relation with population dynamics is developed by quantifying the amount and by evaluating the distribution of the built-up and vegetation cover at different periods, combining the innovative RS technologies, semantic segmentation of aerial data models, and GIS potentialities. The methodological workflow is schematically shown in Figure 3.1.

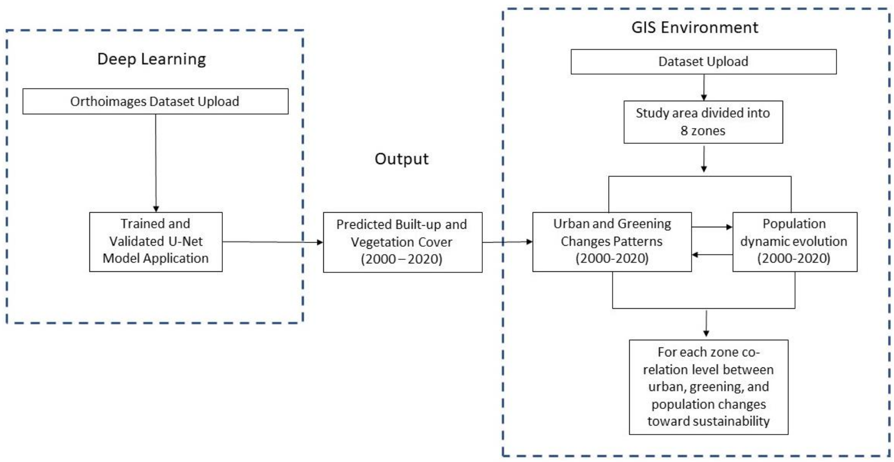


Figure 3.1. Methodological framework to assess the co-relation between urban growth, greening changes, and population dynamics.

Covering an observation period of 20 years, from 2000 to 2020, data about built-up areas and vegetation cover are obtained by applying RS technologies and GIS analysis methods. Specifically, the urban and green features are extracted using the AI-GIS method built in the Laboratory of Territorial and Environmental Planning of the University of Calabria (Francini et al., 2023). The AI algorithm used is a deep learning (DL) model, the U-Net model, that is trained and validated using the "Semantic Segmentation of Aerial Imagery", adopting many data augmentation techniques to improve the model's significance and goodness of fit (Francini et al., 2022). The DL model is tested by classifying and segmenting built-up and vegetation areas from the natural color orthoimage of the study area described in Chapter 4. The trained and validated U-Net model's built-up areas and vegetation cover classification and segmentation accuracy are assessed through the F1-Score. Then, all the classified and segmented buildings and green areas are vectorized and imported into the open-source QGIS platform (QGIS, 2023).

Starting from the results obtained from the automatic classification and segmentation of urban and greening features, the author examined urban and greening changes by considering the population evolution. In particular, the author evaluated the ratio, defined as the mismatch between the supply of built-up and vegetation cover and the demand derived from population needs and law requirements within directional zones obtained from a quadrant analysis.

Within the scientific literature, the geospatial analysis adopted to assess and study urban and greening changes over time are the grid cell analysis (Bai et al., 2022), multi-ring buffer analysis (Kushwaha et al., 2021), and zonal and quadrant analysis (Woldesemayat & Genovese, 2021), whose use differ in purposes and fields of application. The zonal analysis is performed on a zone-by-zone basis within a geographic area. A particular attribute, such as a political boundary, a land cover type, or a geographic feature, usually defines these zones. This method can help analyze and compare different zones within an urban area in a specific way. In grid cell analysis, each cell represents a specific geographic location and contains a value representing a particular attribute. This method is highly suitable for continuous data and common operations, including map algebra, neighborhood analysis, and interpolation. Multi-buffer analysis involves creating multiple concentric zones (buffers) around a specific point or feature. These buffers are typically created at regular intervals and can be used to analyze the distribution of other features relative to the central point. The quadrant analysis consents to establish a spatial relationship between the core and peripheral of the study area and identify the critical direction of land cover and socioeconomic changes. Furthermore, the quadrant analysis allows the integration of multiple data types within each direction, gives a general assessment for strategic decisions, and accounts for the spatial heterogeneity of urban environments.

These reasons led the author to adopt the quadrant analysis to assess urban, greening, and population changes in an integrated and quantitative way. Specifically, the study area is divided into eight zones at 45-degree intervals from the center to the outskirt. Once the zones are defined, thanks to the spatial analysis functions of GIS tools, it becomes possible to compare them with a high level of detail and at various scales. The resulting eight zones are East- North-East (ENE), North-North-East (NNE), North-North-West (NNW), West-North-West (WNW), West-South-West (WSW), South-South-West (SSW), South-South-East (SSE) and East-South-East (ESE) (Mandal et al., 2022).

For each zone, the author assessed the change in the urban greening cover and the population between the time points. The eight sectors' boundaries are marked by geographical coordinates and correspond to the actual quadrant zones of the studied urban area. Using georeferenced boundaries, quadrant analysis can help understand how different quadrant zones of a city differ in terms of urban and greening change levels over time at various scales.

Considering the supply and demand mismatch of urban and vegetation cover, the level of co-relation between urban growth, UGAs, and population changes towards sustainability over time for each of the eight zones is assessed. Indeed, both built-up areas (e.g., residential, commercial, and industrial areas) and green areas (e.g., parks, gardens, and green corridors) in urban areas are forms of supply that must meet the demand of the urban population. As the population increases, there is a higher demand for housing, workplaces, schools, healthcare facilities, and other infrastructures. The creation of these built-up areas is a response to this demand. On the other hand, the increase in UGAs can also be seen as a response to population demand. Urban residents require access to nature for recreation, relaxation, and improving quality of life. Given that, urbanization accompanied by a loss of green areas and population decrease, often referred to as urban shrinkage or depopulation, presents a unique set of challenges for urban sustainability. Urbanization, even with decreasing population, can lead to the loss of UGAs, reducing biodiversity, carbon sequestration, and natural air filtration. Fewer UGAs can negatively impact the well-being of residents by reducing recreational areas and opportunities for social interaction.

2.1. Urban and greening features classification and segmentation

As demonstrated in Chapter 2, the integration of AI and GIS represent a prolific research field for land use land cover mapping and urban features detection within the urban planning field. Many applications include urban scene detection, automatic extraction of urban features from high-resolution aerial images, roof segmentation and land use land cover mapping. Starting from this premise, as detailed information about urban and greening cover cannot be retrieved by existing LULC databases, the author proposed an AI-GIS platform for urban and greening features classification and segmentation. The conceptual framework of this innovative AI-GIS platform is described in Figure 3.2.

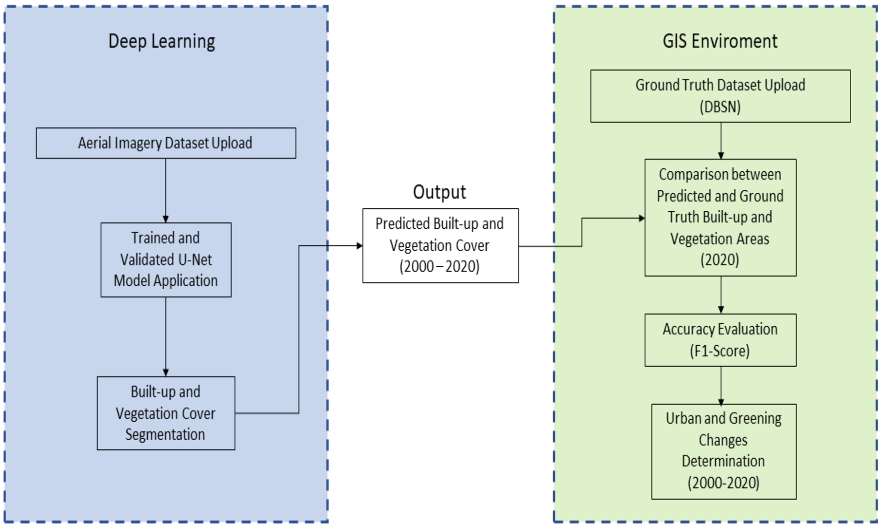


Figure 3.2. Methodological framework to classify and segment urban and greening features.

According to the scientific literature on the use of AI models for urban feature extraction (Chen et al., 2014; He et al., 2016; Majidizadeh et al., 2023), these tasks are generally performed by employing deep learning models as they have a high capacity of feature learning which consent them to achieve high performances. Building on this knowledge, within this study, the author employed a deep learning model for the automatic classification of built-up and vegetation cover over time. Specifically, the author employed the U-Net model, a symmetric encoder-decoder convolutional network

(Ronneberger et al., 2015), to analyze time series of aerial imagery and extract built-up area and green area cover features.

The trained and validated U-Net model is tested by classifying and segmenting the buildings and the vegetation areas from the natural color orthoimage covering a specific urban context.

The author imported and vectorized the output of the tested model in a GIS platform, which, in this study, is the open-source QGIS Desktop software (QGIS, 2023).

To assess the accuracy of the classified and segmented results, the author compared the building and the vegetation polygons with those derived from a ground truth dataset that represents the truth dataset, which verifies the correctness of the proposed model prediction. The author quantitatively assessed the model's accuracy to predict the buildings' and vegetation polygons by determining a specific accuracy metric, the F1-Score.

Once the accuracy of the U-Net model is assessed, the author evaluated specific built-up and vegetation density indicators to determine changes in the vegetation cover and built-up area. In particular, the output of the built-up area and vegetation cover is imported within the QGIS software and processed to quantitatively evaluate the changes in the vegetation and urban features in space and time. Assessing urban and greening changes over time is essential to assess the co-relation between these changes and the population dynamics toward sustainable development.

2.1.1. The U-Net architecture

The U-Net model is a convolutional neural network (CNN) designed for semantic segmentation in image processing tasks characterized by an encoder-decoder architecture capable of working with fewer training images, yielding more precise segmentation. This model was introduced by Ronnerberg et al. (2015) for medical image analysis, but it has been applied to various other domains as well. The name U-Net comes from its characteristic U-shaped architecture (Figure 3.3), which, compared to conventional CNN, consists of a contracting path (left side) followed by an expanding path (right side).

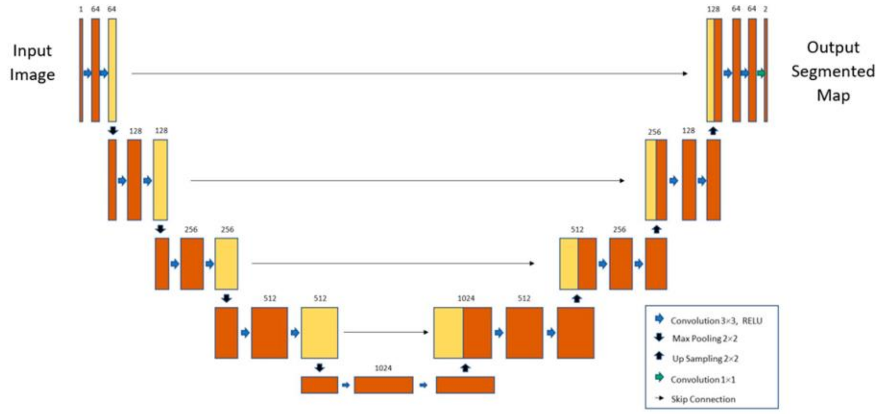


Figure 3.3. U-Net model architecture.

The contracting path, often referred to as the encoder or downsampling path consists of a series of convolutions, each followed by a rectified linear unit (ReLU) and a max-pooling operation, which are responsible for capturing the features and reducing the spatial resolution of the input image. In the contraction, the spatial information is reduced, while feature information is increased. Five convolutional blocks elaborate input data, extracting features at different scales. Each convolutional block is composed of two 3x3 convolutions with ReLU activation.

At the bottom of the U structures is a bottleneck or a central layer with multiple convolutional layers. This layer captures the most abstract and compressed representation of the input.

The expanding path, or the decoder or upsampling path, consists of a series of upsampling and convolutional layers. This part is characterized by a combination of the features and spatial information through a sequence of up-convolutions and concatenations with high-resolution features from the contracting path. In addition, an up-sampling of the feature maps to the original image size is created by passing through five blocks. The expanding path aims to restore the spatial resolution of the image while refining the segmentation results.

One of the critical elements of the U-Net architecture is the skip connections that connect the corresponding layers in the contracting and expanding paths. These skip connections consent to the transfer of detailed spatial information from the encoder to the decoder part to obtain the precise localization of objects within the segmentation task.

The final layer of the network uses a convolutional layer with a soft-max activation function to produce the segmentation mask. The segmentation mask has the exact spatial dimensions as the input image and assigns each pixel to a specific class.

Therefore, the model is designed to capture contextual information while preserving spatial details.

Considering these design characteristics and specifications, the U-Net architecture's ability to capture local and global context and skip connections makes it effective in various image segmentation applications.

Therefore, the U-Net architecture is chosen within this study as it is widely recognized to be well-suited for tasks requiring high-resolution segmentation masks, such as in this case.

2.1.2. Training and validation of the U-Net model

Different steps characterize the training and validation of the U-Net model. The first step involves defining the U-Net model architecture using a specific deep learning framework, such as TensorFlow or PyTorch. After this, the training and validation dataset must be defined and organized. Images of defined spatial resolution with corresponding ground truth segmentation masks must characterize the training and validation dataset. This dataset must be split into training and validation sets to assess the model's performance. Moreover, data preprocessing procedures must be performed to overcome the minor dataset limitation and prepare input images and masks for the training stage. These preprocessing operations include resizing images, normalizing pixel values, and augmenting the data (e.g., rotation, flipping) to increase the diversity of the training set. Then, an appropriate loss function needs to be chosen for segmentation tasks and handling data class imbalance. The loss function has an essential impact on the model accuracy, and usually, the most suitable loss function will depend on the data properties and the class definitions. Subsequently, after selecting an optimizer and an initial learning rate, the training loop can be implemented. The training loop consists of applying the U-Net model to obtain predictions, assessing the loss between predictions and ground truth mask by employing the selected loss function, the computation of the gradients concerning the model parameters, and the following update of the model parameters using the optimizer. These steps must be repeated for each epoch in the training set. The model must be validated after training it for several epochs. This task consents to monitoring the model's performance on unseen data and preventing overfitting.

Within this study, the training and validation tasks are carried out on a Google Colaboratory Pro Plus environment, using 52 GB of RAM and the GPU NVIDIA Tesla P100.

All the project is implemented in Python and the training is developed using Pytorch with TensorFlow backend as the deep learning framework. (https://github.com/ingegnerevitale/U-Net-Semantic-Segmentation-Aerial-Images).

Within this work, the author considered two different loss functions: the Focal Loss and the Intersection over Unit (IoU) based Loss, known as the Jaccard Index.

Focal Loss represents a better solution to the unbalanced dataset problem. Its characteristics allow for reducing the impact of correct predictions and focusing on incorrect examples. Furthermore, the Focal Loss can improve segmentation results. The functional form Focal Loss is derived from Cross-Entropy Loss (CE), and to down-weight easy examples and focus training on hard negatives uses a modulating factor $(1 - p_t)^\gamma$ as reported in Equation 3.1.

$$\mathrm{FL}(\mathrm{p_t}) = -\alpha_\mathrm{t} \cdot (1 - p_t)^\gamma \cdot \log(p_t) \qquad \textit{Equation 3.1}$$

In this Equation, p_t represents the estimated probability of class t, while γ is a hyperparameter greater than zero, which represents the level of reduction of the impact of correct predictions. Similarly, α is a coefficient ranging from 0 to 1 and can be set by inverse class frequency or treated as a hyperparameter. In this research, α is treated as a hyperparameter.

The IoU-based Loss is a standard region-based performance metric for image segmentation problems. Generally, the IoU is adopted to measure the similarity and calculate the ratio of the intersection and the union between the prediction and the ground-truth object in an image, as reported in Equation 3.2.

$$\mathrm{IoU} = \frac{\mathrm{TP}}{\mathrm{FP} + \mathrm{FN} + \mathrm{TP}} \qquad \textit{Equation 3.2}$$

In the IoU Equation, TP are the True Positives, which represent the number of correctly predicted elements, FP is the False Positives, which are the number of entities incorrectly identified as elements to be predicted, FN is False Negative cases, which represent the elements to be predicted incorrectly classified as elements of another category.

For these reasons, the IoU measure is characterized by the properties of scale invariance, symmetricity, and nonnegativity. Its value ranges from 0 to

1, where 0 represents no similarity and 1 is a perfect equivalence between the predictions and the ground truth labels.

The IoU-based Loss function incorporates the IoU measure following Equation 3.3 (Boughorbel et al., 2017).

$$\mathrm{IoU-based\ Loss} = 1 - \mathrm{IoU} \qquad \textit{Equation 3.3}$$

Regards the model optimizer and the initial learning rate definition, within this study, the author selected Adam as a model optimizer (Kingma and Ba, 2015), with an initial learning rate of 0.001 and default hyper-parameters $\beta 1 = 0.9$ and $\beta 2 = 0.999$. The validation task is carried out during the training loop and its loss is calculated and monitored. If validation loss does not improve within four epochs, the learning rate is reduced by a factor of 0.5. To prevent overfitting, the training is stopped if the validation loss does not improve within 100 epochs. At the end of the training process, the model associated with the lowest validation loss is saved.

2.1.3. U-Net model performance assessment

The performance of the U-Net model was assessed considering both the Focal and IoU-based Loss functions. Specifically, the metrics employed by the author to perform this analysis are the Precision, Recall, and F1-Score (Chinchor & Sundheim, 1993). These metrics are commonly employed to assess the performance of classification models, especially for binary classifications, such as positive and negative, as they are based on the concepts of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). As stated in the previous Section of this Chapter, TP is the positive sample predicted by the model, and TN is the negative sample predicted as negative by the model. False Positive FP is the negative sample predicted as positive by the model, and False Negative FN is the negative sample predicted as positive by the model.

Precision gives a measure of positive prediction accuracy as it represents, as demonstrated in Equation 3.4, the ratio of the correctly classified positive observations to the total of predicted positives.

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \qquad \textit{Equation 3.4}$$

Recall, also known as Sensitivity or True Positive Rate, is the ratio of correctly predicted positive observations to all observations in actual class, as defined in Equation 3.5. It consents to measure the ability of the model to predict all the relevant cases.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$ *Equation 3.5*

F1-Score is defined in Equation 3.6 and represents the harmonic mean of Precision and Recall. It provides a balance between Precision and Recall considering both FP and FN and, therefore, can be considered as a complete performance measure. Its value ranges from 0 to 1, where 1 is the best possible F1-score, indicating perfect Precision and Recall, and 0 is the worst.

$$\text{F1} - \text{Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{(\text{Precision} + \text{Recall})}$$ *Equation 3.6*

These metrics are particularly suitable in the case of class imbalance. In situations where one class significantly outweighs the other, relying solely on accuracy may not offer a comprehensive assessment of model performance. Precision, Recall, and F1-score, on the other hand, offer a more refined evaluation, considering the model's performance on positive and negative instances separately.

2.1.4. Geographic transferability assessment

Following the training and validation phases of the U-Net model carried out using the Focal Loss and IoU-based Loss functions, the optimal model is selected based on achieving the highest F1-Score. The selected best model is then employed to classify and segment the built-up area and vegetation cover within the case study. Subsequently, these generated masks are imported into the QGIS desktop platform, converted into vector layers, and juxtaposed with the labeled masks from the ground truth dataset for comparison.

The comparison between the actual and the predicted built-up and vegetation polygons consents to verify that the patterns of spatial autocorrelation between the training and the testing data are removed. This is significant, mainly when the training and validation tasks are carried out, considering that geographic areas differ considerably (Spasov & Petrova-Antonova, 2021). Testing geographic transferability consents to remove patterns of spatial autocorrelation between training and testing data.

The author considered the F1-Score, defined previously, as a performance measure of the model prediction accuracy. The accuracy of the results in terms of the built-up area and vegetation cover prediction is assessed considering the available ground truth data. Once the model's accuracy is defined, the urban and greening development change analysis is performed for the analyzed study area over time.

2.2. *Urban and greening change analysis*

After the classification and segmentation of built-up areas and vegetation cover from a time series of aerial images and orthoimages, the analysis of urban growth and greening development in space and time is performed considering specific urban and greening development indicators. Specifically, the output of the AI-GIS platform in terms of built-up and vegetation cover is processed according to a selection of urban and greening change indicators.

The most used indicator to analyze compact and dispersed urban growth is population density, which is the number of inhabitants per spatial unit. Nonetheless, this indicator alone does not capture the extent of built-up areas. Therefore, the most pertinent density measure for a comprehensive assessment of urban growth processes is built-up density. Built-up area density is also a significant indicator of the complex relationship between urban growth and greening goals, as it is widely recognized that an increasing amount of built-up areas puts pressure on green space conservation and enhancement (Burton, 2002). The most accurate measure of built-up area density is the Floor Area Ratio (FAR) (Abdullahi et al., 2015). This measure is commonly used to express the intensity of urban development, limit the intensity of land use, lessen the environmental impacts of urban development, and control the mass and scale of urban development. FAR is typically calculated by dividing the gross floor area of the building by the total land area or the total buildable land area. Another measure of built-up area density is the Building Coverage Ratio (BCR), expressed as the ratio between the footprint area of the building and the total land site area or the total buildable land site area. The BCR measure ensures open spaces in the land, prevents overcrowded houses, and secures neighborhoods' emergency escape evacuation measures. Since no information about the floor number can be retrieved from the U-Net model automatic classification and segmentation of the buildings and no data about the height of the buildings are available from 3D models, the author considered the BCR as the built-up area density measure.

As described in Chapter 1, the vegetation cover delivers different ecosystem services, such as climate regulation (De Carvalho & Szlafsztein, 2019), air purification, and runoff control, as well as contribute to enhancing human health and well-being (Abdullah et al., 2021). Existing research showed that urban growth – both compact and dispersed – has a significant influence on the quantity, connectivity, size, quality, and accessibility of urban spaces (Haaland & van den Bosch, 2015; Kabisch et al., 2016; Tian et al., 2014). Based on these observations and the available data, the author evaluated the density of the vegetation cover to measure its quantity and distribution changes across space and time. The density of vegetation cover is calculated as the ratio between the vegetation cover predicted by the U-Net model and the reference area.

The indicators used for the urban and greening development analysis in space and time are listed in Table 3.1.

Table 3.1. Urban and greening development indicators.

Indicator	Variable
Built-Up Area Density	Area of Built-Up to Reference Area
Vegetation Cover Density	Area of Vegetation Cover to Reference Area

2.3. *Population data analysis and prediction*

To assess the co-relation between urban and greening changes with population dynamics, population data at a defined scale is needed. When available they can be retrieved from specific population datasets, such as the statistics census and so on. When population data is not available, starting from historical population variation, population prediction and variation are performed in each directional zone by employing the Seigel and Swanson (2004) formula, shown in Equation 3.7.

$$P_i = P_0 \cdot (1 + r)^i \qquad \textit{Equation 3.7}$$

In this Equation, Pi is the predicted population after i number of decades, P0 is the population at the reference year, i is the number of decades (1, 2, 3, …, i), and r is the population growth rate.

2.4. *Indicators to assess the co-relation between urban growth, greening development, and population changes*

The primary goal of this research is to examine the co-relation among urban growth, greenery, and demographic dynamics over time using quadrant analysis. For each of the eight zones within the study area, two distinct indicators about the spatiotemporal dynamics of urban growth, alterations in green cover, and population changes are evaluated. The author considered two different situations: the increase and the decrease in population. Furthermore, considering the uncertainty of the model, the author considered only positive changes in the built-up area. Instances of reduced built-up areas associated with activities such as building demolition or redevelopment and regeneration interventions are not considered within this study at this stage. While these cases hold specific significance in land consumption limitation, the suggested methodology requires further refinement to address such scenarios effectively.

The indicators selected for assessing the co-relation between urban growth, greening changes, and population dynamics are based on the supply-demand mismatch concept. This concept has been widely employed in integrating ES concepts, such as urban policies and plans, within urban planning procedures. Indeed, within the scientific literature, the mismatch in ecosystem services supply and demand has been investigated to better support urban planning through an ecosystem service-based decision-making process capable of prioritizing areas where interventions need to be developed by selecting the best type of interventions (Vignoli et al., 2021; Martnez-Harms & Balvanera, 2012). The primary definition of supply and demand of ecosystem services can be tracked within the study developed by Burkhard et al. (2012). They defined the supply of ecosystem services as the provision of these services, which depends on the biophysical conditions of the ecosystems and their natural and human-induced changes. Demand for ecosystem services represents the consumption or utilization of all goods and services provided by ecosystems within a specific area during a defined time frame. It depends on multiple factors, such as policies, population dynamics, economic factors, advertising, and cultural and social trends (Curranand de Sherbinin, 2004) and, according to what is defined by the European Environment Agency (Uhel et al., 2010), it represents the actual use of ecosystem goods and services.

The indicators employed within this study to assess the co-relation between urban growth, greening policies, and population dynamics move from research on supply-demand mismatch assessment in the context of the ecosystem services-based urban planning field. Indeed, the author introduced two new indicators, the Urban Supply Demand Mismatch Index (USDMI) and the Green Supply Demand Mismatch Index (GSDMI), based on the supply-demand mismatch of urban and greening development, respectively.

The USDMI represents the ratio between the provision of built-up area and the built-up area standards to satisfy the demand of the population changes. The formula adopted for the USDMI indicator definition is Equation 3.8.

$$\mathrm{USDMI} = \frac{\Delta \mathrm{U}}{\Delta \mathrm{P} \cdot \mathrm{SUL}}$$ *Equation 3.8*

In Equation 3.8, ΔU and ΔP represent the variation of built-up area (m^2), and the population variation (inhabitants) during the reference period, while SUL is the standard quantity of built-up area per capita (m^2/inhabitants). According to the Building Regulations of Matera, this standard corresponds to 40 m^2/inhabitants (Building Regulations of Matera, 2021).

The GSDMI represents the ratio between the UGA variation and the minimum UGA standard to satisfy the population demand variation. Its formula is presented in Equation 3.9.

$$\mathrm{GSDMI} = \frac{\Delta \mathrm{V}}{\Delta \mathrm{P} \cdot \mathrm{MGS}}$$ *Equation 3.9*

ΔV is UGAs changes (m^2) for the reference period, ΔP is the population variation (inhabitants) during the reference period, and MGS is the minimum area of UGAs per capita (m^2/inhabitants). The minimum UGA standard is 9 m^2/inhabitants. This minimum standard of UGAs in terms of area per inhabitant is defined by norms and regulations at the international and national level (DM 1444/1968; WHO, 2016).

The combination of the two indicators described above and the definition of specific interval variations allows us to evaluate how spatiotemporal changes in built-up and UGAs, concerning population dynamics, are related to sustainability level (Table 3.2 and Table 3.3).

Table 3.2. USDMI and GSDMI co-relation towards sustainability related to positive population variation (ΔP>0).

Condition	0≤USDMI≤1 and GSDMI≥1	USDMI>1 and GSDMI≥1 or 0≤USDMI≤1 and 0≤GSDMI<1	USDMI>1 and 0≤GSDMI<1 or USDMI>1 and GSDMI<0 or 0≤USDMI≤1 and GSDMI<0
Level of sustainability	GOOD	QUITE GOOD	POOR

Table 3.3. USDMI and GSDMI co-relation towards sustainability related to negative population variation (ΔP<0).

Condition	USDMI<0 and GSDMI<0	USDMI<0 and GDSMI>0
Level of sustainability	POOR	BAD

Considering the increase in resident population scenario during the analyzed period, 0≤USDMI≤1 and GSDMI≥1 identify the best scenario regarding the co-relation between urban growth, greening, and population changes. Indeed, aiming to limit land take, 0≤USDMI≤1 indicates that the newly increased population demand is satisfied for the best standards requirements at maximum. At the same time, a GDSMI>=1 denotes an increase in green coverage in terms of surface area, which meets the green space minimum requirement.

When USDMI>1 and GSDMI≥1 or 0≤USDMI≤1 and 0≤GSDMI<1, the scenario can be identified as characterized by a quite good level of sustainable interaction. In this case, an alternate condition of the following two has occurred: (i) the urban area has grown, exceeding the needs generated by the increase in population demand even if the green area meets the requirements of the standard; (ii) the green area growth does not meet the minimum standards requirements even if the urban development satisfies at maximum the requirements of the standard.

A poor sustainable scenario occurs when USDMI>1 and 0≤GSDMI<1 or USDMI>1 and GSDMI<0 or 0≤USDMI≤1 and GSDMI<0. In this case, the population increase is accompanied by (i) soil sealing and an insufficient provision of UGAs, (ii) soil sealing and vegetated land converted into built-up land, or (iii) sufficient provision of built-up area and loss of vegetative land.

Considering, over the reference period, a decrease in the population, negative values of USDMI and GSDMI (USDMI<0 and GSDMI<0) related to the soil sealing phenomenon denote a poor level of sustainability in urban and greening dynamics. The worst scenario occurs when USDMI is negative and GSDMI is positive (USDMI<0 and GDSMI>0) because of both negative terms in the numerator and denominator of the functional equation. This case corresponds to a population contraction followed by unjustified built-up growth and reduced UGAs.

3. Identifying priority areas for the dense urban and green development of the built environment at the urban scale

This Section describes the second step of the proposed methodological framework. As mentioned previously, this step consists of a suitability analysis method for identifying priority areas for urban densification and urban greening interventions in the built environment. This methodology aims to provide a generic approach for decision-making referring to the densification potential in urban contexts. Based on a literature review, an indicator-based methodology to guide decision-making for urban densification and/or greening intervention is developed. Specifically, this method aims to determine and estimate the potential of any city to accommodate the increase in urban density or, on the other side, the increase of greening in the urban environment.

The flowchart of the overall methodology adopted in this study is shown in Figure 3.4.

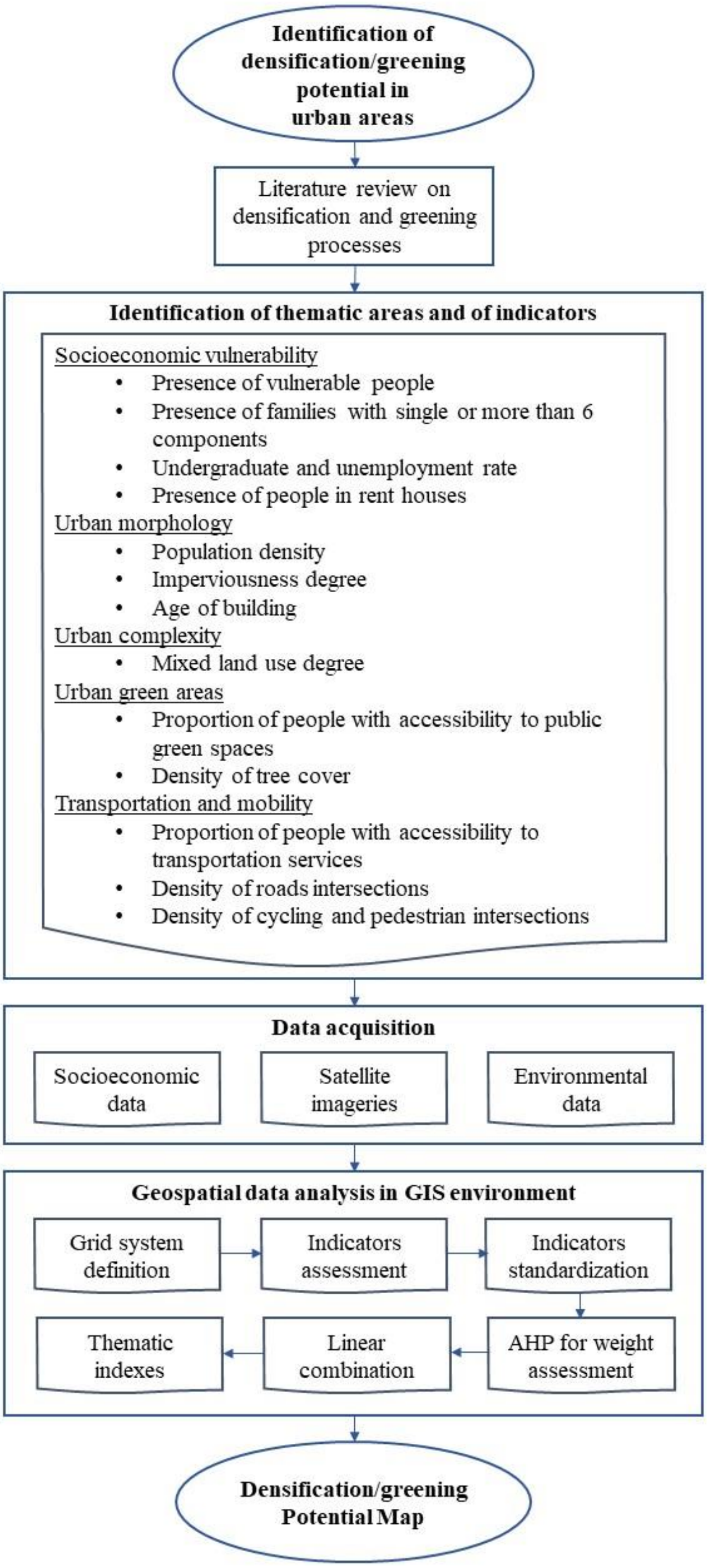

Identification of densification/greening potential in urban areas
Literature review on densification and greening processes
Identification of thematic areas and of indicators
Socioeconomic vulnerability
Presence of vulnerable people
Presence of families with single or more than 6 components
Undergraduate and unemployment rate
Presence of people in rent houses
Urban morphology
Population density
Imperviousness degree
Age of building
Urban complexity
Mixed land use degree
Urban green areas
Proportion of people with accessibility to public green spaces
Density of tree cover
Transportation and mobility
Proportion of people with accessibility to transportation services
Density of roads intersections
Density of cycling and pedestrian intersections
Data acquisition
Socioeconomic data
Satellite imageries
Environmental data
Geospatial data analysis in GIS environment
Grid system definition
Indicators assessment
Indicators standardization
AHP for weight assessment
Linear combination
Thematic indexes
Densification/greening Potential Map

Figure 3.4. Methodological workflow to assess densification and/or greening potentiality of urban areas.

Initially, the study area and the index system are established. In this work, the author identifies specific urban planning thematic areas and indicators related to them, as one of the main objectives of the proposed method is to overcome the deviation in urban densification that has resulted from single-issue research approaches (Breheny, 1992; Williams et al., 1996). Following this, the necessary data is gathered and prepared. Subsequently, a multi-criteria decision analysis uses GIS to process data. A suitability map is generated through spatial data analysis performed using GIS, and the findings are subsequently showcased.

The proposed methodology represents a theoretical foundation for implementing densification and greening interventions at the urban level and a systematic approach for urban planners and decision-makers at the municipal level.

3.1. Establishment of the index system

The presented method considers different core dimensions, defined as thematic areas, to identify the most potential areas for densification and greening interventions.

The considered core dimensions are socioeconomic vulnerability, urban morphology, urban complexity, urban green areas, transportation, and mobility. These five thematic areas are, according to the scientific literature review, the most important in the definition of the right interaction between densification and urban greening processes.

Each core dimension is defined by different indicators, namely factors that influence the difficult relationship between densification and greening interventions. The author first identified many indicators (39), from which only 17 indicators are filtered and selected, since they are very easy to find in the public database, defining, then, the final indicator system.

The indicators employed within this study are shown in Table 3.4, indicating their specific impact on the compact development (and, so, on greening goals).

Table 3.4. Selected indicators for assessing densification and/or greening potential of urban areas.

Thematic areas	Variable	Indicator	Unit	Effect
Socioeconomic vulnerability	SEV1	The proportion of the population aged 15-74 years	%	+
	SEV2	The proportion of families with only one component	%	-
	SEV3	The proportion of families with 6 or more components	%	-
	SEV4	Undergraduate rate	%	-
	SEV5	Unemployment rate	%	-
	SEV6	Proportion of population in rent house	%	-
Urban morphology	UM1	Population density	inh./ha	-
	UM2	Imperviousness degree	%	-
	UM3	Building age	years	-
Urban complexity	UC	Mixed land use degree	n°	+/-
Urban green areas	UGA1	The proportion of the population with accessible urban green areas with a size lower than 0.25 ha in a 100 m distance	%	+
		The proportion of the population with accessible urban green areas with sizes between 0.25 and 1 ha in a 300 m distance		
		The proportion of the population with accessible urban green areas with size between 1 and 5 ha in 500 m distance		
		The proportion of the population with accessible urban green areas with sizes more than 5 ha in 700 m distance		
	UGA2	Tree cover density	%	+
Transportation and mobility	TM1	The proportion of the population with accessible urban bus stops within a 200 m distance	%	+
	TM2	The proportion of the population with accessible extra-urban/metro/train stops in 400 m distance	%	+

	TM3	The proportion of the population with accessible train stations within 800 m distance	%	+
	TM4	Density of road intersections	n°/grid	+
	TM5	Density of cycle path intersections	n°/grid	+

The “+” denotes a positive impact, which means increasing indicators correspond to a greater need to densify or not. In the case of accessibility, both to green areas and to different modes of transport, for example, indicators have a positive impact, meaning that the increase of indicators corresponds to a greater need to densify and less need to be greening.

Conversely, the “-” denotes a negative impact/effect of the indicator; the more significant its value, the smaller the need for densification and the larger the need for greening. For example, population density and imperviousness degree indicators hurt the densification process.

Urban complexity indicator has a double-sided effect on urban development. On the one hand, it can positively impact the densification process. On the other hand, it can harm the densification process. The positive impact denotes the need to densify for residential use as higher mixed land use corresponds to urban densification. In contrast, the negative impact means dense urban development aims to improve mixed land use.

3.1.1. Socioeconomic vulnerability

The socioeconomic vulnerability of the urban context influences densification and greening processes. Socioeconomic vulnerability must be assessed and evaluated considering different social, demographic, and economic factors, which must describe the capacity of social systems to adapt to spatial transformation and the perception of the effects produced by those changes on the population living in that specific urban context. Land use transformation, both related to densification and greening transformations, if not correctly planned, could have negative impacts on vulnerable populations, such as socioeconomically deprived populations, children, and elderly populations (Kabisch & Bosch, 2017).

3.1.2. Urban morphology

The potential of densification and greening actions in an urban context depends specifically on the morphological and structural characteristics of the urban environment. Densification and, conversely, greenification potential depend on the land's density and impervious rate. These two factors are the most used to assess densification and greenification actions (Burton, 2000; OECD, 2012). Density is the most used indicator to assess compact urban development (Burton, 2002). The density can represent the density of functions in a determined context, assessed as the ratio between the activities in an urban area and its built land, as well as the physical density, such as population density (the ratio between the population and the land) or the built-up density.

Dense areas are more efficient in terms of spatial organization, infrastructure organization, and accessibility to services. They can contribute to limiting the urban sprawl phenomenon. However, more dense urban areas lack urban green areas (Artmann, 2013). For these reasons, the density indicator must be considered. Among different density indicators, the most used is population density, the ratio between the population and the surface area.

A further element to consider is the impervious cover rate, the covering of the soil with impermeable materials, as it is recognized as the leading cause of soil degradation (European Commission, 2006). This process negatively affects essential ecosystem services produced by the soil, such as soil filtering, surface flow, food production, microclimatic regulation, and biodiversity. Therefore, high levels of impervious cover correspond to a low quality and quantity of urban green spaces.

3.1.3. Urban complexity

Urban complexity, understood as the degree of diversity of the functions within an urban context, is a further factor influencing the densification and greenification processes. The high mix of functions guarantees several economic and social benefits thanks to the reduction of travel times for reaching urban services relating to the private and social spheres.

In the scientific literature, the degree of diversity of the functions is assessed through different indicators. In some cases, the diversity index is calculated as a relation between residential and non-residential use (Nadeem et al., 2021), while, in others, specific methods such as entropy or Shannon diversity index are used (Abdullahi et al., 2015). These indicators, however, provide qualitative information about the degree of function diversity without considering their adequate quantity and distribution in the area.

The indicator proposed for evaluating the degree of diversity of the functions consists of quantifying the number of functions present within a given area. The functions considered include commercial and various services (education, equipment of collective interest, sports equipment, cultural activities, and socio-assistance services).

3.1.4. Urban green areas

Urban green areas are the leading supplier of urban ecosystem services, such as microclimatic regulation, air filtering and purification, and water surface runoff. Moreover, these spaces can contribute to enhancing human health and well-being (WHO, 2016).

The urban environment's need and capacity to be greenified depends on the status quo of existing urban green areas. In the scientific literature, different indicators have been used to assess the status quo of urban green areas. They can be classified into availability, connectivity, quality, and accessibility indicators.

The most widely used indicator to assess the availability of green areas in the urban environment is the ratio between their total area and the total population (m^2/inhabitants). However, as already highlighted by many authors (De la Barrera et al., 2016), this indicator – an area of urban green areas per inhabitant – does not provide information on how urban green areas are distributed in the space and, therefore, on the accessibility to these services. Moreover, the only availability of urban green areas does not provide any information about the quality of these spaces.

Therefore, to identify priority areas for densification and/or greening interventions, in the proposed framework, the author proposes availability, accessibility, and quality-based indicators since they are the most determinant of the usability and attractiveness of these spaces.

The urban green areas considered in this work are all the usable and accessible natural spaces by the population since they are the leading supplier of urban ecosystem services (Niemelä, 2014). These spaces include urban parks and urban forests.

Urban green areas accessibility is very often discussed in the context of sustainable urban development. Ensuring a high level of accessibility to urban green areas is strongly connected to promoting public health and the concept of environmental justice. In the scientific literature, the accessibility to green spaces is measured through various GIS-based methodologies, from the definition of circular buffer to network analysis. Although this latter gives more accurate results, it needs further information (i.e., street network, slope) and is more computationally burdensome.

Following these assumptions, the accessibility of the UGAs is performed through circular buffer zones producing circle polygons of “served” and “non-served” populations. Even if a linear distance of 300 m is suggested by

WHO (2016), following the results provided by many researchers (De Luca et al., 2021; Grunewald et al., 2017), the author proposes the hierarchical distinction of GSs by applying different linear distance to each category of GSs shown in Table 3.5.

Table 3.5. Employed distances for different surfaces of urban green areas.

Urban green area surface (ha)	Distance (m)
< 0.5	100
0.5 – 1	300
1 – 5	500
> 5	700

The quality of UGAs depends on the type and the quantity of vegetation cover inside the UGAs (De la Barrera et al., 2016). The vegetation cover is the main quality parameter of UGAs, and it is highly correlated to the capacity of the UGA to provide/supply ecosystem services. Moreover, Pont et al. (2021) have identified a low vegetation cover during the densification process of urban areas as well as in already dense areas. Therefore, to assess the quality of UGAs, the author assessed the vegetation cover density of UGAs.

3.1.5. Transportation and mobility

The last core dimension is related to the transportation system and mobility since they represent the core part of urban areas. The proposed methodology aims to assess these services' current conditions (status quo) in terms of their accessibility and connectivity. The latter is a crucial factor since it describes the service's continuity degree.

Since there is not a specific reference to linear distance to be considered, the author proposes a classification of the different means of transport to which a specific value of linear distance is related to analyze the accessibility to transportation and mobility services (Table 3.6).

Table 3.6. Employed distances for different transportation and mobility services.

Transportation and mobility service	Distance (m)
Local bus stops	200
Train stops; Extra-urban bus stops; tram stops	400
Train stations	800

To assess the connectivity of the public transportation system, the author assessed the density of road intersections and cycle intersections as the number of intersections in a specific area. A high level of street network connectivity reduces traffic volume (Ayo-Odifiri et al., 2017), delays, and trip time (Zlatkovic et al., 2019). At the same time, the cycle path continuity has a positive influence on the users' perception as well as on their willingness to use the service (Fistola et al. 2020).

3.2. Determination of indicators weights through Analytic Hierarchy Process

Within this work, the Analytic Hierarchy Process (AHP) method was employed to assess the importance of each criterion and determine the significance of primary and secondary factors. AHP is a Multi-Criteria Decision Analysis (MCDA) employed to address complex issues characterized by numerous interconnected goals (Saaty 1987, 2008; Ouma & Tateishi, 2014). It accommodates a hierarchical structure for the criteria, facilitating a more refined focus on specific criteria and sub-criteria when allocating weights. This feature encourages the active involvement of decision-makers in the comprehensive exploration of all feasible alternatives. It also makes it possible to compare the relative importance of factors, determine priorities between them, and put qualitative judgment in relation to quantitative parameters that, in other cases, would not be comparable.

As described by Saaty in 1987 and 2008, the AHP procedure comprises four fundamental stages. The first step involves decomposing the problem into a hierarchical structure, where the specified criteria are created and then subdivided into sub-criteria.

Subsequently, decision matrices are generated at each level in the second step. A pairwise comparison matrix is formulated, where each factor is evaluated concerning its importance relative to other factors using a scale from 1 to 3, different from the one proposed by Saaty and Vargas (1987). In this scale, 1 denotes an equivalent preference between two factors, and 3 is a high preference for one factor over another. This pairwise comparison process enables an independent assessment of the contribution of each factor, thereby simplifying the decision-making process.

In the third stage, following the establishment of the ratio matrix, each primary and sub-factor within the matrix underwent normalization. This normalization process entailed dividing the value of each factor in every column by the sum of that respective column. Subsequently, the relative weights, also known as the normalized principal eigenvector, were determined for each factor by calculating the mean value of the rows using the pairwise comparison method. To assess the reliability of the computed weights, it was imperative to calculate the Consistency Ratio (CR), which needed to be below 0.10 to ensure consistency, as per the guidelines outlined by Saaty in 1987 and 2008. The CR value was computed using Equation 3.10.

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}$$

Equation 3.10

In this Equation, RI is the Random Consistency Index, evaluated depending on the number of factors (n) as defined in Saaty's RI table (Table 3.7), and CI is the Consistency Index.

Table 3.7. CI values according to Saaty (2008).

n	3	4	5	6	7	8	9	10
RI	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

CI is evaluated considering the principal Eigenvalue $\lambda_{\max}$ and n is the number of factors through Equation 3.11.

$$\mathrm{CI} = \frac{\lambda_{\max} - \mathrm{n}}{\mathrm{n} - 1}$$

Equation 3.11

The calculation of $\lambda_{\max}$ involved summing the products obtained by multiplying each element of the priority vector by the corresponding column totals.

3.3. Densification and/or greening potential assessment

The methodology adopted for densification and greening potential assessment is shown in Figure 3.5.

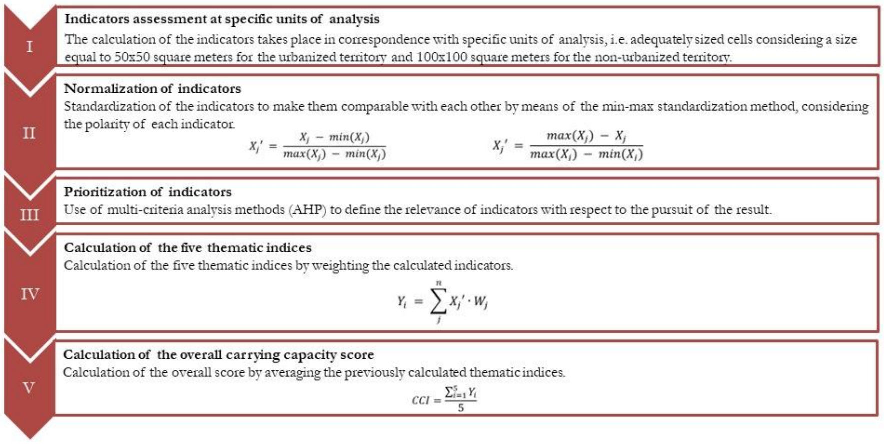


Figure 3.5. Methodology for densification and/or greening potential assessment.

The author employed a grid cell system to calculate each indicator to assess the potentialities of densification and greening interventions in urban areas at a very high level of detail. The author chose this kind of visualization because it is more effective for spatial data assessment and visualization than other kinds, such as zones, districts, etc. Moreover, the grid system division of space consents to overcome the problem of using irregular cartography divisions (Cabrera-Jara et al., 2017), characterized by varying spatial boundaries and a lack of standardized area units for spatial and statistical computations. The uniform grid system adopted in this study is characterized by cells configured at 50 meters x 50 meters for the urbanized territory and 100 meters x 100 meters for the non-urbanized territory.

After evaluating each indicator defined previously at the level of the adopted grid systems, the min-max standardization method, also known as the min-max scaling method, is performed to normalize all indicators and convert them into dimensionless values. Moreover, as the indicators have a specific directional impact on densification and greening interventions, the formula used for the standardization is different (Wang et al., 2014; Li et al., 2021). Those indicators with a positive impact are treated with the Equation 3.12, while those with a negative impact follow Equation 3.13.

$$X_j' = \frac{X_j - min(X_j)}{max(X_j) - min(X_j)}$$ *Equation 3.12*

$$X_j' = \frac{\max(X_j) - X_j}{\max(X_j) - \min(X_j)}$$ *Equation 3.13*

In these Equations, X_j is the original value of indicator j, X_j' is the normalized value of indicator j, $\max(X_j)$ and $\min(X_j)$ are the maximum and the minimum values of indicator j. According to this normalization process, the value range of X_j' is [0;1]. The indicators for each core dimension must be aggregated to calculate a synthetic index for each core dimension.

The author, then, calculated the thematic index for each core dimension using Equation 3.14.

$$Y_i = \sum_{j}^{n} X_j' \cdot W_j$$ *Equation 3.14*

Here, Y_I is the thematic index of core dimension i, X_j' is the normalized value of indicator j, n is the number of indicators for each core dimension and W_j is the weight of each indicator calculated by AHP.

Finally, the "Carrying Capacity Index", namely the potential of each grid cell to be densified (and, therefore, greened), is calculated as the mean value of the calculated thematic index (Equation 3.15).

$$CCI = \frac{\sum_{i=1}^{5} Y_i}{5}$$ *Equation 3.15*

For a better analysis of results and a more comparative analysis, CCI was divided and mapped into 5 categories: "Very Low" – "Low" – "Medium" – "High" – "Very High" dividing the range by 0.20.

4. Implementing a WebGIS platform prototype for mapping, managing, and visualizing the results

The third and final step of the methodological framework for sustainable urban planning proposed within this work deals with the definition of an innovative web-based geospatial decision support system for mapping, managing, and visualizing the results from the first and second phases results of the proposed framework. The main objective of this step is to develop an innovative WebGIS platform for dealing with the complex relationship between urban and greening, as well as to support policymakers and planners on the definition of proper planning policies regarding these two kinds of policies. Furthermore, another objective of this methodological part is to propose an innovative WebGIS characterized by specific and defined functions, which can represent valuable support for the urban planning process in general.

As described in Chapter 2, Information and Communication Technology (ICT) plays a vital role in modern urban planning practice. It offers tools and technologies that significantly enhance decision-making processes' efficiency and data management. Integrating ICT solutions in urban planning enhances cities' capacity to make informed decisions, engage citizens, and create sustainable and resilient urban environments. It also contributes to the development of smart cities that leverage technology to improve the quality of life for residents. In this context, WebGIS tools help urban planners analyze spatial data to make informed decisions about land use and infrastructure development.

Specifically, WebGIS allows urban planners to visualize and analyze land use patterns, helping them make well-informed choices regarding zoning regulations and spatial planning for sustainable development. WebGIS also represents valuable support for environmental management from a green space planning point of view. WebGIS is also a valuable tool for urban planning based on scenario assessment. Indeed, through specific systems, this system allows decision-makers to define multiple planning scenarios and assess their impacts in all the sustainability domains.

From the community engagement side, WebGIS platforms are a sound system for ensuring community engagement and public participation in decision-making processes, which aligns with the main objectives of urban and territorial planning. These systems allow citizens to provide input on urban planning choices and strengthen their sense of ownership. Indeed, WebGIS platforms make spatial data accessible to a wide range of stakeholders, promoting transparency and collaboration in urban development initiatives.

Moreover, WebGIS allows real-time monitoring of urban development projects, helping authorities track progress, identify issues, and make timely adjustments to ensure sustainable outcomes. WebGIS is also of valuable importance in the context of disaster management planning. Indeed, these systems help to assess and map natural disasters, enabling the implementation of measures to mitigate the impact of disasters on urban areas.

WebGIS solutions consent to integrate various data from multiple sources, including satellite imageries, sensor data, geo-topographical data, and demographic information, providing a comprehensive understanding of urban and territorial environments. This data can also be integrated with Internet of Things (IoT) devices to collect and analyze real-time data for innovative city initiatives, optimizing resource use and enhancing efficiency. Furthermore, through complex spatial analysis, WebGIS permits to support evidence-based decision-making.

By leveraging WebGIS for sustainable urban development management, cities can make informed decisions, optimize resource utilization, and work towards creating livable and resilient urban environments. As demonstrated, this tool plays a crucial role in sustainable urban development management by providing a platform for integrating, analyzing, and visualizing spatial data related to urban environments.

In line with this, the proposed Web-GIS platform prototype provides a rational and objective systematic approach to spatial decision analysis. It enables the decision-makers in planning and monitoring processes to assess the implications of feasible strategic interventions and any countermeasures in the presence of natural and anthropic risks.

The innovative element consists of the possibility of both a bottom-up and a top-down decision-making approach, allowing certified users to perform operations on the output. The permit and development user, seeking planning permission, can submit an intervention solution to be investigated by the other decision-makers (platform administrators and local authorities). Local planning authorities make a final decision. They can evaluate an application proposal by comparing it with detailed plans. An applicant submits a development or management and control intervention using Web-GIS tools. The GIS engine compares the submitted intervention with the detailed plan in real-time. This procedure can also be applied in the case of the management of emergencies connected to natural risks and the management and control processes of the territory. If the proposed intervention meets the strategic guidelines and the plan's requirements, development permission will be granted, and the urban database will be updated accordingly. Otherwise, the intervention will be discussed by a technical committee with decision-making authority. The final configuration of the interventions aimed at planning and monitoring territorial processes is shared with the interested public through the Web-GIS platform.

4.1. The architecture of the WebGIS prototype

The platform and the project philosophy are based on open-source technologies. The employment of open-type software and technological solutions favors the exchange of information and data between the involved stakeholders, who, for various reasons, participate in creating and experimenting with the proposed system. Software licenses guarantee a very high level of customization and great freedom in distributing computer codes and design solutions developed ad hoc to achieve the project objectives. On the other hand, closed-source software is often characterized by codes with a closed and inflexible structure, with minimal freedom (depending on the level of license purchased) for distributing the designed and developed products.

An open-source solution is supported by a large team of developers worldwide who periodically release new versions of the distributed software, correcting bugs and developing new functions that allow greater speed in developing various design solutions.

The platform concept was created to guarantee the fundamental principles of modularity, scalability, and data interoperability. Modularity ensures the progressive development of new modules and functionalities to the system without redesigning the entire structure every time. Scalability allows rapid extension and adaptation of the platform's scale to different contexts. Finally, interoperability allows the homogenization and harmonization of data with different structures and characteristics.

Figure 3.6 describes the general overview of the system architecture, indicating different levels of information.

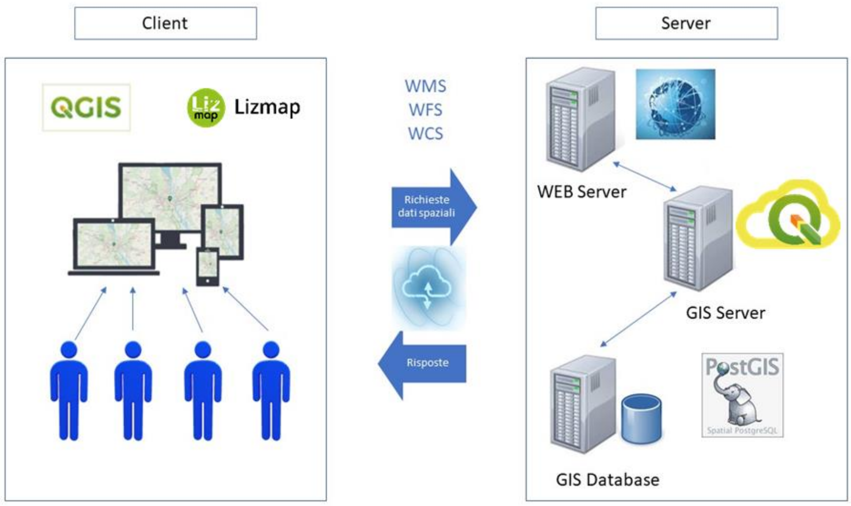


Figure 3.6. General overview of the WebGIS platform architecture.

The Web-GIS design is based on the client/server model. The actual engine of the system is the client module, a geodatabase structure developed in QGIS Desktop, which collects, analyzes, and processes spatial data. QGIS is an open-source GIS desktop that can run on all the most popular operating systems and Android and iOS systems related to mobile devices. As mentioned in the previous section, the software allows users to create, edit, analyze, view, and publish geospatial information.

All data is managed by the QGIS server module, processed by the client module, and returned to users through the reverse flow, using the appropriate services such as, for example, the Web Map Service (WMS), Web Feature Service (WFS), and Web Coverage Service (WCS). The QGIS server has been configured to share, modify, query, and process geospatial data via the web. Furthermore, this module can be easily interfaced with the most used libraries for managing user and graphical interfaces, such as Lizmap, Leaflet, Mapbox, and OpenLayers, through the OGC services.

End users will use the information through an interface managed by Lizmap libraries. Lizmap is open-source software designed by 3Liz (https://www.3liz.com/), which facilitates publishing web mapping applications from QGIS by employing a QGIS server (QGIS Development Team, 2023).

The concept diagram in Figure 3.7 shows the process flow in demand by the users, with the request and receive/view processes. The administrator works to load, stylize, and configure a .qgs project via QGIS and Lizmap plugin and, via Lizmap Web Client (LWC), configure a needed LWC repository (rights/permissions) where to store the QGIS project. The QGIS project, served by the QGIS server, and read by LWC, produces WebMap for end users.

The innovative element of the platform is that the user can perform operations on the output layers. End users can directly upload in LWC to the QGIS Server a couple of (dataset and .qgs) files that allow LWC to create a new map. All changes for permitted users will be stored in the database. Therefore, the proposed platform envisages a top-down and bottom-up information processing and management strategy. This feature is of fundamental importance to activate urban and territorial planning processes based on sharing information between the various stakeholders and a participatory interaction on strategic and design choices.

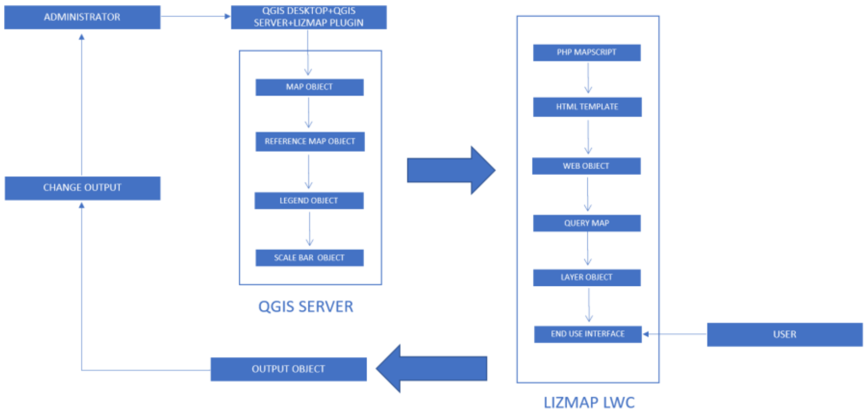


Figure 3.7. Definition of the WebGIS platform architecture with user interface concept diagram.

Based on the described characteristics, the proposed WebGIS platform prototype serves as a system to map, visualize, and manage the information retrieved from the other two steps of the methodological framework described within this study.

The main objective of the WebGIS platform is also to create advanced functions that automatize the operations and obtain the output automatically. This feature of the proposed WebGIS platform is still in progress and needs to be further developed. Therefore, the first results associated with this methodological framework step are described in Chapter 4.

4.2. The main functions of the WebGIS prototype

The publication of layers depends on activating the WFS capabilities in the GIS server (Figure 3.8), which provides layers' selection and configuration options for publishing.

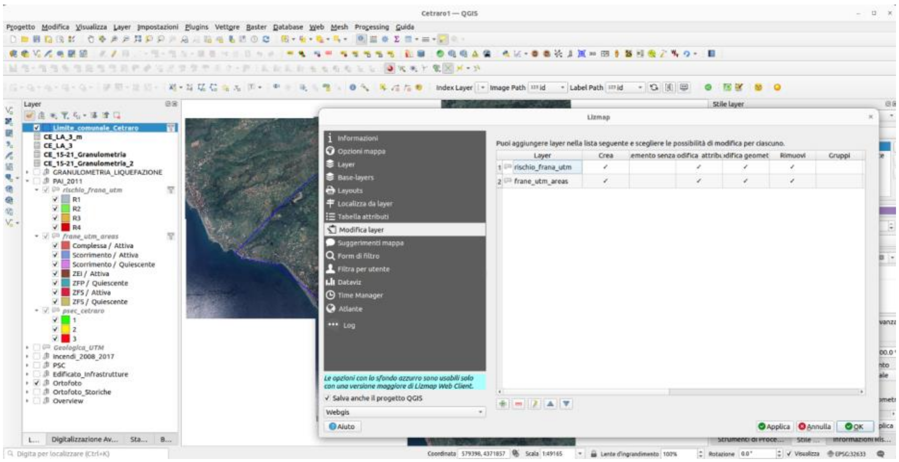


Figure 3.8. Activation of "Layer editing" in the Lizmap plugin.

Lizmap is characterized by a predefined style and map management functionalities. The home page of the proposed Web-GIS prototype shown in Figure 3.9 contains the main functions of the service.

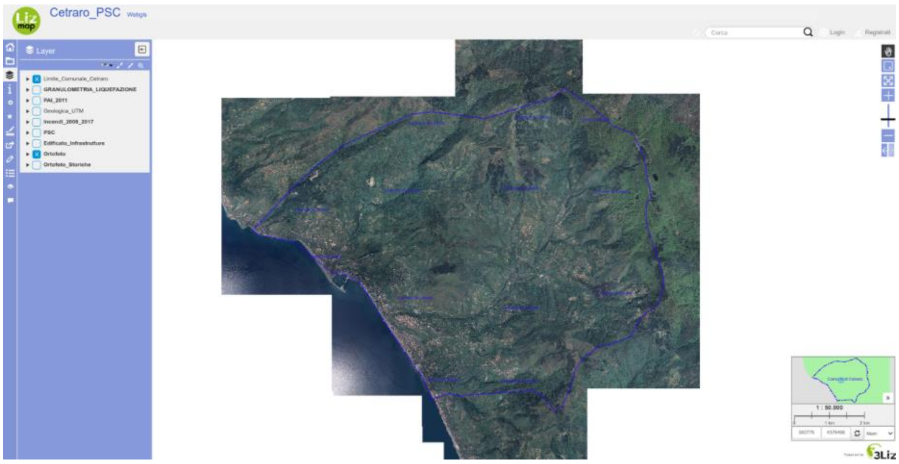


Figure 3.9. Web-GIS prototype homepage.

The Web-GIS platform is characterized by a title that helps to identify the project and its scope. It is also characterized by a map viewer, which consents to visualize the various layers loaded into the Web-GIS platform.

The toolbar is characterized by specific buttons which represent the following functions:

- to activate and deactivate the layer management tool, containing the list of layers present within the Web-GIS platform that can be activated and deactivated;
- to obtain information about the map description, set properties, and contacts;
- to select, filter, and display the information about the geometries of a single layer;
- to run geospatial processes:
- to measure the perimeter, length, and area of geometries;
- to create a new layer and modify it;
- to visualize the attribute table linked to the layers;
- to see geoprocessing results;
- to retrieve information about the selected data.

On the right side of the Web-GIS platform, there are the main navigation functions, such as the map overview panel and the toolbar navigation functions. The map overview panel contains the map overview, the scale bar, the coordinates, and the reference system, while the navigation functions toolbar contains the following functions:

- to move around the map;
- to zoom in on a specific area by defining a rectangle;
- to zoom to the initial map scale;
- to zoom in and zoom out the map through the scale bar;
- to scroll the zoom history going from the previous to the next zoom.

Authorized users, such as technicians, planners, and local authorities, following the bottom-up paradigm, can operate on layers creation, editing attributes, and geometries, and deleting all made actions. Those actions can be saved directly in the database, and the new layers can be defined with a determined symbology according to the map legend (Figure 3.10).

Figure 3.10. Web client creation of new geometry.

4. Testing and validating the innovative methodological approach to assess the relationship between urban growth and greening goals

1. The assessment of the urban and greening development changes over time and their sustainability in combination with population dynamics

Expanding upon the conceptual framework introduced in Chapter 3, this Section seeks to contribute to the ongoing discourse by testing the first phase of the proposed framework in an urban area in the municipality of Matera.

As already proved in the previous Chapters, while numerous authors have noted the decline in green cover corresponding to the expansion of built-up areas, both in densification and sprawling processes, leading to the deterioration of crucial environmental services vital for ecosystem and societal well-being, only a limited number of studies have quantified the comprehensive spatiotemporal evolution of greenery in conjunction with urban development through advanced remote sensing (RS) technologies. Furthermore, the scientific literature lacks methods assessing the co-relation level between urban changes, greening development, and population dynamics and their sustainability level over time.

Addressing these gaps, the author presents an original methodology for examining changes in urban and green spaces over time, incorporating Deep Learning (DL) techniques to classify and segment built-up areas and vegetation cover in satellite and aerial imagery, complemented by Geographic Information System (GIS) tools. The methodology's core involves a trained and validated U-Net model, which undergoes testing in the urban area of Matera (Italy) from 2000 to 2020. The information about urban and greening retrieved from the application of this AI-GIS informatics platform has been processed and put in a co-relationship with population dynamics to have an overview of the sustainability level of the transformation that happened during the observed period.

1.1. Study area

The methodology consisting of the first phase of the proposed methodological framework aimed at identifying and measuring the co-relation between urban growth, greening, and population dynamics towards sustainability over time is tested on an urban area of the municipality of Matera in the Basilicata region, Italy. The study area is shown in Figure 4.1.

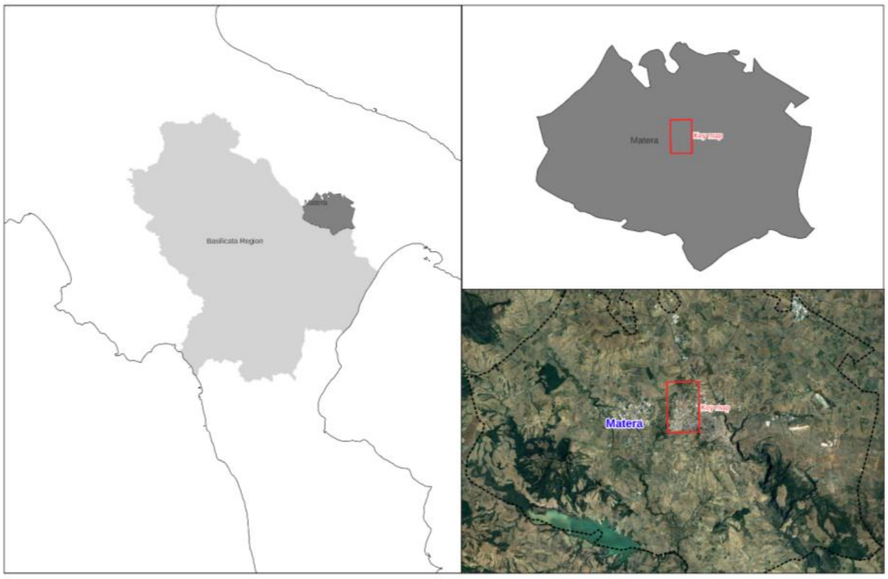


Figure 4.1. Location of the study area in Matera (Italy).

According to the statistical information available for the municipality of Matera, Matera counts an overall population of 59,748 inhabitants distributed over a surface area of 392.08 km^2. The population density characterizing the study area equals 152.39 inhabitants/ km^2.

The municipality of Matera has gained international recognition as the City of Stones, owing to its unique features of prehistoric caves carved into the rock, marking one of the earliest human settlements in Italy. In 1993, Matera's Stones was the first site in Southern Italy designated as a UNESCO World Heritage Site under the category of "Cultural Landscape." Additionally, Matera earned the title of European Capital of Culture in 2019, contributing to its growing prominence on both national and international scales.

Despite these honors, Matera has experienced economic decline in various sectors, except for tourism. According to the national population census (Population Trend Matera 2001-2021, 2023), Matera's population has dwindled over time, while land consumption has increased (Munafò, 2022), leading to the gradual depletion of natural resources. Although Matera is predominantly characterized by rural areas, urban expansion has occurred. Consequently, the municipality of Matera serves as a valuable case study to investigate the shifts in urban development and vegetation cover over time. The combination of territorial transformations, historical significance, and the size of the inhabited center makes Matera a critical case study, with findings that can be widely applicable and transferable.

As shown in Figure 4.1, the proposed method undergoes testing within an urban region in the northwest sector of the Matera municipality. This area, constituting an expansion zone, spans 6.59 square kilometers, equivalent to 1.70% of the entire municipal area. Over time, this zone has experienced significant growth in built-up infrastructure, driven by the construction of new residences, urban amenities, and commercial/industrial structures. These pivotal elements have contributed to a consistent uptrend in land utilization. Consequently, the spatial-temporal analysis aims to enhance our comprehension of the impact of urban planning strategies and policies on the evolving land cover in this context.

1.2. Data

The initial step for identifying and assessing the co-relation between urban growth, greening development, and population dynamics is to train and validate the AI-GIS informatics platform to classify and segment built-up area and vegetation cover at a high resolution with a training and validation dataset. Specifically, the training and validation tasks are performed employing the “Semantic Segmentation of Aerial Imagery” dataset. It is an open-access dataset annotated for a joint project with the Mohammed Bin Rashid Space Center in Dubai, the UAE (Semantic Segmentation Dataset, 2022). The dataset consists of 72 aerial imageries of Dubai obtained by MBRSC satellites and annotated with pixel-wise semantic segmentation in six classes: building, land, road, vegetation, water, and unlabeled (Figure 4.2). The images were segmented by the trainees of the Roia Foundation in Syria. The samples for the model training and validation are 65 images and 7 images, respectively.

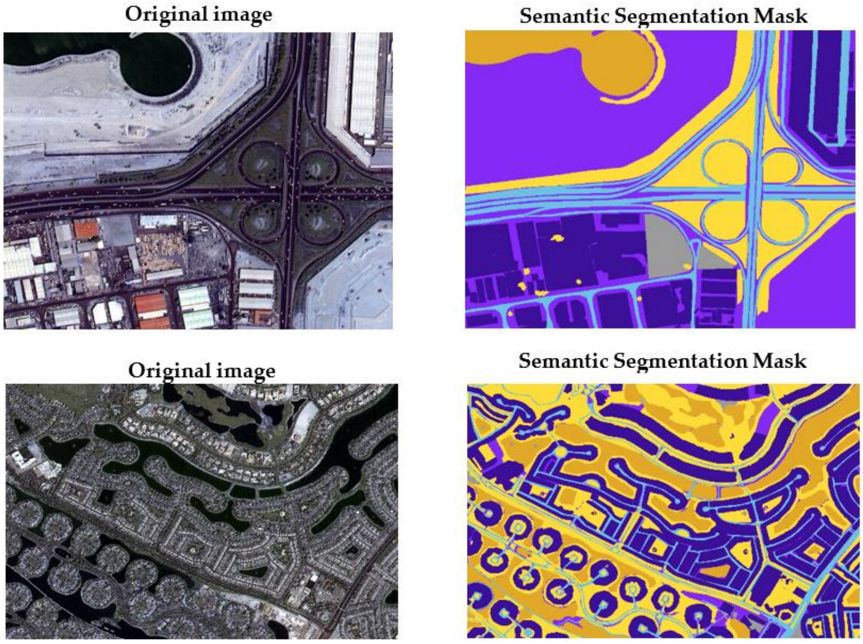


Figure 4.2. Example of the training and validation dataset.

The accuracy of deep learning models, particularly in computer vision (CV) techniques, is intricately tied to the training data's quality, quantity, and contextual significance. A significant challenge in employing deep learning methods for image semantic segmentation applications lies in the limited data availability for training and validation purposes. Recently, to address this constraint, increased attention has been devoted to leveraging data augmentation methods to generate well-qualified training and validation datasets. The primary objective of data augmentation is to enhance the adequacy and diversity of the training and validation data by creating a synthetic dataset (Yang et al., 2022). It can be asserted that the augmented dataset is derived from a distribution closely resembling the original one, facilitating a more comprehensive configuration (Minaee et al., 2022).

Within this study, the author adopted various data augmentation strategies for both the training and validation datasets to overcome the limitation of the small image sample size and improve the quantity and diversity of the training and validation data. The augmentation operations were applied to the input images and their corresponding semantic segmentation masks. One strategy involves under-sampling, where an image is randomly cropped multiple times with a crop size 512 × 512. Additionally, the author randomly applied operations such as flipping, rotating, translating, side-viewing, and zooming to enhance the model's robustness. Furthermore, all inputs were manipulated, their saturation, contrast, and brightness adjusted, the color space and band order were converted, and Gaussian noise and filtering operations were randomly introduced. The images undergo distinct data augmentation operations based on the chosen data augmentation strategy. The total number of images used for training and validation tasks is 715 for training and 77 for validation.

To assess changes in built-up areas and vegetation from 2000 to 2020, the U-Net model, which was trained and validated, is employed on satellite images from the years 2000, 2011, and 2020 covering the study area (Geoportale Regione Basilicata, 2023). Specifically, orthoimages with a resolution of 0.423 meters per pixel (approximately 1-foot) are considered (Figure 4.3).

Figure 4.3. Testing dataset.

After testing the AI-GIS informatics platform in the case study of Matera and, therefore, obtaining the built-up area and vegetation cover for 2000, 2011, and 2020, covering the period from 2000 to 2020, the accuracy of the model is assessed. In particular, the built-up area and vegetation cover prediction is compared with reference data: the land use land cover data retrieved from the National Synthesis DataBase (DBSN, 2023).

After having the built-up area and vegetation cover changes occurred between 2000 and 2020 at a very high resolution, they are combined with population data retrieved from the National Institute of Statistics (ISTAT, 2001; ISTAT, 2011).

1.3. Results

1.3.1. Training and validation of the U-Net model results

As defined in Chapter 3, the AI-GIS informatics platform proposed in this study is based on the U-Net model. The U-Net model is trained and validated using the "Semantic Segmentation of Aerial Imagery" of Dubai considering two different loss functions: the Focal Loss and the IoU-based Loss. The performance of the training and validation stages is evaluated through the F1-Score metric.

By training and validating the U-Net model considering the Focal Loss function, Figure 4.4 depicts the training and validation loss curves of the model, and Figure 4.5 shows the F1-Score with the change of epochs. These diagrams indicate that the loss and F1-Score curves of the model become smoother after about 50 epochs, and the model reaches convergence as the epochs continue to increase. The best model reached the convergence at epoch 70, with, in the validation task, a loss function value of 0.485 and an F1-Score value of 0.63.

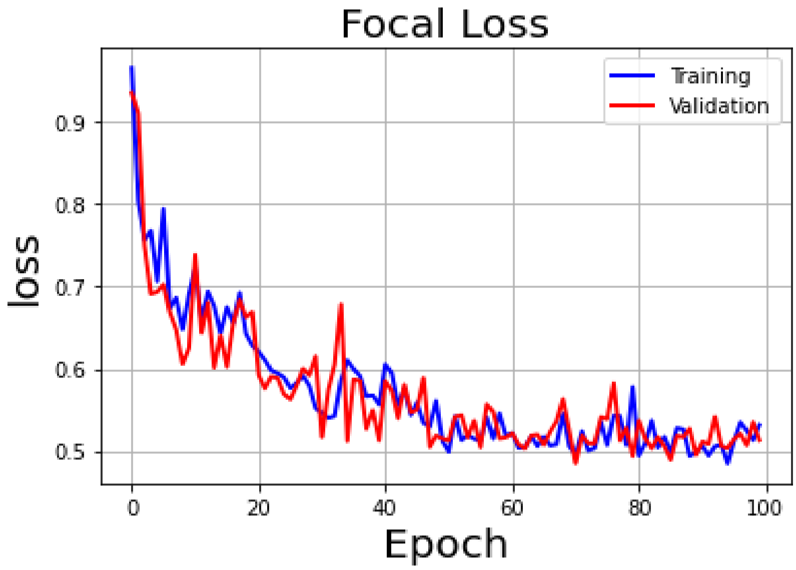


Figure 4.4. Focal Loss curve during training and validation.

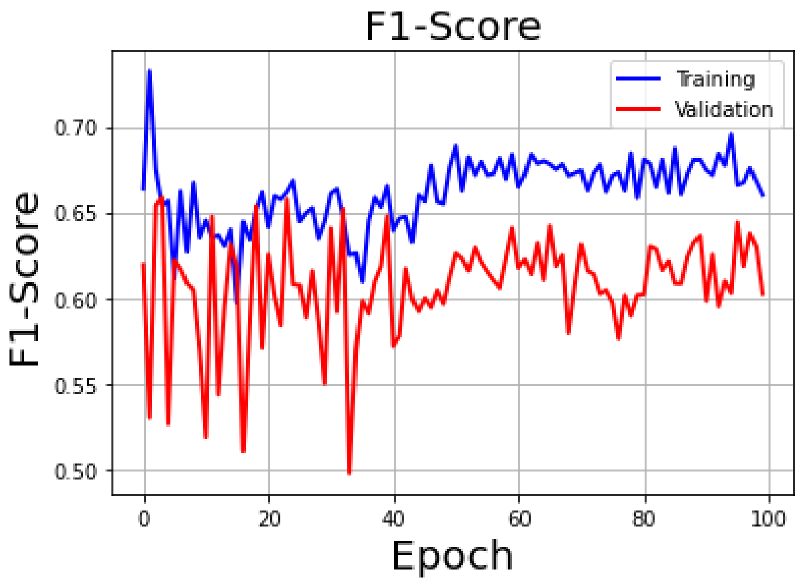


Figure 4.5. F1-Score during training and validation using Focal Loss.

Figure 4.6 and Figure 4.7 shows the training and validation loss curves of the U-Net model with IoU-based loss, and the F1-Score with the change of epochs, respectively. From these results, it can be noted that, by training and validating the U-Net model considering the IoU-based Loss function, the best model reaches the convergence at epoch 91 with, in the validation task, a loss function value of 0.634 and F1-Score value of 0.72.

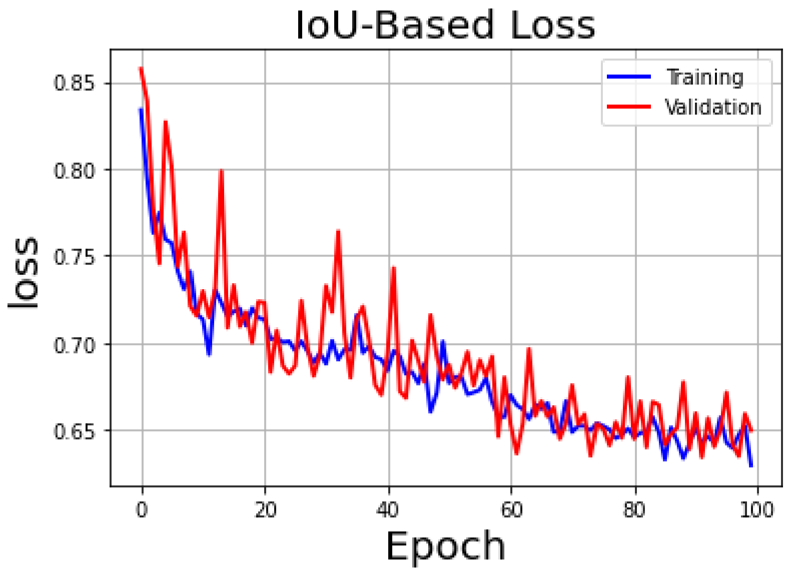


Figure 4.6. IoU-based Loss curve during training and validation.

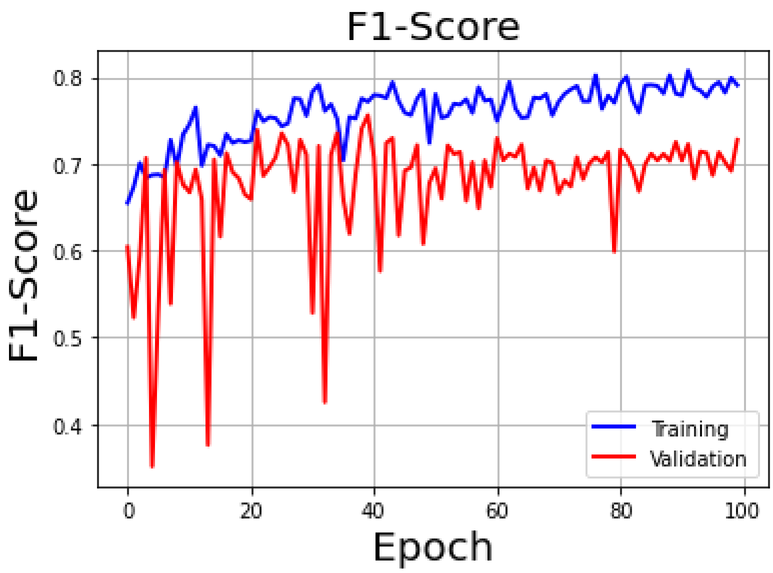


Figure 4.7. F1-Score during training and validation using IoU-based Loss.

The main results obtained in the training and validation tasks are summarized in Table 4.1, which highlights how the U-Net model with IoU-based Loss has better results in terms of Precision, Recall, and F1-Score. Under the IoU-based Loss, Precision exhibited a notable improvement with an increase of 0.14, although Recall experienced a slight decrease of 0.03. Adopting the IoU-based Loss function significantly enhanced F1-Score, elevating it by 0.14 to 0.72.

Table 4.1. U-Net model performance metrics considering different loss functions.

Model	Precision	Recall	F1-Score
U-Net (Focal Loss)	0.49	0.87	0.63
U-Net (IoU-based Loss)	0.63	0.84	0.72

Building on the obtained results, the AI-GIS informatics platform proposed within this study is based on the U-Net model trained and validated using the IoU-based Loss function as it ensures more accurate results.

The training phase was carried out in a Google Colaboratory Pro Plus environment, using 52 GB of RAM and the GPU NVIDIA Tesla P100. All the project was implemented in Python and the training was developed using Pytorch, with TensorFlow backend as the deep learning framework. A sample of the programming code are shown in Figure 4.8.

Data loader and data augmentation

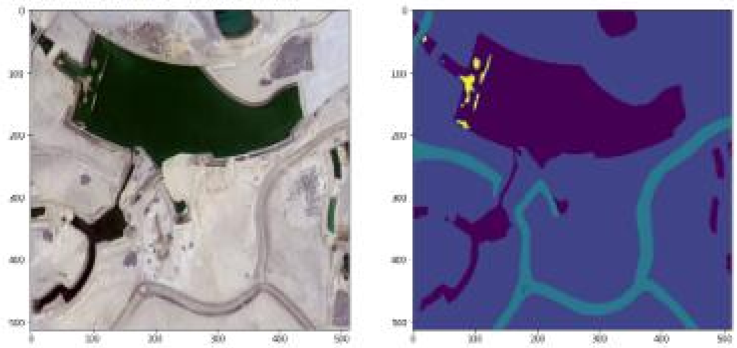
```
[ ] import os
    import numpy as np
    import torch
    import torch.utils.data
    import torchvision.transforms as transforms
    import PIL
    import random
    from scipy import ndimage


    class segDataset(torch.utils.data.Dataset):
        def __init__(self, root, training, transform=None):
            super(segDataset, self).__init__()
            self.root = root
            self.training = training
            self.transform = transform
            self.IMG_NAMES = sorted(glob(self.root + '/*/images/*.jpg'))
            self.BGR_classes = {'Water' : [ 41, 169, 226],
                                'Land' : [246,  41, 132],
                                'Road' : [228, 193, 110],
                                'Building' : [152,  16,  60],
                                'Vegetation' : [ 58, 221, 254],
                                'Unlabeled' : [155, 155, 155]} # in BGR

            self.bin_classes = ['Water', 'Land', 'Road', 'Building', 'Vegetation', 'Unlabeled']


        def __getitem__(self, idx):
            img_path = self.IMG_NAMES[idx]
            mask_path = img_path.replace('images', 'masks').replace('.jpg', '.png')

            image = cv2.imread(img_path)
            mask = cv2.imread(mask_path)
            cls_mask = np.zeros(mask.shape)
            cls_mask[mask == self.BGR_classes['Water']] = self.bin_classes.index('Water')
            cls_mask[mask == self.BGR_classes['Land']] = self.bin_classes.index('Land')
            cls_mask[mask == self.BGR_classes['Road']] = self.bin_classes.index('Road')
            cls_mask[mask == self.BGR_classes['Building']] = self.bin_classes.index('Building')
            cls_mask[mask == self.BGR_classes['Vegetation']] = self.bin_classes.index('Vegetation')
            cls_mask[mask == self.BGR_classes['Unlabeled']] = self.bin_classes.index('Unlabeled')
```

```
[ ] color_shift = transforms.ColorJitter(.1,.1,.1,.1)
    blurriness = transforms.GaussianBlur(3, sigma=(0.1, 2.0))

    t = transforms.Compose([color_shift, blurriness])
    dataset = segDataset('./Semantic segmentation dataset', training = True, transform= t)

    len(dataset)
```

```
72
```

```
[ ] d = dataset[1]
    plt.figure(figsize=(15,15))
    plt.subplot(1,2,1)
    plt.imshow(np.moveaxis(d[0].numpy(),0,-1))
    plt.subplot(1,2,2)
    plt.imshow(d[1].numpy())
```

```
<matplotlib.image.AxesImage at 0x7fe7G0G81a90>
```

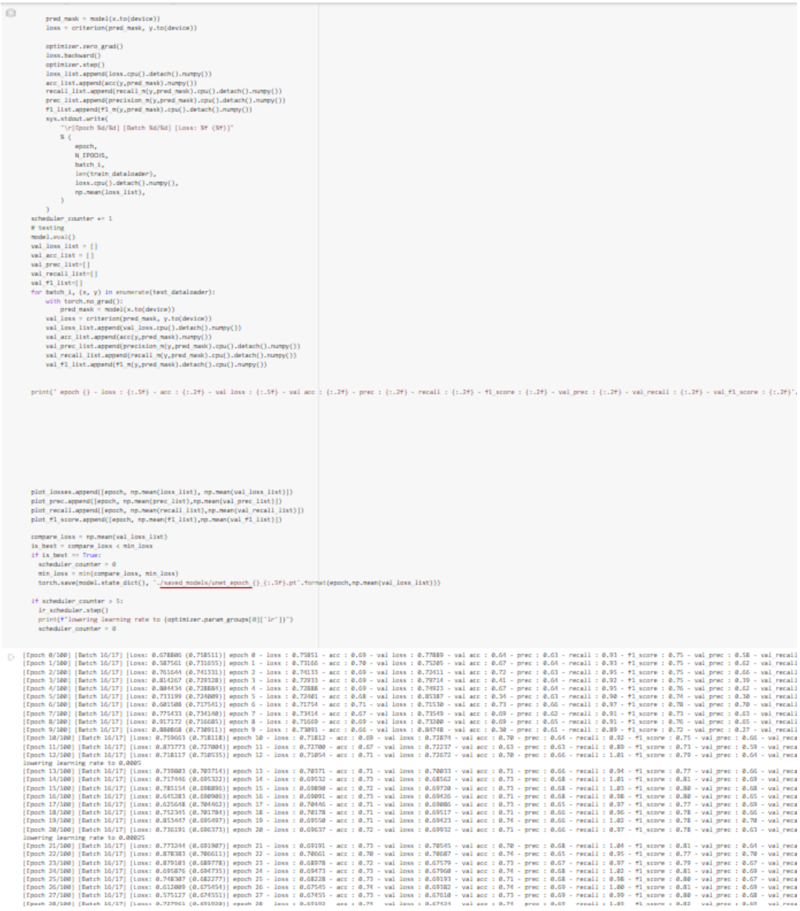



```
[ ] test_num = int(0.1 * len(dataset))
    print(f'test data : {test_num}')
    train_dataset, test_dataset = torch.utils.data.random_split(dataset, [len(dataset)-test_num, test_num], generator=torch.
```

```
test data : 7
```

```
[ ] BACH_SIZE = 4
    train_dataloader = torch.utils.data.DataLoader(
        train_dataset, batch_size=BACH_SIZE, shuffle=True, num_workers=4)

    test_dataloader = torch.utils.data.DataLoader(
        test_dataset, batch_size=BACH_SIZE, shuffle=False, num_workers=1)
```

```
/usr/local/lib/python3.7/dist-packages/torch/utils/data/dataloader.py:566: UserWarning: This DataLoader will create 4 wor
  cpuset_checked))
```



```
        pred_mask = model(x.to(device))
        loss = criterion(pred_mask, y.to(device))

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        loss_list.append(loss.cpu().detach().numpy())
        acc_list.append(acc(y,pred_mask).numpy())
        recall_list.append(recall_m(y,pred_mask).cpu().detach().numpy())
        prec_list.append(precision_m(y,pred_mask).cpu().detach().numpy())
        f1_list.append(f1_m(y,pred_mask).cpu().detach().numpy())
        sys.stdout.write(
            "\r[Epoch %d/%d] [Batch %d/%d] [Loss: %f (%f)]"
            % (
                epoch,
                N_EPOCHS,
                batch_i,
                len(train_dataloader),
                loss.cpu().detach().numpy(),
                np.mean(loss_list),
            )
        )
    scheduler_counter += 1
    # testing
    model.eval()
    val_loss_list = []
    val_acc_list = []
    val_prec_list=[]
    val_recall_list=[]
    val_f1_list=[]
    for batch_i, (x, y) in enumerate(test_dataloader):
        with torch.no_grad():
            pred_mask = model(x.to(device))
        val_loss = criterion(pred_mask, y.to(device))
        val_loss_list.append(val_loss.cpu().detach().numpy())
        val_acc_list.append(acc(y,pred_mask).numpy())
        val_prec_list.append(precision_m(y,pred_mask).cpu().detach().numpy())
        val_recall_list.append(recall_m(y,pred_mask).cpu().detach().numpy())
        val_f1_list.append(f1_m(y,pred_mask).detach().cpu().numpy())


    print(' epoch {} - loss : {:.5f} - acc : {:.2f} - val loss : {:.5f} - val acc : {:.2f} - prec : {:.2f} - recall : {:.2f} - f1_score : {:.2f} - val_prec : {:.2f} - val_recall : {:.2f} - val_f1_score : {:.2f}'.


    plot_losses.append([epoch, np.mean(loss_list), np.mean(val_loss_list)])
    plot_prec.append([epoch, np.mean(prec_list),np.mean(val_prec_list)])
    plot_recall.append([epoch, np.mean(recall_list),np.mean(val_recall_list)])
    plot_f1_score.append([epoch, np.mean(f1_list),np.mean(val_f1_list)])

    compare_loss = np.mean(val_loss_list)
    is_best = compare_loss < min_loss
    if is_best == True:
      scheduler_counter = 0
      min_loss = min(compare_loss, min_loss)
      torch.save(model.state_dict(), "./saved_models/unet_epoch_{}_{:.5f}.pt".format(epoch,np.mean(val_loss_list)))

    if scheduler_counter > 5:
      lr_scheduler.step()
      print(f"lowering learning rate to {optimizer.param_groups[0]['lr']}")
      scheduler_counter = 0

[Epoch 0/100] [Batch 16/17] [Loss: 0.678806 (0.758511)] epoch 0 - loss : 0.75851 - acc : 0.69 - val loss : 0.77889 - val acc : 0.64 - prec : 0.63 - recall : 0.93 - f1_score : 0.75 - val_prec : 0.58 - val_recall
[Epoch 1/100] [Batch 16/17] [Loss: 0.587561 (0.731655)] epoch 1 - loss : 0.73166 - acc : 0.70 - val loss : 0.75205 - val acc : 0.67 - prec : 0.64 - recall : 0.93 - f1_score : 0.75 - val_prec : 0.62 - val_recall
[Epoch 2/100] [Batch 16/17] [Loss: 0.761644 (0.741331)] epoch 2 - loss : 0.74133 - acc : 0.69 - val loss : 0.72411 - val acc : 0.72 - prec : 0.63 - recall : 0.95 - f1_score : 0.75 - val_prec : 0.66 - val_recall
[Epoch 3/100] [Batch 16/17] [Loss: 0.814267 (0.729328)] epoch 3 - loss : 0.72933 - acc : 0.69 - val loss : 0.79714 - val acc : 0.41 - prec : 0.64 - recall : 0.92 - f1_score : 0.75 - val_prec : 0.39 - val_recall
[Epoch 4/100] [Batch 16/17] [Loss: 0.804434 (0.728884)] epoch 4 - loss : 0.72888 - acc : 0.69 - val loss : 0.74923 - val acc : 0.67 - prec : 0.64 - recall : 0.95 - f1_score : 0.76 - val_prec : 0.62 - val_recall
[Epoch 5/100] [Batch 16/17] [Loss: 0.733199 (0.724009)] epoch 5 - loss : 0.72401 - acc : 0.68 - val loss : 0.85387 - val acc : 0.34 - prec : 0.63 - recall : 0.90 - f1_score : 0.74 - val_prec : 0.30 - val_recall
[Epoch 6/100] [Batch 16/17] [Loss: 0.601508 (0.717541)] epoch 6 - loss : 0.71754 - acc : 0.71 - val loss : 0.71530 - val acc : 0.73 - prec : 0.66 - recall : 0.97 - f1_score : 0.78 - val_prec : 0.70 - val_recall
[Epoch 7/100] [Batch 16/17] [Loss: 0.775433 (0.734140)] epoch 7 - loss : 0.73414 - acc : 0.67 - val loss : 0.73549 - val acc : 0.69 - prec : 0.62 - recall : 0.91 - f1_score : 0.73 - val_prec : 0.63 - val_recall
[Epoch 8/100] [Batch 16/17] [Loss: 0.917172 (0.716685)] epoch 8 - loss : 0.71669 - acc : 0.69 - val loss : 0.73200 - val acc : 0.69 - prec : 0.65 - recall : 0.91 - f1_score : 0.76 - val_prec : 0.65 - val_recall
[Epoch 9/100] [Batch 16/17] [Loss: 0.880868 (0.730911)] epoch 9 - loss : 0.73091 - acc : 0.66 - val loss : 0.84748 - val acc : 0.30 - prec : 0.61 - recall : 0.89 - f1_score : 0.72 - val_prec : 0.27 - val_recall
[Epoch 10/100] [Batch 16/17] [Loss: 0.759663 (0.718118)] epoch 10 - loss : 0.71812 - acc : 0.69 - val loss : 0.72874 - val acc : 0.70 - prec : 0.64 - recall : 0.92 - f1_score : 0.75 - val_prec : 0.66 - val_reca
[Epoch 11/100] [Batch 16/17] [Loss: 0.873773 (0.727004)] epoch 11 - loss : 0.72700 - acc : 0.67 - val loss : 0.72237 - val acc : 0.63 - prec : 0.63 - recall : 0.89 - f1_score : 0.73 - val_prec : 0.59 - val_reca
[Epoch 12/100] [Batch 16/17] [Loss: 0.718117 (0.710535)] epoch 12 - loss : 0.71054 - acc : 0.71 - val loss : 0.72672 - val acc : 0.70 - prec : 0.66 - recall : 1.01 - f1_score : 0.79 - val_prec : 0.64 - val_reca
lowering learning rate to 0.0005
[Epoch 13/100] [Batch 16/17] [Loss: 0.739803 (0.703714)] epoch 13 - loss : 0.70371 - acc : 0.71 - val loss : 0.70033 - val acc : 0.71 - prec : 0.66 - recall : 0.94 - f1_score : 0.77 - val_prec : 0.66 - val_reca
[Epoch 14/100] [Batch 16/17] [Loss: 0.717446 (0.695322)] epoch 14 - loss : 0.69532 - acc : 0.73 - val loss : 0.68562 - val acc : 0.73 - prec : 0.68 - recall : 1.01 - f1_score : 0.81 - val_prec : 0.69 - val_reca
[Epoch 15/100] [Batch 16/17] [Loss: 0.785154 (0.698896)] epoch 15 - loss : 0.69890 - acc : 0.72 - val loss : 0.69720 - val acc : 0.73 - prec : 0.68 - recall : 1.03 - f1_score : 0.80 - val_prec : 0.68 - val_reca
[Epoch 16/100] [Batch 16/17] [Loss: 0.645283 (0.690906)] epoch 16 - loss : 0.69091 - acc : 0.73 - val loss : 0.69426 - val acc : 0.71 - prec : 0.68 - recall : 0.98 - f1_score : 0.80 - val_prec : 0.65 - val_reca
[Epoch 17/100] [Batch 16/17] [Loss: 0.635648 (0.704463)] epoch 17 - loss : 0.70446 - acc : 0.71 - val loss : 0.69006 - val acc : 0.73 - prec : 0.65 - recall : 0.97 - f1_score : 0.77 - val_prec : 0.69 - val_reca
[Epoch 18/100] [Batch 16/17] [Loss: 0.752345 (0.701784)] epoch 18 - loss : 0.70178 - acc : 0.71 - val loss : 0.69517 - val acc : 0.71 - prec : 0.66 - recall : 0.96 - f1_score : 0.78 - val_prec : 0.66 - val_reca
[Epoch 19/100] [Batch 16/17] [Loss: 0.853447 (0.695497)] epoch 19 - loss : 0.69550 - acc : 0.71 - val loss : 0.69423 - val acc : 0.74 - prec : 0.66 - recall : 1.02 - f1_score : 0.78 - val_prec : 0.70 - val_reca
[Epoch 20/100] [Batch 16/17] [Loss: 0.736191 (0.696373)] epoch 20 - loss : 0.69637 - acc : 0.72 - val loss : 0.69932 - val acc : 0.71 - prec : 0.66 - recall : 0.97 - f1_score : 0.78 - val_prec : 0.63 - val_reca
lowering learning rate to 0.00025
[Epoch 21/100] [Batch 16/17] [Loss: 0.773244 (0.691907)] epoch 21 - loss : 0.69191 - acc : 0.73 - val loss : 0.70545 - val acc : 0.70 - prec : 0.68 - recall : 1.04 - f1_score : 0.81 - val_prec : 0.64 - val_reca
[Epoch 22/100] [Batch 16/17] [Loss: 0.878383 (0.706611)] epoch 22 - loss : 0.70661 - acc : 0.70 - val loss : 0.70687 - val acc : 0.74 - prec : 0.65 - recall : 0.95 - f1_score : 0.77 - val_prec : 0.70 - val_reca
[Epoch 23/100] [Batch 16/17] [Loss: 0.879103 (0.689778)] epoch 23 - loss : 0.68978 - acc : 0.72 - val loss : 0.67579 - val acc : 0.73 - prec : 0.67 - recall : 0.97 - f1_score : 0.79 - val_prec : 0.67 - val_reca
[Epoch 24/100] [Batch 16/17] [Loss: 0.695876 (0.694735)] epoch 24 - loss : 0.69473 - acc : 0.73 - val loss : 0.67960 - val acc : 0.74 - prec : 0.68 - recall : 1.02 - f1_score : 0.81 - val_prec : 0.69 - val_reca
[Epoch 25/100] [Batch 16/17] [Loss: 0.748307 (0.682277)] epoch 25 - loss : 0.68228 - acc : 0.73 - val loss : 0.69193 - val acc : 0.71 - prec : 0.68 - recall : 0.98 - f1_score : 0.80 - val_prec : 0.67 - val_reca
[Epoch 26/100] [Batch 16/17] [Loss: 0.612009 (0.675454)] epoch 26 - loss : 0.67545 - acc : 0.74 - val loss : 0.69382 - val acc : 0.74 - prec : 0.69 - recall : 1.00 - f1_score : 0.81 - val_prec : 0.69 - val_reca
[Epoch 27/100] [Batch 16/17] [Loss: 0.575127 (0.674551)] epoch 27 - loss : 0.67455 - acc : 0.73 - val loss : 0.67610 - val acc : 0.73 - prec : 0.69 - recall : 0.99 - f1_score : 0.80 - val_prec : 0.68 - val_reca
```

Figure 4.8. A sample of the programming code in the Google Colaboratory environment (Google Colab).

1.3.2. Built-up area and vegetation cover classification and segmentation results

The trained and validated U-Net model with the IoU-based Loss function is applied to the natural color orthoimages of the study area for the years 2000, 2011, and 2020 to analyze changes in urban and greening cover across 20 years, from 2000 to 2020. The obtained results are shown in Figure 4.9, Figure 4.10, and Figure 4.11 where the predicted outlines of built-up and vegetation derived from the U-Net model application are depicted in red and green, respectively. Given that the U-Net model is specifically trained to predict only built-up and vegetation polygons, any unclassified features are identified as unlabeled elements and are visualized in gray.

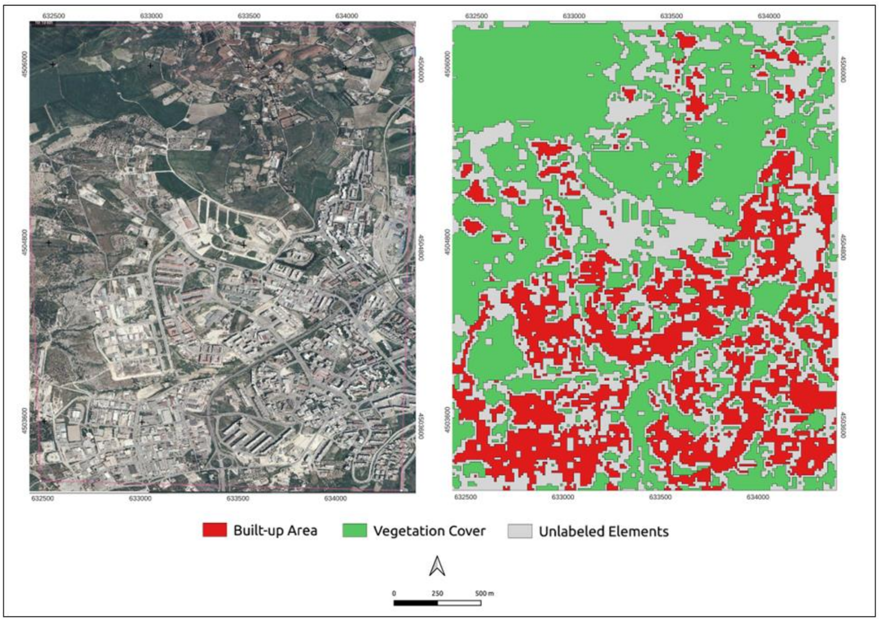


Figure 4.9. Built-up area and vegetation cover classification and segmentation for 2000.

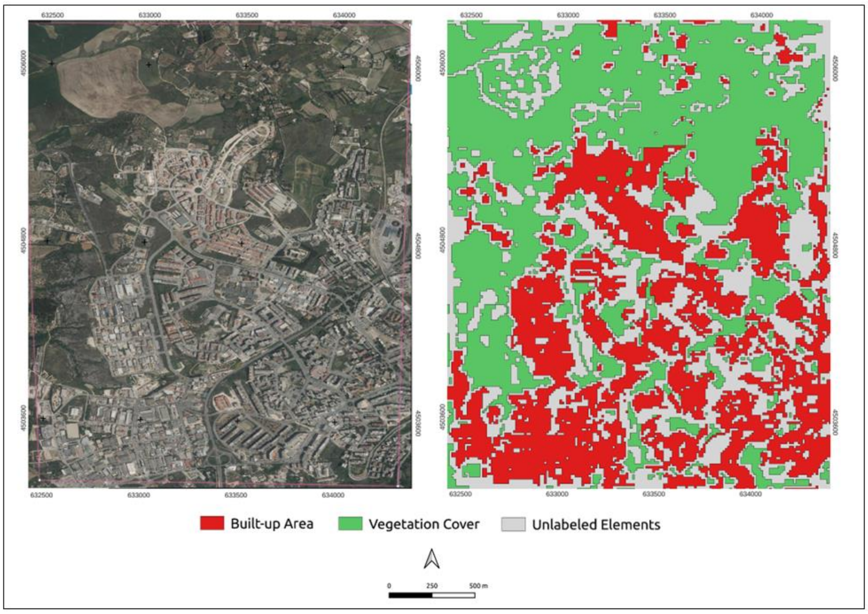


Figure 4.10. Built-up area and vegetation cover classification and segmentation for 2011.

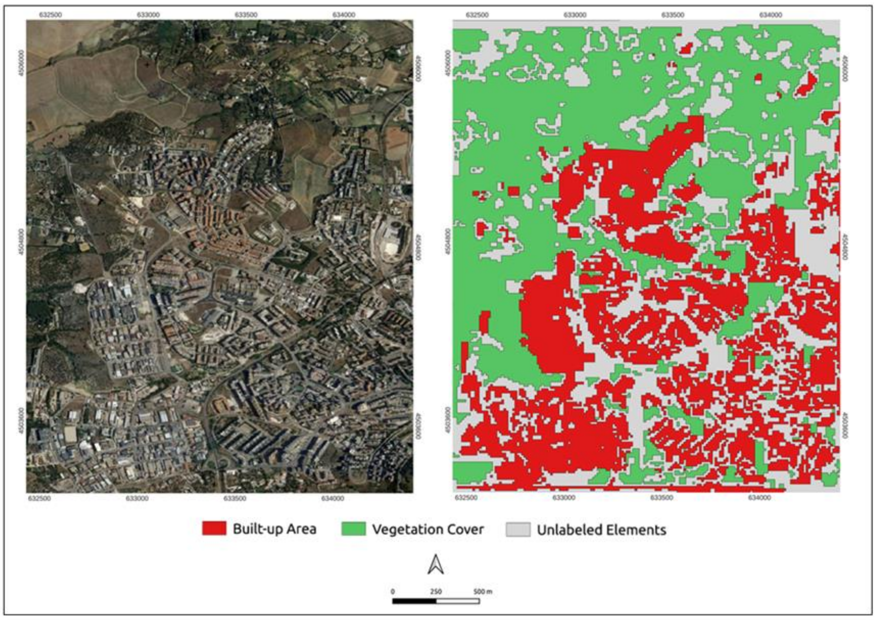


Figure 4.11. Built-up area and vegetation cover classification and segmentation for 2020.

The accuracy of the U-Net model to predict the built-up area and vegetation cover is assessed following what is defined in Chapter 3. In particular, the actual (retrieved from the DBSN) and the predicted built-up area and vegetation cover from the U-Net model are compared considering 2020 as the reference year. The overall accuracy of the U-Net model application is quantitatively assessed through the evaluation of the F1-Score.

According to the ground truth represented by the built-up and vegetation polygons from the land use land cover stored in the DBSN, in 2020, 40.37% of the overall study area is characterized by built-up, while 53.06% represents the area covered by vegetation.

By comparing the actual with the predicted built-up and vegetation polygons, the results in terms of F1-Score, shown in Table 4.2, depict a great level of accuracy of the U-Net model to predict built-up areas and vegetation cover for the case study of Matera.

Table 4.2. Accuracy assessment of the U-Net model for the built-up area and vegetation cover prediction.

Labels	F1-Score
Built-up Area	0.95
Vegetation Cover	0.97

These findings demonstrate great accuracy, especially considering the application of the U-Net model to geographic areas it has not encountered previously. This suggests a close alignment between the actual and predicted features. There are undetected built-up polygons (false positives, FP) in the peripheral regions and some gaps (false negatives, FN) within the more densely populated urban areas, the expansion zone, and the industrial/productive zone. Upon examining the vegetation cover predictions, some predicted vegetation polygons are identified as non-vegetation (FP). However, the model fails to predict numerous actual vegetation polygons (FN).

Even if Figure 4.9, Figure 4.10, and Figure 4.11 have already highlighted a distinct change in the spatial patterns of the built-up area and vegetation cover between 2000 and 2020, the assessment of the indicators defined in Chapter 3 helped to define the entity of built-up and greening changes over time. Building on those indicators, the results are shown in Table 4.3.

Table 4.3. Coverage and density of urban and greening in 2000, 2011, and 2020.

Labels	2000		2011		2020	
	Coverage (ha)	Density (%)	Coverage (ha)	Density (%)	Coverage (ha)	Density (%)
Built-Up	147.44	22.38	194.45	29.51	202.03	30.66
Vegetation	272.31	41.33	246.82	37.46	238.49	36.19
Unlabeled	239.16	36.30	217.64	33.03	218.40	33.15
Total	658.91	100	658.91	100	658.91	100

Natural color orthoimage from 2000 classification and segmentation indicates that a significant portion of the study area is covered by vegetation (272.31 ha or 41.33%) and unlabeled elements (239.16 ha or 36.30%), while the built-up area constitutes 147.4 ha, with a density rate of 22.38%.

Results from the 2011 orthoimage classification reveal that the highest density rate is associated with vegetation cover, amounting to 246.82 ha (37.46%), while unlabeled elements and the built-up area coverage are equal at 217.64 ha (33.03%) and 194.95 ha (29.51%), respectively.

Upon applying the DL model to the 2020 orthoimage, the built-up area coverage is determined to be 202.03 ha, with a density rate of 30.66%. The vegetation cover for 2020 is 238.49 ha (36.19%), and the coverage of unlabeled elements is equal to 218.40 ha (33.15%).

Following these results, Table 4.4 shows the coverage and the density of built-up, vegetation, and unlabeled elements changes for the 20-year observation period.

Table 4.4. Coverage and density of urban and greening development between 2000-2011, and 2011-2020.

Labels	**2000-2011**		**2011-2020**	
	Coverage (ha)	**Density (%)**	**Coverage (ha)**	**Density (%)**
Built-Up	47.01	7.14	7.57	1.15
Vegetation	-25.49	-3.87	-8.33	-1.27
Unlabeled	-21.52	-3.26	0.75	0.12

Over the 20-year observation span, the most significant modifications in urban and greening features within the case study were noted between 2000 and 2011. In this timeframe, there was a 47.01 ha increase in the built-up area, accompanied by a 7.14% rise in density compared to the previous coverage. Conversely, vegetation cover and the density of unlabeled elements experienced a decrease of 3.87% and 3.26%, resulting in a loss of 25.49 ha and 21.52 ha, respectively.

From 2011 to 2020, the built-up area density continued its upward trajectory with a 1.15% increase, accounting for an additional 7.57 ha. Concurrently, vegetation cover density continued its decline, registering a 1.27% reduction and a corresponding decrease of 8.33 ha. The density rate of unlabeled elements slightly rose by 0.12%, contributing to an increased area of 0.75 ha.

Overall, encompassing the entire study period (2000-2020), the built-up area exhibited a significant expansion of 54.58 ha, accompanied by an 8.29% density increase. Conversely, the vegetation cover was reduced by 33.82 ha, reflecting a density reduction of 5.14% over the same period. The coverage of unlabeled elements decreased by 20.77 ha, corresponding to a density rate of 3.15%, from 2000 to 2020.

The findings illustrate a sequence of urban and green changes in the study area during the analyzed period (2000-2020). The study area experienced significant built-up area growth processes, resulting in a notable decline in vegetation cover. This urban and greening trend aligns with the outcomes of a specific study conducted by Munafò (2022).

1.3.3. Urban, greening changes and population dynamics co-relation assessment

After classifying and segmenting the built-up area and vegetation cover through the proposed AI-GIS informatics platform and assessing the urban and greening changes that occurred within the study area for the analyzed period, the author divided the study into eight zones: ENE, NNE, NNW, WNW, WSW, SSW, SSE, and ESE.

Therefore, the changes in urban and greening that occurred within the eight zones are evaluated and reported in Table 4.5.

Table 4.5. Built-up area and vegetation cover changes in m2 in each directional zone for 2000-2011 and 2011-2020.

Directional zone	Built-Up Area Change 2000-2011 (m^2)	Vegetation Area Change 2000-2011 (m^2)	Built-Up Area Change 2011-2020 (m^2)	Vegetation Area Change 2011-2020 (m^2)
ENE	40091	12729	0	-26403
NNE	70708	61326	4824	-75045
NNW	146398	-131932	0	-20182
WNW	6814	-566	0	81212
WSW	14061	-20854	15734	48017
SSW	109139	-55373	19181	-61677
SSE	67007	-113149	1533	-20896
ESE	15767	-7019	57050	-8401

Table 4.5 highlights that most of the quadrants had a decline in vegetation cover during the analyzed period. The highest value of vegetation cover decline for the period 2000-2011 was registered for the NNW and SSE quadrants. It was equal to -131932 m^2 and -113149 m2, respectively. Only the quadrants ENE and NNE had an increase in the vegetation cover for 12729 m^2 and 61326 m^2, respectively. For the period 2011-2020, the highest decline in vegetation cover, equal to -75045 m^2, is registered for the NNE quadrant.

The population data from ISTAT are processed and, as no information for population exists for 2020, the exponential model described in Chapter 3 for forecasting population growth is employed to estimate the population in 2020, considering the statistics between 2000-2011, for each of the eight sectors (Table 4.6). The population of each of the eight sectors is obtained by considering the sum of the population of all the ISTAT census areas contained in each directional zone. This operation is performed in the QGIS environment.

Table 4.6. Population for each directional zone for 2001, 2011, and 2020.

Directional zone	Population 2001 (inhabit.)	Population 2011 (inhabit.)	Population 2020 (inhabit.)
ENE	2063	2271	2500
NNE	461	1219	3223
NNW	268	1713	10949
WNW	287	433	653
WSW	958	862	776
SSW	1974	1815	1668
SSE	9691	9855	10023
ESE	3992	3804	3625

The population variation, the built-up area, and vegetation cover changes made it possible to value the USDMI and the GSDMI and, therefore, assess the co-relation between urban, greening and population changes toward sustainability over time. Specifically, the numerical results are shown in Table 4.7, while the geospatial analysis is represented in Figure 4.12.

Table 4.7. USDMI and GSDMI values in each directional zone for the 2000-2011 and 2011-2020 periods.

Directional zone	USDMI 2000-2011	GSDMI 2000-2011	USDMI 2011-2020	GSDMI 2011-2020
ENE	14.46	6.80	0	-12.81
NNE	7.00	9.00	0.18	-4.16
NNW	7.60	-10.15	0	-0.24
WNW	3.50	-0.43	0	41.02
WSW	-10.96	24.14	-13.72	-62.04
SSW	-51.48	38.70	-9.79	46.62
SSE	30.64	-76.66	0.69	-13.82
ESE	-6.30	4.15	-23.90	5.22

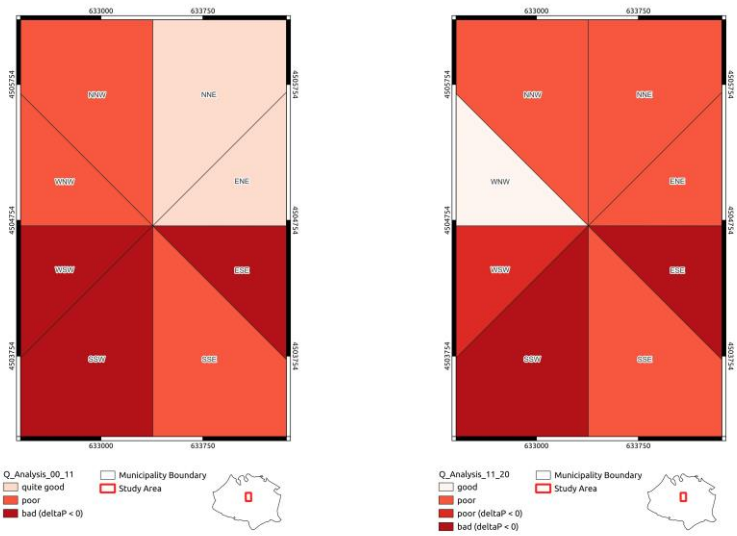


Figure 4.12. Urban and greening level of interaction towards sustainability in each directional zone for the 2000-2011 and 2011-2020 periods.

Analyzing the co-relation between urban, green, and population changes between 2000-2011, all the quadrants showed poor sustainable development. During this period, in none of the directional zones of the study area, there has been optimal urban growth aligned with the optimal development of the UGAs. During this timeline, NNE and ENE's quadrants experienced a quite good co-relation between urban, greening, and population changes. On the one hand, it can mean that there has been an increase in built-up beyond the demand for residence accompanied by an increase in UGAs, satisfying the request for UGAs to reach a better quality of the built environment. On the other hand, it can be explained as the increase in the built-up area beyond the demand required by the increase in the population and, at the same time, an increase in the UGAs that goes beyond the request by users. Both NNE and ENE quadrants fall in the case of an increase in the built-up area beyond the demand requirements associated with the increased availability of urban green areas per capita. During the same period, NNW, WNW, and SSE showed poor coexistence between urban growth and greening goals. In all these cases, it was related to an exceeding realization of built-up area and a decline in the vegetation cover, which determined a negative amount of UGAs. Instead, WSW, SSW, and ESE experienced the worst scenario, as they showed a decrease in the population while realizing newly built-up area and having a loss in the vegetative land.

Between 2011 and 2020, only the WNW quadrant manifested good coexistence between urban and greening development. In this case, there has been a balance between the increase in the built-up area and the vegetative land growth. On the contrary, ESE and SSW quadrants exhibited the worst level of coexistence between urban growth and achievement of greening goals as the population decreased. At the same time, the built-up area increased, and the vegetation cover declined. The other quadrants, such as NNW, NNE, ENE, SSE, and WSW, showed poor sustainable coexistence between urban growth and greening goals. Specifically, in ENE, NNE, NNW, and SSE, a built-up area realization has not exceeded the standard requirements associated with a decline in vegetative coverage. Instead, WSW experienced a decline in the population accompanied by an unjustified increase in the built-up area and urban green areas.

1.4. Discussion of the results

This Section discusses the outcomes of the methodology's testing phase to evaluate the co-relation between urban growth, greening changes, and population dynamics in urban areas.

The results obtained from the AI-GIS platform for classifying and segmenting built-up areas and vegetation cover reveal significant modifications in urban and greening cover between 2000 and 2020. Across the entire study area, over the analyzed 20-year period, there was an 8.28% increase in built-up area density, accompanied by a 5.13% decrease in vegetation cover density. This finding suggests a noticeable trend of urbanization in the study area, contributing to a reduction in vegetation cover.

The ongoing urban growth processes and the decline in vegetation cover observed in the analysis of urban and greening changes are linked explicitly to the development of new residential zones and urban facilities in the northern part of the study area. Additionally, the completion of industrial and productive areas in the western part is notable. The construction of new residential buildings and corresponding urban services during this period adhered to urban planning policies, bridging the core and peri-urban areas. Conversely, developing industrial and productive areas followed the location of previously established enterprises. This land cover development pattern appears to be influenced by population growth, prompting the need for new residential areas, urban services, and job opportunities.

A significant urban growth pattern on the northwest side of the study area occurred between 2000 and 2011 due to the construction of new residences and industrial/productive structures. The new residential area seamlessly connected the urban texture, bridging the core and peripheral areas. The U-Net model effectively predicts this development by classifying and segmenting natural orthoimages from 2000 to 2011. The expansion of built-up areas and the reduction in vegetation cover are further validated by numerical results derived from applying urban and greening indicators to prediction masks from 2000 and 2011.

Between 2011 and 2020, the residences connecting the core and peripheral areas and the industrial/productive zone in the north and west parts of the study area were nearly completed, resulting in the complete removal of vegetation cover in those regions. The applied DL method accurately predicts these changes.

Comparing the predictive outcomes with the changes observed in orthoimages, the trend identified by the proposed methodology closely aligns with the patterns evident in the analyzed orthoimages. Additionally, the numerical results derived from applying the suggested indicators validate the expansion of built-up areas and the concurrent reduction in vegetation areas, as Munafò (2022) previously evaluated.

Analyzing the geographical depiction of urban and greening changes within the study area reveals a peripheral urban growth phenomenon. These findings suggest the presence of a decentralized planning policy in the area, contributing to a sprawling process. Furthermore, this analysis highlights that adding new green spaces does not counterbalance the loss of vegetation cover beyond the core urban area.

Despite planning policies promoting efficient integration between core and peripheral areas through the implementation of integrated urban and territorial services, including transportation systems and high-rank services, there is a notable depletion of vegetation cover. This depletion results in a loss of ESs, accentuated by a higher urban growth rate outside the inner city, leading to increased consumption of natural resources and vegetation. This trend of vegetation cover loss underscores the impact of urban development outside the denser urban environment, exerting pressure on vegetation cover and negatively affecting the livability and sustainability of urban and territorial areas.

Results spanning the 20 years from 2000 to 2020 demonstrate the effectiveness of the DL model in predicting urban features such as built-up and vegetation cover with high accuracy and short computational times. The methodology exhibits a commendable capacity to swiftly identify urban and greening development changes from simple orthoimages from different years.

With an F1-Score of 0.95 for built-up areas and 0.97 for vegetation cover, the proposed U-Net model accurately predicts a geographic area it has not encountered before. This achievement indicates a nearly complete removal of spatial autocorrelation between actual and predicted labels.

The co-relation between urban growth, greening, and population changes reveals that, between 2000 and 2011, the study area achieved a relatively good level of sustainable co-relation only in the NNE and ENE quadrants. Conversely, in all other cases during the same period, the level of co-relation was poor and, in some instances, bad. Between 2011 and 2020, the situation worsened, except for the WNW quadrant, which exhibited a good level of co-relation based on the urban and greening supply-demand mismatch indexes analysis. These results clarified the trajectories of urban growth and greening planning policies and their co-relation with population dynamics toward sustainability.

The proposed methodology is valuable for comprehending the dynamics between urban growth, greening goals, and population changes. It aids decision-makers in analyzing effective changes in urban and greening over time, assessing their co-relation with population dynamics in achieving sustainable development. By applying innovative DL algorithms to a time series of RS data and quantifying urban and greening changes in co-relation with population dynamics, public administrators, technicians, planner, and academics can obtain informative data to define improved urban land use planning policies.

Based on the integration between DL technology and GIS techniques, the proposed methodology can be used as a rapid system to estimate built-up areas and vegetation cover accurately. It provides a quantitative assessment of urban and greening development changes over time, serving as a valuable indicator and predictor of future urban and greening development directions. Planners, decision-makers, and stakeholders can apply this integrated methodology to efficiently monitor and predict land cover changes in urban and territorial areas. Thanks to this approach, a swift estimation of urban and greening changes over time with an excellent level of accuracy is achievable. The proposed method demonstrates how the land use assessment by applying innovative DL models and geospatial analysis techniques is highly effective in evaluating and monitoring the effect of urban planning policies on land cover changes. Additionally, it serves as a helpful support system for urban planning practices to devise suitable strategies to balance urban development with the delivery of crucial ESs from vegetation cover.

The proposed methodology, leveraging the potential of RS and GIS, provides valuable insights into land use dynamic patterns. It aids planners and decision-makers in realizing sustainable land management, offering a rapid tool to quantify and visualize the actual consumption of natural resources in a semi-automatic manner. Furthermore, it can be an early warning system to identify unauthorized or unapproved land cover changes.

In this study, the proposed tool was tested in a pilot area of the municipality of Matera, and the obtained results suggest its applicability in larger areas beyond the analyzed one. However, challenges exist, such as comparing orthoimages from different periods due to exposure variations and weather conditions, influencing orthoimage processing and affecting results. Despite these challenges, the proposed methodology's ability to accurately predict built-up areas and vegetation cover remains robust, providing a rapid and effective way to assess urban and greening development changes over time.

To enhance the proposed research, testing other DL architectures for better performance in predicting built and vegetation cover and incorporating additional labels for a comprehensive assessment of land use and cover changes are recommended. Additionally, deepening the analysis by introducing socioeconomic and environmental indicators to study the drivers and impacts of urban and greening development over time and space can contribute to a more comprehensive understanding.

Ultimately, decision-makers can leverage the outcomes of this methodology to formulate policies and solutions aimed at promoting compact and mixed-use development patterns, implementing green infrastructure, protecting existing UGAs, employing smart growth planning principles, and monitoring the effectiveness of urban planning strategic decisions on a large scale.

2. The identification of priority areas for densification and green areas planning at the urban scale

This Section aims to investigate the results of the application of the second step of the methodological approach proposed within this study to a specific case study: the Union of Municipalities of Terre d'Argine in the Emilia Romagna region (Italy).

2.1. Study area and data

The Union of Municipalities of Terre d'Argine includes four municipalities, such as Carpi, Novi di Modena, Soliera, and Campogalliano (Figure 4.13).

Figure 4.13. Localization of Terre d'Argine (Italy) study area.

At the beginning of 2020, Terre d'Argine registered a population of 107,090 inhabitants distributed as follows: 8,745 inhabitants in Campogalliano, 72,641 in Carpi, 10,050 in Novi di Modena and 15,654 in Soliera municipality.

Figure 4.14 represents the dynamic change in population between 2010-2020. It shows a decrease in population over time in Campogalliano, and Novi di Modena. The latter case, specifically, experienced a remarkable decrease in the population over the analyzed period. On the contrary, Carpi and Soliera demonstrated an increase in the population during the same period.

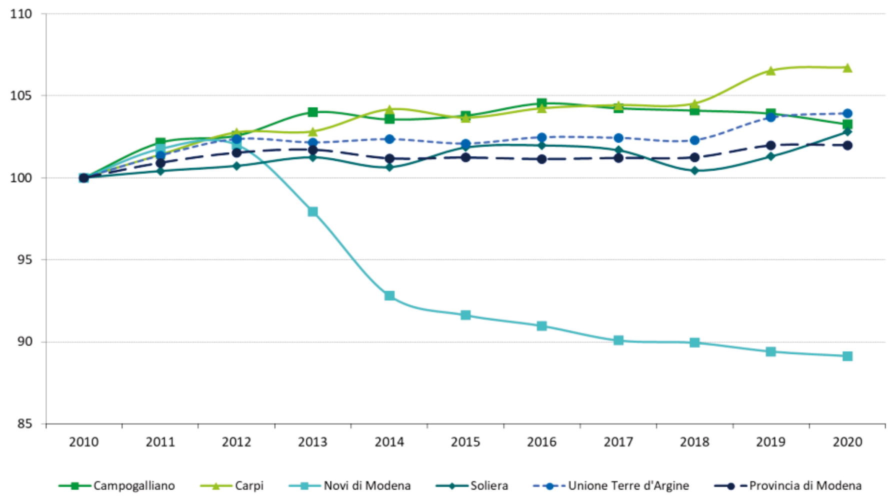


Figure 4.14. Population dynamics in Terre d'Argine from 2010 to 2020 (PUG TdA, 2023).

Considering the population density, the Union of Municipality of Terre d'Argine is characterized by a population density of 396 inhabitants/km^2. Specifically, Campogalliano, Carpi, Novi di Modena, and Soliera have a population density of 244 inhabitants/km^2, 552 inhabitants/km^2, 193 inhabitants/km^2, and 306 inhabitants/km^2, respectively.

This area is selected as a suitable case study as representative of many Italian territorial contexts as well as because the Emilia Romagna Region defined specific policies for contrasting soil consumption and, therefore, defined a balance between urban growth and the promotion of sustainable policies, such as the definition of greening policies.

The Urbanistic Law of the Emilia Romagna Region (2017) aims to contain soil consumption by consuming soil at "zero balance," which is to be achieved by 2050. To this aim, the Urbanistic Law identifies the maximum limit of 3% of the urbanized territory surface until 1 January 2018, the day of entry into force of the Regional Urbanistic Law 24/2017.

To perform the data analysis, the buildings' footprints were retrieved from the Topographic Database of the Emilia Romagna Region (DBTR, 2022). The socioeconomic data used to perform the population vulnerability analysis are retrieved from the ISTAT (ISTAT, 2022).

Data on the imperviousness of land are retrieved from the raster dataset produced by the European Program of Observation Data (Copernicus). Specifically, the author employed the imperviousness dataset related to the High-Resolution Layer (HRL) that analyzes the soil imperviousness degree related to 2015. The HRL imperviousness is defined as the soil imperviousness level per area unit. The soil imperviousness is expressed as a percentage (0-100%); it is produced at a resolution of 20 m, and then it is aggregated to a resolution of 100 m. The imperviousness is assessed through a semiautomatic classification based on the Normalized Difference Vegetation Index (NDVI).

Data on the land use land cover and the land use in the Municipality Union of Terre d'Argine are defined by Corine Land Cover (CLC, 2018). This information is updated by using the information about the urban services available in the area (PUG TdA, 2022; PRG Novi; PRG Carpi; PSC Campogalliano; PSC Soliera). This latter is also used to assess the urban services available in the Terre d'Argine area.

The information about public transportation is retrieved from the province (PTCP Modena) database and the Carpi database (PUMS Carpi) for the extra-urban and urban public transportation systems, respectively.

2.2. Results

2.2.1. Determining criteria weights Using the Analytic Hierarchy Process

The author calculated the indicators defined in Chapter 3 in correspondence to the defined grid cell system. The grid system is 50 m x 50 m cells for the built environment and 100 m x 100 m for rural areas. The raw data are normalized using the min-max normalization method according to the polarity of each indicator to the densification and greening potential.

Subsequently, the author performed the AHP multi-criteria decision-making technique to assess the weight of each indicator defined in Chapter 3, which is aimed at assessing the suitability of urban areas to accommodate densification and/or greening interventions.

In particular, the criteria factors are ranked according to a pairwise comparison. The pairwise comparison matrix among the criteria factors is defined for each thematic area. The pairwise comparison matrices are defined based on the author's judgment, which is strictly connected to the frequency and the relevance of those criteria within the scientific literature on densification and greening. The comparison between one criteria factor versus another is conducted according to the assessment of their relative importance based on a scale from 1 to 3, where 1 indicates equal importance, 2 indicates moderate importance, and 3 indicates strong importance. This evaluation scale is adapted from the one defined by Daniel (2018).

Table 4.8, Table 4.9, Table 4.10, and Table 4.11 present the results from the pairwise comparisons.

Table 4.8. Pairwise comparison matrix for socioeconomic vulnerability factors.

	SEV1	SEV2	SEV3	SEV4	SEV5	SEV6
SEV1	1	3	3	1	1	2
SEV2	1/3	1	1	1/3	1/3	1/2
SEV3	1/3	1	1	1/3	1/3	1/2
SEV4	1	3	3	1	1	2
SEV5	1	3	3	1	1	2
SEV6	1/2	2	2	1/2	1/2	1

Table 4.9. Pairwise comparison matrix for urban morphology factors.

	UM1	UM2	UM3
UM1	1	1/2	2
UM2	2	1	2
UM3	1/2	1/2	1

Table 4.10. Pairwise comparison matrix for urban green areas factors.

	UGA1	UGA2
UGA1	1	2
UGA2	1/2	1

Table 4.11. Pairwise comparison matrix for transportation and mobility factors.

	TM1	TM2	TM3	TM4	TM5
TM1	1	1	1	2	1
TM2	1	1	1	2	1
TM3	1	1	1	2	1
TM4	1/2	1/2	1/2	1	1/2
TM5	1	1	1	2	1

Based on the pairwise comparison matrix, the calculation of the final weights is conducted following the AHP process steps presented in Chapter 3. Table 4.12 shows the weights of the used criteria.

Table 4.12. Identification of weights for each indicator.

Thematic areas	Variable	Indicator	Unit	Effect	Weight
Socioeconomic vulnerability	SEV1	The proportion of the population aged 15-74 years	%	+	0.2386
	SEV2	The proportion of families with only one component	%	-	0.0761
	SEV3	The proportion of families with 6 or more components	%	-	0.0761
	SEV4	Undergraduate rate	%	-	0.2386
	SEV5	Unemployment rate	%	-	0.2386
	SEV6	Proportion of population in rent house	%	-	0.1321
Urban morphology	UM1	Population density	inh./ha	-	0.3119
	UM2	Imperviousness degree	%	-	0.4905
	UM3	Building age	years	-	0.1976
Urban complexity	UC	Mixed land use degree	n°	+/-	1
Urban green areas	UGA1	The proportion of the population with accessible urban green areas with a size lower than 0.25 ha in a 100 m distance	%	+	0.6667
		The proportion of the population with accessible urban green areas with sizes between 0.25 and 1 ha in a 300 m distance			
		The proportion of the population with accessible urban green areas with sizes between 1 and 5 ha in a 500 m distance			
		The proportion of the population with accessible urban green areas with sizes more than 5			

		ha in a 700 m distance			
	UGA2	Tree cover density	%	+	0.3333
Transportation and mobility	TM1	The proportion of the population with accessible urban bus stops within a 200 m distance	%	+	0.2222
	TM2	The proportion of the population with accessible extra-urban/metro/train stops within a 400 m distance	%	+	0.2222
	TM3	The proportion of the population with accessible train stations within 800 m distance	%	+	0.2222
	TM4	Density of road intersections	n°/grid	+	0.1111
	TM5	Density of cycle path intersections	n°/grid	+	0.2222

The consistency of the pairwise comparison matrix and the calculated weight for each thematic area is satisfied if the consistency ratio (CR) is less than 0.1 (Saaty, 2008). Referring to the calculation, consistency is ensured and satisfied for each thematic area.

2.2.2. Assessing the suitability for densification and/or greening interventions

After assessing the weights of the indicators, each indicator is evaluated using a grid cell system since the proposed method aims to analyze densification potential at a very high level of resolution. The author, specifically, considered 50 m x 50 m for the urban environment and 100 m x 100 m for rural areas.

First, the author assessed the indicators for each thematic area. Then, they are combined, considering the weights above to assess the thematic indexes. Results for the different thematic areas and the overall score are presented in the following Figures. In the Tables, the author evaluated the area and percentage for the entire territory and each municipality, characterized by the different levels of densification potential considering the overall territorial area and the urbanized area.

Figure 4.15 shows the densification potential according to the socioeconomic vulnerability factors.

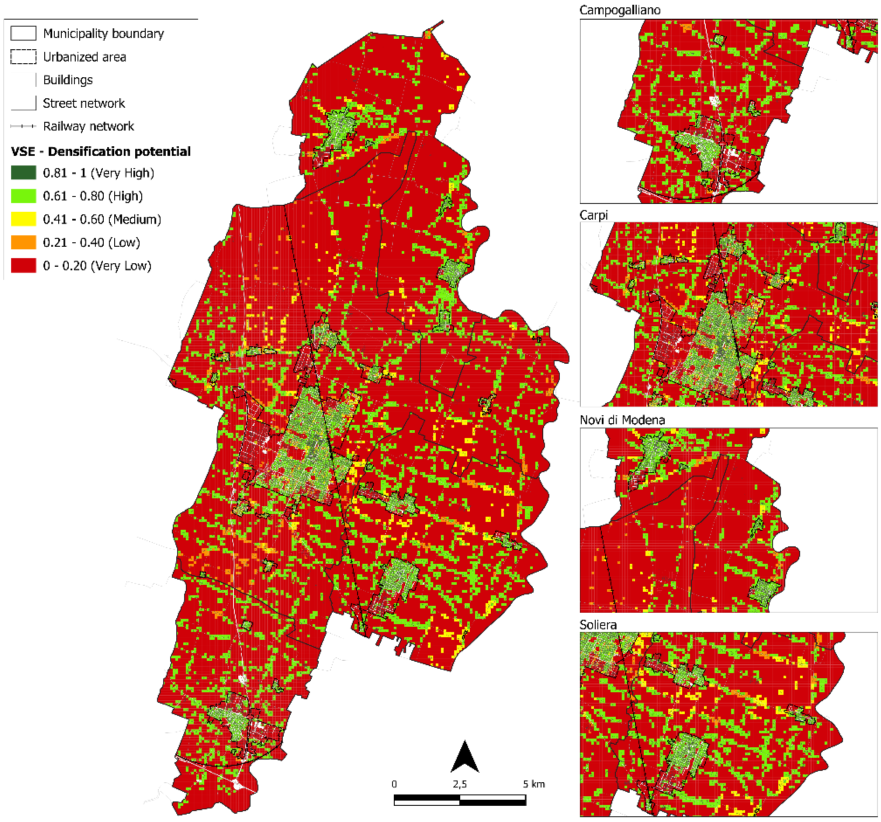


Figure 4.15. Densification potential map according to socioeconomic vulnerability factors.

Table 4.13 and Table 4.14 present the area and the percentage of the entire territory and each municipality according to the level of densification and/or greening potential related to socioeconomic vulnerability considering the entire territory.

Table 4.13. Densification potential, expressed in area, according to the socio-economic vulnerability factors.

Potentiality	Area (ha)				
	Terre d'Argine	**Campogalli ano**	**Carpi**	**Novi di Modena**	**Soliera**
Very High	7.50	0.00	7.50	0.00	0.00
High	49375.06	7538.04	21551.06	8894.87	11391.10
Medium	6918.11	0.00	4041.68	879.38	1997.05
Low	4270.88	135.87	3378.53	356.69	399.53
Very Low	209311.63	27469.13	102530.48	41724.09	37588.20

Table 4.14. Densification potential, expressed in percentage, according to the socio-economic vulnerability factors.

Potentiality	Percentage (%)				
	Terre d'Argine	**Campogalli ano**	**Carpi**	**Novi di Modena**	**Soliera**
Very High	0.00	0.00	0.01	0.00	0.00
High	18.29	21.45	16.39	17.15	22.17
Medium	2.56	0.00	3.07	1.70	3.89
Low	1.58	0.39	2.57	0.69	0.78
Very Low	77.56	78.16	77.96	80.46	73.16

The results revealed that considering the entire territory, both rural and urban areas, Terre d'Argine demonstrates a very low level of densification potential referring to the socioeconomic vulnerability, covering an area of 209311.63 ha (77.56% of the entire territory). The 18.29% of the territory, corresponding to 49375.06 ha, is characterized by high potentiality. The lowest values obtained for the densification potential considering the socioeconomic vulnerability factors are related to medium (2.56%) and low (1.58%) levels of potentiality, covering a surface of 6918.11 ha and 4270.88 ha, respectively. According to the results of each municipality, the municipalities characterized by the highest value of very low densification potential are Novi di Modena (80.46%) and Carpi (77.96%). The municipality areas characterized by those levels of potentiality are 102530.48 ha and 41724.09 ha, respectively. Soliera (22.17%) and Campogalliano (21.45%) present the highest share of high potentiality according to socioeconomic vulnerability for an area of 11391.10 ha and 7538.04.

Table 4.15 and Table 4.16 present the area and the percentage of the entire territory and each municipality according to the level of densification and/or greening potential related to socioeconomic vulnerability considering the urbanized area.

Table 4.15. Densification potential of the urbanized area, expressed in area, according to socio-economic vulnerability factors.

Potentiality	Area (ha)				
	Terre d'Argine	**Campogalliano**	**Carpi**	**Novi di Modena**	**Soliera**
Very High	7.50	0.00	7.50	0.00	0.00
High	13436.57	1344.90	7373.45	2270.87	2447.36
Medium	1645.12	0.00	1577.05	0.31	67.76
Low	743.07	17.27	721.91	3.89	0.00
Very Low	11509.79	1906.70	7160.51	533.95	1908.63

Table 4.16. Densification potential of the urbanized area, expressed in percentage, according to socio-economic vulnerability factors.

Potentiality	Percentage (%)				
	Terre d'Argine	**Campogalliano**	**Carpi**	**Novi di Modena**	**Soliera**
Very High	0.03	0.00	0.04	0.00	0.00
High	49.14	41.14	43.78	80.84	55.32
Medium	6.02	0.00	9.36	0.01	1.53
Low	2.72	0.53	4.29	0.14	0.00
Very Low	42.10	58.33	42.52	19.01	43.15

Looking at the results obtained for the densification potential for only the urbanized areas, the author found that the entire territory is mainly characterized by low and high densification potential according to socioeconomic vulnerability factors. In particular, the entire territory shows a high level of densification potential for 49.14% of the urban area, for an area of 13436.57 ha. In comparison, 42.10% is characterized by a very low potential for densification, covering an urbanized area of 11509.79 ha.

In particular, the highest share of the urban environment with a very low level of potentiality for densification characterizes Campogalliano (58.33%), covering an area of 1906.70 ha. In comparison, the lowest characterizes Novi di Modena (19.01%) for an area of 533.95 ha. The highest share of urban areas with high potential for densification interventions characterizes Novi di Modena (80.84%) for an area of 2270.87 ha. Soliera (55.32%), Carpi (43.78%), and Campogalliano (41.14%) present quite the same percentages in terms of urbanized areas, showing a high potential for densification interventions according to socioeconomic vulnerability factors.

Figure 4.16 shows the spatial distribution of the densification/greening intervention potential according to the urban morphology of urban areas for Terre d'Argine.

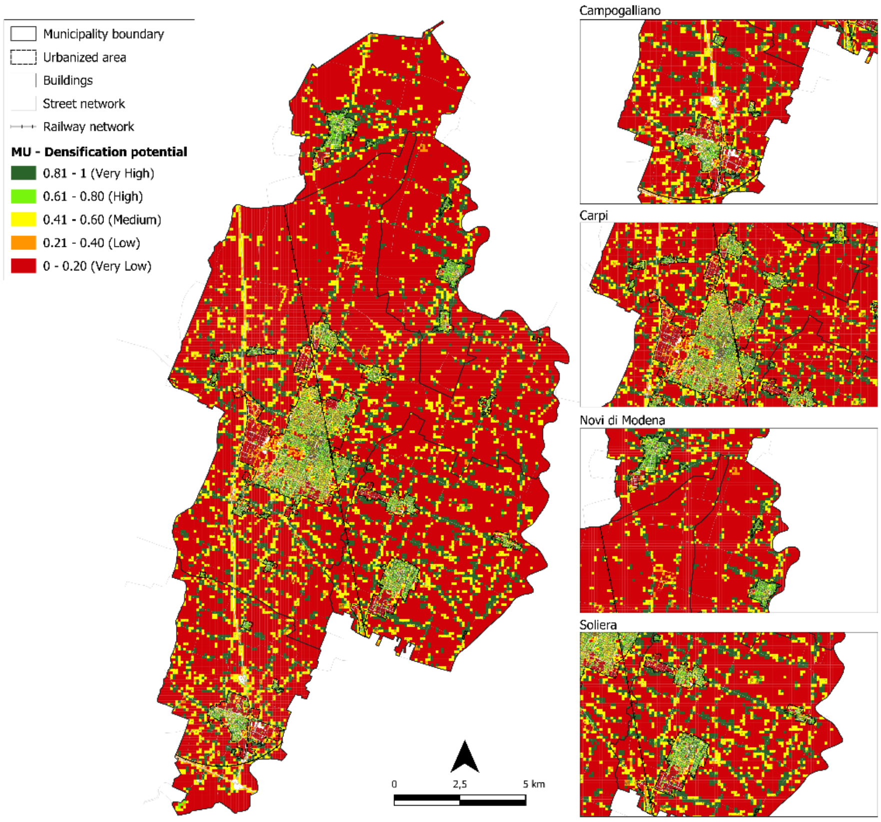


Figure 4.16. Densification potential map according to urban morphology factors.

In Table 4.17 and Table 4.18, the author evaluated the area and the percentage of the entire territory, and each municipality characterized by the different levels of densification potential according to the urban morphology factors. In Table 4.19 and Table 4.20, the author considered only the urbanized area.

Table 4.17. Densification potential, expressed in area, according to the urban morphology factors.

Potentiality	Area (ha)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	30602.09	4067.87	13380.74	5597.95	7555.53
High	8003.03	781.27	4185.51	1600.37	1435.87
Medium	39893.41	6103.20	21030.01	5133.86	7626.34
Low	5789.13	1377.43	3300.56	392.63	718.51
Very Low	185595.53	22813.25	89612.43	39130.22	34039.63

Table 4.18. Densification potential, expressed in percentage, according to the urban morphology factors.

Potentiality	Percentage (%)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	11.34	11.58	10.17	10.80	14.71
High	2.97	2.22	3.18	3.09	2.79
Medium	14.78	17.37	15.99	9.90	14.84
Low	2.15	3.92	2.51	0.76	1.40
Very Low	68.77	64.92	68.14	75.46	66.26

According to the urban morphology characteristics, the prevailing densification potential for the whole territory is low (68.77%), covering an area of 185595.53 ha. It is followed by 14.78% of Terre d'Argine with a medium potential to be densified (39893.41 ha) and 11.34% with a very high potential (30602.09 ha). The 2.97% and 2.15% of the total area of Terre d'Argine corresponds to the high and low densification potential.

Among the individual municipalities, Soliera shows the highest percentage of municipality area characterized by a very high densification potential related to the morphological characteristics of the urban context: 14.71% of the entire municipality for an area of 7555.53 ha. Novi di Modena shows the highest share (75.46%) of municipality area characterized by a very low level of densification potential according to the urban morphology factors. The interested area reaches 39130.22 ha. Campogalliano, instead, presents the highest percentage of municipality area characterized by an average densification potential (17.37%) for an area of 6103.20 ha. Almost the same share of territory characterizes all the municipalities with a high level of densification potential, ranging from 2.22% (Campogalliano) to 3.18% (Carpi).

Table 4.19. Densification potential of the urbanized area, expressed in surface area, according to urban morphology factors.

Potentiality	Area (ha)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	2699.60	274.29	1454.83	467.47	503.01
High	7160.41	610.41	3912.27	1406.80	1230.93
Medium	7643.80	685.84	5317.05	521.18	1119.73
Low	2815.55	298.57	2009.91	129.49	377.57
Very Low	7022.69	1399.75	4146.36	284.07	1192.51

Table 4.20. Densification potential of the urbanized area, expressed in percentage, according to urban morphology factors.

Potentiality	Percentage (%)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	9.87	8.39	8.64	16.64	11.37
High	26.19	18.67	23.23	50.08	27.83
Medium	27.96	20.98	31.57	18.55	25.31
Low	10.30	9.13	11.94	4.61	8.54
Very Low	25.68	42.82	24.62	10.11	26.96

Considering the urbanized territory, according to the urban morphology factors, Terre d'Argine, in general, shows mostly a medium (27.96%) to a high level (26.19%) of densification potential for urbanized areas of 7643.80 ha and 7160.41 ha, respectively. Among the four municipalities, Campogalliano presents the highest share of urbanized territory with a very low level of densification potential (42.82%) for an urbanized area of the municipality equal to 1399.75 ha. On the other hand, Novi di Modena presents the highest share of high (50.08%) and very high (16.64%) levels of densification potentiality according to urban morphological parameters. The urbanized area of Novi di Modena municipality interested in these conditions is 1406.80 ha and 467.47 ha, respectively. The urbanized area of Carpi is primarily characterized by a medium level of densification potential (31.57%) covering an urbanized area of 5317.05 ha.

Figure 4.17 presents the patterns of urban densification potential according to the positive effect of urban complexity factors for Terre d'Argine and its four municipalities. The positive effect of urban complexity factors is considered as the conditions for residential densification intervention potentiality.

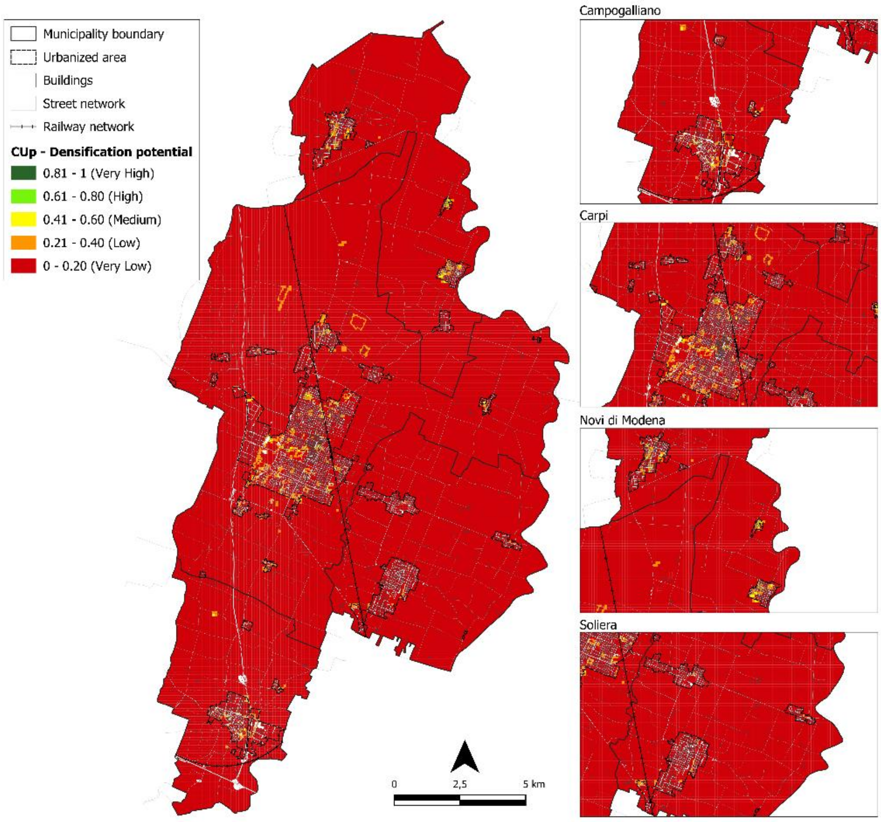


Figure 4.17. Densification potential map according to the positive effect of urban complexity factors.

Table 4.21 and Table 4.22 show the numerical results for the entire territory.

Table 4.21. Densification potential, expressed in area, according to the positive effect of urban complexity factors.

Potentiality	**Area (ha)**				
	Terre d'Argine	**Campogalliano**	**Carpi**	**Novi di Modena**	**Soliera**
Very High	2.50	0.00	2.50	0.00	0.00
High	9.64	0.00	9.64	0.00	0.00
Medium	427.04	59.12	247.89	120.03	0.00
Low	3659.78	446.75	2517.45	540.13	155.45
Very Low	265784.23	34637.17	128731.77	51194.87	51220.42

Table 4.22. Densification potential, expressed in percentage, according to the positive effect of urban complexity factors.

Potentiality	Percentage (%)				
	Terre d'Argine	**Campogalliano**	**Carpi**	**Novi di Modena**	**Soliera**
Very High	0.00	0.00	0.00	0.00	0.00
High	0.00	0.00	0.01	0.00	0.00
Medium	0.16	0.17	0.19	0.23	0.00
Low	1.36	1.27	1.91	1.04	0.30
Very Low	98.48	98.56	97.89	98.73	99.70

The results revealed that the entire territory is characterized by a very low level of densification potential according to a positive effect of urban complexity, meaning that densification potential related to the increase of residences is very low. The Terre d'Argine area characterized by this condition is 265784.23 ha, 98.48% of the entire territorial area. It is confirmed that it also considers all the municipalities. Considering the positive effect of urban complexity factors, the lowest share of shallow densification potential characterizes Carpi (97.89%) for an area of 128731.77 ha. Table 4.23 and Table 4.24 presents the results considering the urbanized area.

Table 4.23. Densification potential of the urbanized area, expressed in area, according to the positive effect of urban complexity factors.

Potentiality	Area (ha)				
	Terre d'Argine	**Campogalliano**	**Carpi**	**Novi di Modena**	**Soliera**
Very High	2.50	0.00	2.50	0.00	0.00
High	9.64	0.00	9.64	0.00	0.00
Medium	360.49	36.76	216.79	106.93	0.00
Low	2812.62	323.95	1924.77	453.16	110.74
Very Low	24156.81	2908.15	14686.72	2248.93	4313.01

Table 4.24. Densification potential of the urbanized area, expressed in percentage, according to the positive effect of urban complexity factors.

Potentiality	Percentage (%)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	0.01	0.00	0.01	0.00	0.00
High	0.04	0.00	0.06	0.00	0.00
Medium	1.32	1.12	1.29	3.81	0.00
Low	10.29	9.91	11.43	16.13	2.50
Very Low	88.35	88.97	87.21	80.06	97.50

Looking at the urbanized area, the densification potential is distributed for the entire territory between the low and the very low levels. A very low-level potentiality condition characterizes 88.35% of the overall urbanized area of Terre d'Argine, which is equal to 24156.81 ha. Furthermore, Terre d'Argine presents 2812.62 ha of the urbanized area in a low-level potentiality condition according to the positive effect of urban complexity factors, which corresponds to 10.29% of the total urbanized area of the analyzed union of the municipality. This situation is similar in every municipality. Soliera presents the highest share (97.50%) of urbanized territory with a very low level of densification potential according to a positive effect of urban complexity. In comparison, Novi di Modena has the lowest (80.06%). This latter presents the highest share of the urbanized area in a medium densification potential condition for a positive effect of urban complexity factors (3.81%) covering an area of 106.93 ha. Campogalliano, Novi di Modena, and Soliera present no area characterized by very high and high levels of densification potential.

Figure 4.18 shows the densification potential according to a negative effect of urban complexity.

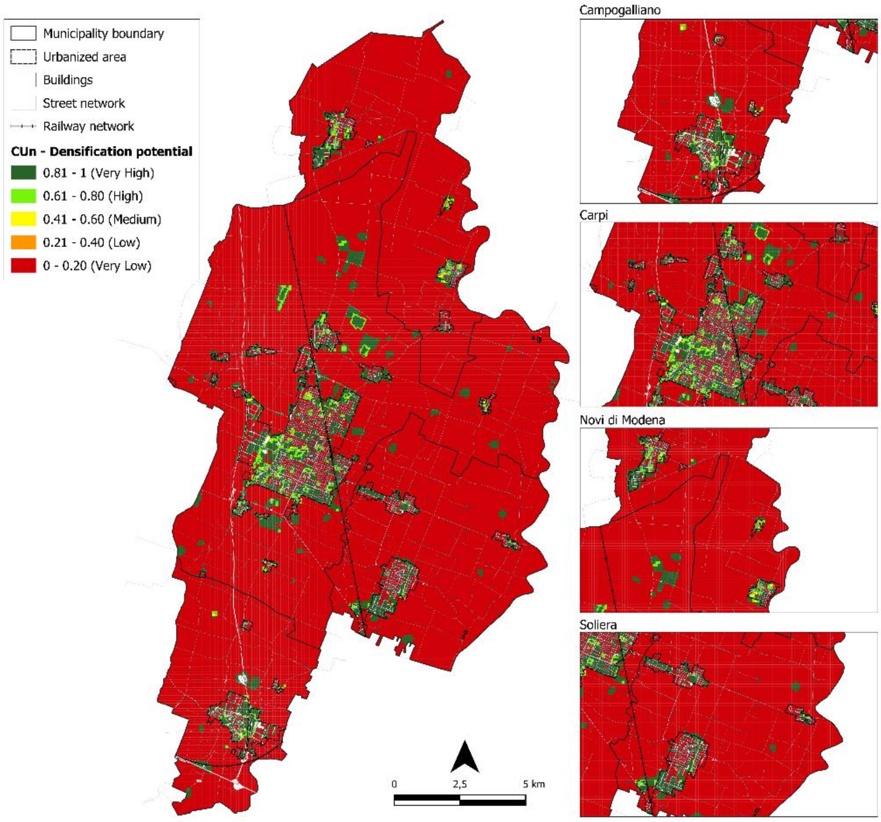


Figure 4.18. Densification potential map according to the negative effect of urban complexity factors.

Table 4.25 and Table 4.26 illustrates the numerical results for the entire territory.

Table 4.25. Densification potential, expressed in area, according to the negative effect of urban complexity factors.

Potentiality	**Area (ha)**				
	Terre d'Argine	**Campogalliano**	**Carpi**	**Novi di Modena**	**Soliera**
Very High	18787.43	2320.89	12283.66	1623.56	2559.32
High	3659.78	446.75	2517.45	540.13	155.45
Medium	427.04	59.12	247.89	120.03	0.00
Low	9.64	0.00	9.64	0.00	0.00
Very Low	246999.30	32316.28	116450.60	49571.32	48661.11

Table 4.26. Densification potential, expressed in percentage, according to the negative effect of urban complexity factors.

Potentiality	Percentage (%)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	6.96	6.60	9.34	3.13	4.98
High	1.36	1.27	1.91	1.04	0.30
Medium	0.16	0.17	0.19	0.23	0.00
Low	0.00	0.00	0.01	0.00	0.00
Very Low	91.52	91.96	88.55	95.60	94.72

The results show that 91.52% of the entire territory, corresponding to 246999.30 ha, is characterized by a very low level of densification potential, considering the negative effect of urban complexity. In comparison, 6.96%, equal to 18787.43 ha, shows a very high level of potentiality. Novi di Modena presents the highest municipality area (49571.32 ha) with a very low level of densification potential, reaching a share of 95.60%. In contrast, Carpi presents the lowest (88.55%), corresponding to an area of 116450.60. Furthermore, Carpi represents 9.34% of the municipality area, corresponding to 12283.66 ha, with a very high densification potential. In this sense, Carpi demonstrates the highest percentage of municipality area in this condition compared to the other municipalities.

Table 4.27 and Table 4.28 present the results obtained considering the urbanized area.

Table 4.27. Densification potential of the urbanized area, expressed in surface area, according to the negative effect of urban complexity factors.

Potentiality	Area (ha)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	10847.58	1330.46	6774.10	1001.93	1741.09
High	2812.62	323.95	1924.77	453.16	110.74
Medium	360.49	36.76	216.79	106.93	0.00
Low	9.64	0.00	9.64	0.00	0.00
Very Low	13311.73	1577.69	7915.12	1247.00	2571.92

Table 4.28. Densification potential of the urbanized area, expressed in percentage, according to the negative effect of urban complexity factors.

Potentiality	Percentage (%)				
	Terre d'Argine	**Campogalliano**	**Carpi**	**Novi di Modena**	**Soliera**
Very High	39.67	40.70	40.23	35.67	39.36
High	10.29	9.91	11.43	16.13	2.50
Medium	1.32	1.12	1.29	3.81	0.00
Low	0.04	0.00	0.06	0.00	0.00
Very Low	48.69	48.26	47.00	44.39	58.14

Considering only the urbanized area, Terre d'Argine is characterized by 48.69% of a very low level of densification potential and 39.67% and 10.29% of a very high and high level of densification, respectively. Regarding urbanized areas interested in these conditions, 13311.73 ha reflects very low densification potential, 10847.58 ha has a very high potentiality, and 2812.62 presents high potentiality. There is no urbanized area interested in a low level of densification potential. Each municipality shows a great share of the urbanized area characterized by a very low level of densification potential and a very high level of density. Novi di Modena, for instance, is characterized by 44.39% of the urbanized area, equivalent to 1247.00 ha, with a very low densification potential considering the negative effect of urban complexity factors. It is the lowest share among the four municipalities. The municipality with the highest share of the urbanized area interested in high potentiality level is Novi di Modena (16.13%) for an area of 453.16 ha. In comparison, Campogalliano presents the highest share of the urbanized area with a very high densification potential (40.70%), equal to 1330.46 ha, considering the negative effect of urban complexity factors.

Figure 4.19 shows the spatial patterns of urban densification potential according to urban green areas factors.

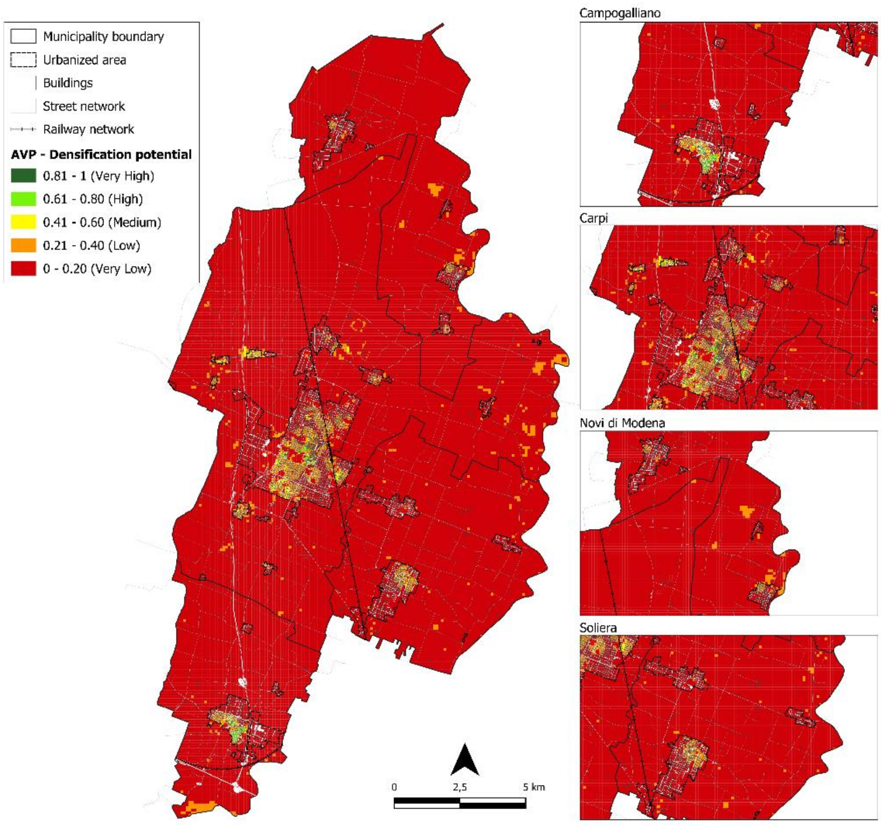


Figure 4.19. Densification potential map according to the urban green areas factors.

Table 4.29 and Table 4.30 show the numerical results for the entire territory.

Table 4.29. Densification potential, expressed in area, according to the urban green areas factors.

Potentiality	**Area (mq)**				
	Terre d'Argine	**Campogalliano**	**Carpi**	**Novi di Modena**	**Soliera**
Very High	5.00	0.00	5.00	0.00	0.00
High	335.47	173.29	162.19	0.00	0.00
Medium	807.22	91.39	699.57	0.00	16.26
Low	8639.84	1006.48	5849.38	871.38	912.60
Very Low	260095.65	33871.88	124793.12	50983.64	50447.01

Table 4.30. Densification potential, expressed in percentage, according to the urban green areas factors.

Potentiality	Percentage (%)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	0.00	0.00	0.00	0.00	0.00
High	0.12	0.49	0.12	0.00	0.00
Medium	0.30	0.26	0.53	0.00	0.03
Low	3.20	2.86	4.45	1.68	1.78
Very Low	96.37	96.38	94.89	98.32	98.19

A shallow level of densification potential characterizes Terre d'Argine according to factors related to urban green areas. Indeed, in this case, the share of the area marked by a shallow level of densification potential is equal to 96.37%, corresponding to 260095.65 ha. This trend is confirmed for each municipality. The share of the municipality area interested in a very low level of densification potential ranges from 94.89% (Carpi) to 98.32% (Novi di Modena). Carpi demonstrates the highest share of municipality area with a low densification potential. It is equal to 4.45% and corresponds to 5849.39 ha. None of the municipalities presents very high levels of densification potential.

Table 4.31 and Table 4.32 show the numerical results for the urbanized area.

Table 4.31. Densification potential of the urbanized area, expressed in area, according to the urban green areas factors.

Potentiality	Area (ha)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	5.00	0.00	5.00	0.00	0.00
High	335.46	173.29	162.17	0.00	0.00
Medium	721.39	90.62	614.50	0.00	16.26
Low	5169.46	433.43	3913.99	280.64	541.40
Very Low	21110.74	2571.52	12144.76	2528.38	3866.09

Table 4.32. Densification potential of the urbanized area, expressed in percentage, according to the urban green areas factors.

Potentiality	Percentage (%)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	0.02	0.00	0.03	0.00	0.00
High	1.23	5.30	0.96	0.00	0.00
Medium	2.64	2.77	3.65	0.00	0.37
Low	18.91	13.26	23.24	9.99	12.24
Very Low	77.21	78.67	72.12	90.01	87.39

Terre d'Argine presents 77.21% of the urbanized area with a very low level of densification potential, corresponding to 21110.74 ha, while 18.91% is represented by a low level (5169.46 ha). The medium and high levels of densification potential represent 2.64% and 1.23% of the urbanized area, respectively. Only 0.02% of the urbanized area, for a surface of 5.00 ha, presents a very high level of densification potential. Among the four municipalities, Novi di Modena presents the worst situation in terms of densification potential related to urban green areas as it is characterized by the highest share of the urbanized area with a very low level of densification potential (90.01%) covering a surface of 2528.38 ha. Carpi presents the lowest share (72.12%) of urbanized areas with a very low level of densification potential with a surface of 12144.76 ha. Campogalliano is characterized by the highest percentage of the urbanized area with a high level of densification potential (5.30%) for an area of 173.29 ha.

In Figure 4.20 the densification potential patterns according to transportation and mobility are presented.

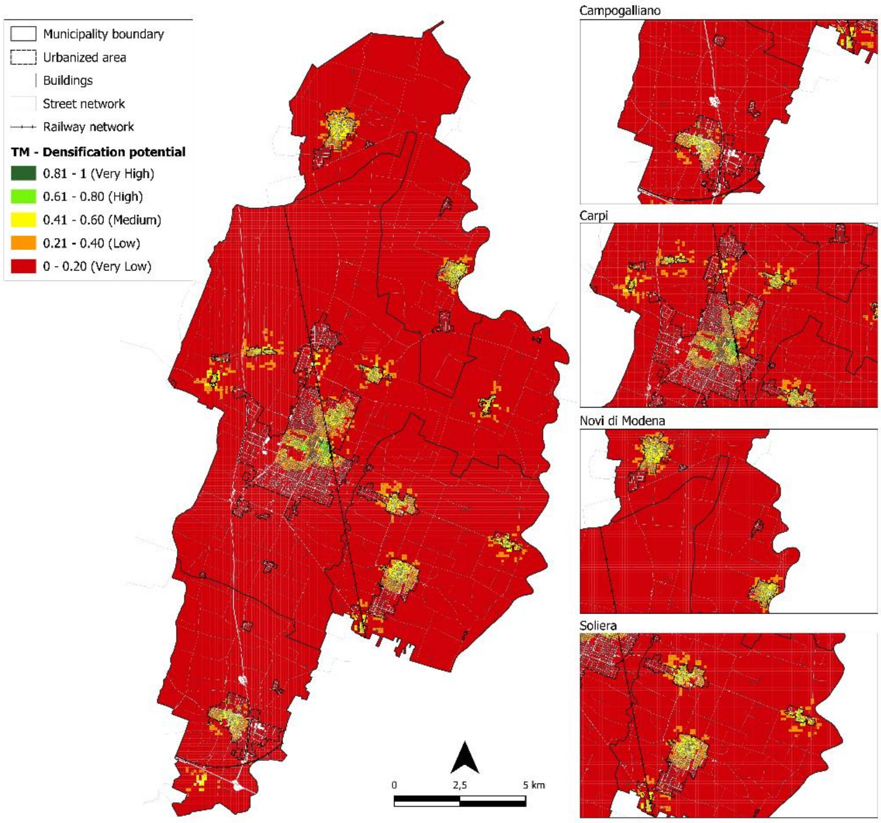


Figure 4.20. Densification potential map according to the transportation and mobility factors.

The mapped results are analytically presented in Table 4.33 and Table 4.34 for the entire territory.

Table 4.33. Densification potential, expressed in area, according to the transportation and mobility factors.

Potentiality	Area (ha)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	0.00	0.00	0.00	0.00	0.00
High	259.81	2.50	257.31	0.00	0.00
Medium	4471.70	470.95	1902.86	898.81	1199.09
Low	8936.28	815.81	4469.46	1570.37	2080.65
Very Low	256215.38	33853.78	124879.62	49385.84	48096.14

Table 4.34. Densification potential, expressed in percentage, according to the transportation and mobility factors.

Potentiality	Percentage (%)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	0.00	0.00	0.00	0.00	0.00
High	0.10	0.01	0.20	0.00	0.00
Medium	1.66	1.34	1.45	1.73	2.33
Low	3.31	2.32	3.40	3.03	4.05
Very Low	94.94	96.33	94.96	95.24	93.62

Also in this case, the entire territory of Terre d'Argine is characterized mostly by a very low level of densification potential according to transportation and mobility criteria (94.94%) for an area of 256215.38 ha. Among the four municipalities, Soliera is characterized by the lowest share of municipality area with a very low level of densification potential (93.62%), while Campogalliano retains the highest (96.33%). Soliera also shows the highest share of the municipality area in a low (4.05%) and in a medium (2.33%) level densification potential. The area amounts to 2080.65 ha and 1199.09 ha, respectively.

Table 4.35 and Table 4.36 summurize the results referred to the urbanized area.

Table 4.35. Densification potential of the urbanized area, expressed in area, according to the transportation and mobility factors.

Potentiality	Area (mq)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	0.00	0.00	0.00	0.00	0.00
High	259.21	2.50	256.71	0,00	0,00
Medium	3820.66	333.57	1570.18	837.80	1079.11
Low	5241.65	569.50	2729.18	886.27	1056.70
Very Low	18020.53	2363.29	12284.35	1084.95	2287.94

Table 4.36. Densification potential of the urbanized area, expressed in percentage, according to the transportation and mobility factors.

Potentiality	Percentage (%)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	0.00	0.00	0.00	0.00	0.00
High	0.95	0.08	1.52	0.00	0.00
Medium	13.97	10.20	9.32	29.83	24.39
Low	19.17	17.42	16.21	31.55	23.89
Very Low	65.91	72.30	72.95	38.62	51.72

Considering the urbanized area, Terre d'Argine is characterized by 65.91% of the urbanized area with a very low level of densification potential, 19.17% with a low level, 13.97% with a medium level, and 0.95% with high densification potential according to the transportation and mobility factors. No area in the Terre d'Argine context is characterized by a very high level of densification potential.

Considering the four municipalities, the share of the urbanized area characterized by a high to very high level of densification potential is very low for every municipality. Indeed, Carpi presents the highest share of the urbanized area with a high level of densification potential (1.52%) for an area of 256.71 ha. Novi di Modena presents the highest share of the urbanized area at a medium level of densification potential related to transportation and mobility criteria (29.83%) corresponding to an area of 837.80 ha. In comparison, Carpi presents the lowest (9.32%) for an area of 1570.18 ha. This latter shows the lowest share of the urbanized area characterized by a low densification potential of 16.21% and corresponds to an area of 2729.18 ha. Finally, considering the very low level of densification potential, Novi di Modena is characterized by the lowest (38.62%) share of urbanized areas, while Carpi presents the highest (72.95%).

After assessing the thematic indexes, they are combined linearly to evaluate the densification and/or greening potential. Also, in this case, two possibilities are considered: the first, according to which the densification aims to satisfy the residential demand. At the same time, the second is related to the densification aimed at increasing the service supply.

The densification potential for new residences of the entire territory of Terre d'Argine is shown in Figure 4.21.

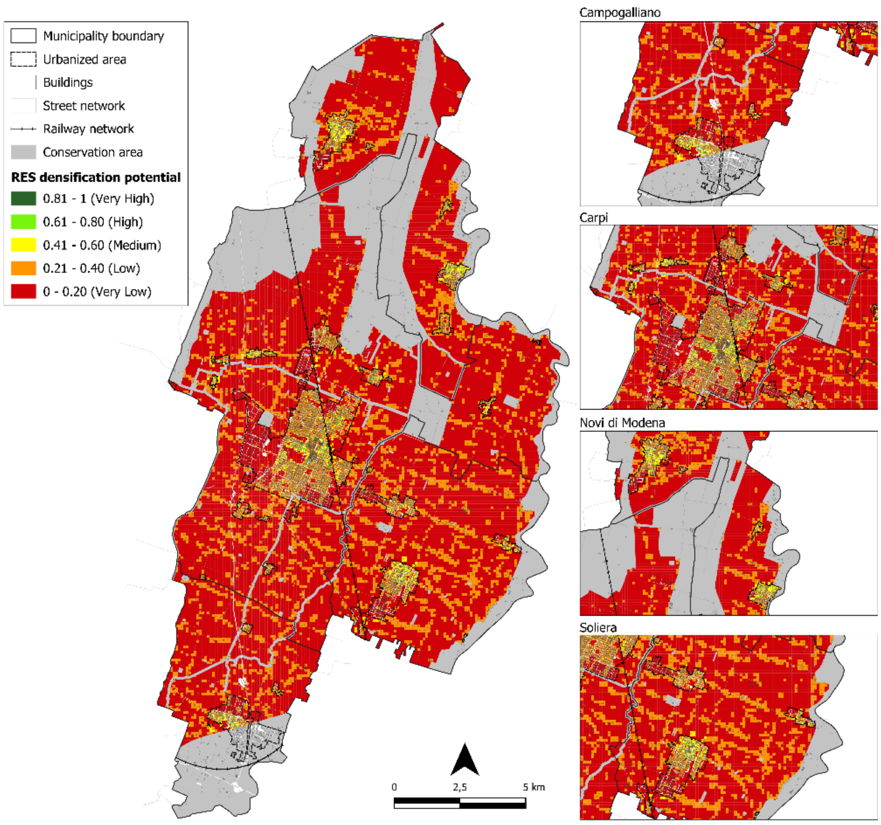


Figure 4.21. Residential densification potential map.

Table 4.37 and Table 4.38 resume the obtained results numerically referring to the entire territory.

Table 4.37. Residential densification potential expressed in area.

Potentiality	Area (mq)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	0.00	0.00	0.00	0.00	0.00
High	12.50	0.00	12.50	0.00	0.00
Medium	4392.57	588.83	2244.20	798.79	760.75
Low	54753.06	7085.08	25863.62	9133.92	12670.44
Very Low	210725.06	27469.13	103388.93	41922.32	37944.68

Table 4.38. Residential densification potential expressed in percentage.

Potentiality	Percentage (%)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	0.00	0.00	0.00	0.00	0.00
High	0.00	0.00	0.01	0.00	0.00
Medium	1.63	1.68	1.71	1.54	1.48
Low	20.29	20.16	19.67	17.61	24.66
Very Low	78.08	78.16	78.62	80.85	73.86

Reflecting on the entire territorial context, Terre d'Argine generally demonstrates a very low (78.08%) to low (20.29%) level of densification potential for new residences for areas equal to 210725.06 ha and 54753.06 ha, respectively. The 1.63% of the territorial area presents a medium level of densification potential, corresponding to 4392.57 ha.

Specifically, Novi di Modena shows the highest share of territory in a very low potential (80.85%), corresponding to 41922.32 ha. In comparison, Soliera presents the highest share of municipality area characterized by a low level of densification potential (24.66%) for an area of 12670.44 ha. Carpi has the highest share of territorial area exposed to medium densification potential. It is equal to 1.71% which corresponds to 2244.20 ha.

The results obtained considering only the urbanized area are shown in Table 4.39 and Table 4.40.

Table 4.39. Residential densification potential of the urbanized area expressed in surface area.

Potentiality	Area (mq)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	0.00	0.00	0.00	0.00	0.00
High	12.50	0.00	12.50	0.00	0.00
Medium	3616.75	507.55	1827.36	673.31	608.54
Low	12155.32	854.35	7787.84	1601.76	1911.37
Very Low	11557.48	1906.97	7212.73	533.95	1903.83

Table 4.40. Residential densification potential of the urbanized area expressed in percentage.

Potentiality	Percentage (%)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	0.00	0.00	0.00	0.00	0.00
High	0.05	0.00	0.07	0.00	0.00
Medium	13.23	15.53	10.85	23.97	13.76
Low	44.46	26.14	46.24	57.02	43.21
Very Low	42.27	58.34	42.83	19.01	43.04

Considering only the urbanized area, in general, Terre d'Argine is characterized by a high share of the urbanized area with very low (42.27%) and low (44.46%) densification potential for an area of 11557.48 ha and 12155.32 ha, respectively. Among the four municipalities, Novi di Modena presents higher values of densification potential for new residences. Indeed, 23.97% of the urbanized area is characterized by medium densification potential, 57.02% by low levels, and 19.01% by very low levels. Carpi presents the lowest share (10.85%) of the urbanized area in a medium level of densification potential, corresponding to 1827.36 ha. In contrast, Campogalliano presents the highest share of very low densification potential for an area of 1906.97 ha.

In Figure 4.22 the densification potential patterns aimed at the intensification of urban services are presented.

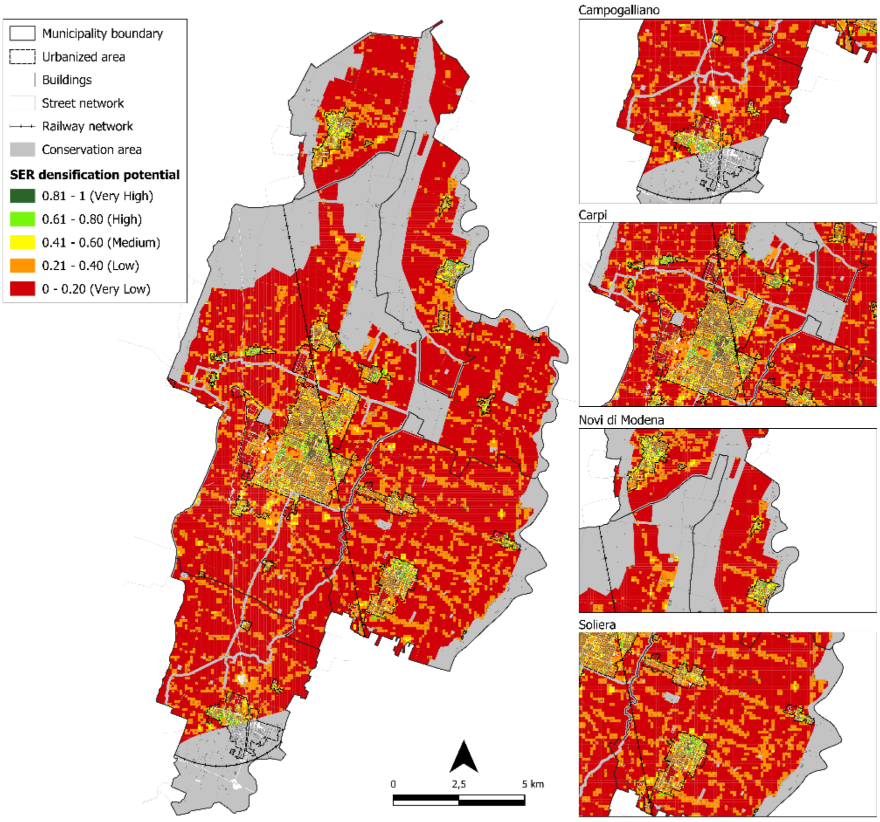


Figure 4.22. Urban services densification potential map.

Table 4.41 and Table 4.42 present the results for the entire territory.

Table 4.41. Services densification potential expressed in surface area.

Potentiality	**Area (mq)**				
	Terre d'Argine	**Campogalliano**	**Carpi**	**Novi di Modena**	**Soliera**
Very High	0.00	0.00	2.50	0.00	0.00
High	1509.09	260.14	855.51	160.04	233.39
Medium	9083.02	928.89	5374.93	1558.97	1220.23
Low	61313.31	8005.26	30647.44	8947.05	13713.56
Very Low	197975.27	25948.74	94628.87	41188.97	36208.69

Table 4.42. Services densification potential expressed in percentage.

Potentiality	Percentage (%)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	0.00	0.00	0.00	0.00	0.00
High	0.56	0.74	0.65	0.31	0.45
Medium	3.37	2.64	4.09	3.01	2.38
Low	22.72	22.78	23.30	17.25	26.69
Very Low	73.36	73.84	71.96	79.43	70.48

Analyzing the spatial distribution of urban services densification potential, although 73.36% of the territorial area is characterized by a very low level of densification potential, there are areas characterized by a high level of densification potential (0.56%) for an amount of 1509.09 ha. The results obtained for the case study demonstrate that 22.72% of the entire area corresponds to a low urban services densification potential and 3.37% corresponds to a medium level. A very high level of densification potential does not characterize the study area. This condition distinguishes the four municipalities considering both rural and urban parts. In particular, Campogalliano presents the highest share of municipality area in a high level of densification potentiality for urban services which is equal to 0.74% and corresponds to 260.14 ha. Carpi, instead, is characterized by 4.09% of the municipality area with a medium densification potential. The highest share of low (26.69%) and very low (79.43%) densification potential for urban services characterizes Soliera and Novi di Modena for an area of 13713.56 ha and 41188.97 ha, respectively.

Table 4.43 and Table 4.44 present the results considering the urbanized area.

Table 4.43. Services densification potential of the urbanized area expressed in area.

Potentiality	Area (mq)				
	Terre d'Argine	Campogalliano	Carpi	Novi di Modena	Soliera
Very High	2.50	0.00	2.50	0.00	0.00
High	1314.36	251.25	730.90	123.87	208.34
Medium	6535.41	627.25	3856.66	1182.83	868.67
Low	14623.30	1347.25	9358.99	1351.63	2565.43
Very Low	4866.48	1043.11	2891.37	150.68	781.32

Table 4.44. Services densification potential of the urbanized area expressed in percentage.

Potentiality	Percentage (%)				
	Terre d'Argine	**Campogalliano**	**Carpi**	**Novi di Modena**	**Soliera**
Very High	0.01	0.00	0.01	0.00	0.00
High	4.81	7.69	4.34	4.41	4.71
Medium	23.90	19.19	22.90	42.11	19.64
Low	53.48	41.21	55.57	48.12	57.99
Very Low	17.80	31.91	17.17	5.36	17.66

The urbanized area of Terre d'Argine is mainly characterized by low (53.48%) and medium (23.90%) potential for urban services densification, covering areas of 14623.30 ha and 6535.41 ha, respectively. A high level of densification potential characterizes 4.81% of the urbanized area, while 17.80% presents a very low level. Among the four municipalities, Novi di Modena offers a higher potential for urban services densification interventions, while Carpi and Soliera are quite similar. 42.11% of the Novi di Modena urbanized area presents a medium densification potential, corresponding to 1182.83 ha, while only 5.36% has a shallow level of potentiality. The highest share of the urbanized areas with a low level of densification is equal to 57.99% and characterizes Soliera for an area of 2565.43 ha. Campogalliano is characterized by 7.69% of the municipality's urbanized area having a high potential for urban service densification, corresponding to 251.25 ha.

2.3. Discussion of the results

The proposed methodology applied to the case study of Terre d'Argine aims to provide a flexible and easy indicator-based approach to assess the potential of urban areas to accommodate urban densification interventions or, on the other side, greening interventions. The applied methodology represents a geospatial data-driven framework for the spatial explicit quantification and evaluation of densification and/or greening potential, which, for its definition, can be applied to different geographical contexts and which criteria can be adapted to local data availability.

As the analysis of densification and/or greening potential represents a crucial part of the urban planning decision-making process, in this Chapter, the author managed to demonstrate through a practical application how the proposed methodology can help decision-makers and planners in assessing where and how to increase population density, infrastructure, and development while promoting sustainability and livability.

The proposed and tested method integrates appropriately georeferenced data into a GIS platform, which evaluates the potential of different areas for densification based on defined criteria and weights. Indeed, the core parts of the proposed methodology are identifying the thematic areas and selecting factors and criteria. The definition of thematic areas and the collection of criteria for densification and/or greening potential is crucial in this analysis process and, therefore, assumes notable importance. The assignment of weight to each criterion based on its importance in the decision-making process is also important even if, for the scope of this work, it is only limited to the author's consideration based on the scientific literature review.

The analysis and the results showed that it is possible to identify five levels of densification potential related to different planning strategies. The very high level of densification potential presents the most suitable conditions to accommodate densification interventions. The high level of densification potential also presents a great potential to be densified sustainably. These two cases rely on the possibility of hard densification interventions, such as large-scale policies related to the redevelopment of existing urban structures. Indeed, in these two cases, the existing urban structures can be characterized by unused places, such as brownfields, vacant land, and urban voids, representing an opportunity for this kind of densification intervention. The medium level of densification potential supposes that densification interventions can be implemented, but they must be gradually defined with greening interventions. On the other hand, the low and very low levels of densification potential identify areas characterized by a frequent scarcity of greenery and functional mix where the density levels are too high. In these cases, densification interventions are soft densification interventions, which consist of proceeding through continuous and step-by-step small-scale densification intervention of the urban fabric while giving space to urban greening and urban services reinforcement interventions.

Looking at the densification and/or greening potential of Terre d'Argine to satisfy a residential demand, in general, the territory mainly presents a deficient level of densification potential, while considering the urbanized area, it shows a low to very low densification potential with some areas characterized by medium densification potential. In the urbanized area, Novi di Modena has the highest densification potential because many areas show a medium to low densification potential. The zones with medium densification potential within the urbanized area of Novi di Modena municipality are located primarily near the city center, and the primary services have space for densification interventions in the lot area. The municipality of Carpi is mainly characterized by low densification potential for new residential areas. In particular, the areas with a medium densification potential are characterized by lots with available area for densification interventions located near the primary services and infrastructures, such as the main roads, the railway station, the main urban green areas, such as Parco della Rimembranza or Parco dei Martiri delle Foibe, and the public transportation service. Also, within the urbanized area of the municipality of Soliera, the areas are mainly characterized by a low densification potential for residential demand satisfaction. These areas are mainly located where primary services are provided. In the urbanized area of Campogalliano, the areas are mainly characterized by low densification potential except for some areas with a medium densification potential.

Concerning the densification potential for urban services implementation, Novi di Modena is generally characterized by a medium densification potential, with some areas characterized by a high level of densification potential located near the primary urban center. Specifically, the highest level of suitability characterizes lots with blocks or isolated buildings. Within the municipality of Carpi, the zones characterized by high densification potential for urban services development are mainly localized in the areas near the main infrastructures and the city center. Departing from those areas, the densification potential reaches a medium densification potential until reaching low and very low potentiality in the areas far from the center, which are characterized mostly by residential vocation. In terms of percentage, the municipality of Campogalliano demonstrated the highest value of high densification potential for new urban services development. These zones are also located within the historical part of the city, demonstrating that urban services development is a crucial strategy for this context. The same situation characterizes the municipality of Soliera as it is characterized by the lack of urban services and fewer values of built-up area density.

The results of applying the proposed methodology to the selected case study align with other published work. For example, Erik and Sosa (2017) identified that according to urban services and economic conditions, the suitability of densification intervention, in general, is higher within the consolidated part of urban areas. The higher the accessibility to services, infrastructures, and job opportunities, the higher the opportunities for economic and social agglomeration (Brinkman, 2016). The availability of public transportation services has also affected the potentiality for densification interventions aimed at residential and urban service demand satisfaction. Indeed, implementing compact development policies by ensuring accessibility to railway stations and public transportation stops within feasible walking distance reduces the need for automobile use and the overall levels of traffic congestion and improves livability for people (Goodwill & Hendricksm, 2002). The results confirm that low centrality and low accessibility levels are linked to low and very low densification potential according to a sustainable perspective of these interventions, which was also confirmed by Eggimann et al. (2021). The areas not well served by these services demonstrate lower potentiality levels. At the same time, medium situations are mainly located along the fringe between the areas well served and those not served in every municipality, although they differ substantially. The municipalities demonstrated a high level of potential densification only in the cases of urban services development, namely considering the negative effect of urban complexity indicators. It is justified by the results obtained for the satisfaction of residential demand because results revealed the lack of urban services and infrastructure within the analyzed study area. The results in terms of the high potentiality obtained by the application of the proposed model to the case study emphasize and demonstrate that for these contexts, their integration, not only physical but especially immaterial, oriented to urban services and infrastructure integration, is an essential means for reinforcing their strengths and opportunities.

Even if the primary goal of this research is to present an operational method for estimating the potentiality of urban areas to accommodate densification interventions, this analysis presents some limitations and research opportunities that can be further explored in the following studies to enhance and broaden the scope of the current analysis.

The assessment of urban areas' densification and/or greening potential needs data availability concerning buildings, urban services, infrastructure, and land use land cover data. For example, knowing the refurbishment state of buildings and plots or the specific characteristics of urban green areas consents to deepen knowledge of the densification and/or greening potential of already urbanized areas.

Another limitation of this study, which can be further analyzed in subsequent studies, is the assignment of weights to criteria. First, a sensitivity analysis is needed to analyze the stability of the proposed method, which can be further analyzed. Second, it could be, for example, applicable to consider perceptions as well as decision-maker considerations. The engagement of various stakeholders, including residents, businesses, and government agencies, to gather input and feedback on proposed densification plans and compare their judgment or the results from their judgment. Community engagement can be facilitated by creating web-based interactive mapping and visualization apps. This could be useful to combine the densification suitability analysis results with stakeholders' input to make informed decisions about where and how to densify urban areas. Moreover, through this, planners and decision-makers can continuously monitor the effects of densification and assess whether the anticipated benefits and challenges are being realized. Planners can adjust plans and policies based on such analysis and the observed outcomes.

Furthermore, the proposed method can be integrated with scenario-based modeling to simulate densification potential. Different densification scenarios can be defined by varying factors like building height, density, and land use mix, and the impact of each scenario on the criteria and the overall urban densification potential can be assessed.

Moreover, while the results presented in this study can already provide some valuable insights to planners of urban areas like the case presented within this study, further research should be focused on testing the proposed methodology in different cities and, therefore, assessing its effectiveness in quantifying and assessing densification potential of urban areas.

Although these aspects, considering different indicators related to specific thematic areas, one of the main objectives of the proposed method is to overcome the deviation in urban densification that has resulted from single-issue research approaches (Breheny, 1992; Williams et al., 1996) and assess the suitability and the potentiality of urbanized areas considering different aspects and themes also from a sustainability perspective. Therefore, the proposed methodology represents a theoretical foundation for the implementation of densification and greening interventions at the urban level and a systematic approach for urban planners and decision-makers to evaluate the possibility of creating space for an increasing population, given limited land resources at the municipal level. Moreover, it aims to be a performance-based approach to densification and greening intervention potential assessment in urban areas, especially for the already urbanized.

3. The WebGIS prototype for visualizing, managing, and mapping the obtained results for sustainable urban planning

In this Section, the author presents the results related to the third and last step of the methodological approach proposed in this study to address the relationship between urban growth and greening development. It coincides with the development and implementation of a WebGIS prototype for visualizing, managing, and mapping the methods and results of the first and second steps of the method. Therefore, the usability and validity of the proposed WebGIS platform prototype are assessed to map and assess the results obtained previously.

As described in Chapter 3, publishing layers on the WebGIS prototype depends on activating the WFS capabilities in the GIS server, which provides layer selection and configuration options for publishing. Lizmap is characterized by a predefined style and map management functionalities, explained in Chapter 3.

3.1. Testing the usability of the proposed WebGIS prototype for assessing the co-relation between urban growth, greening development, and population dynamics

In this case, to test the validity and usability of the Web-GIS platform prototype, this latter is employed to assess and map the relationship between urban growth, greening development, and population dynamics.

First, all the layers are imported into the WebGIS platform through PostgreSQL (Figure 4.23).

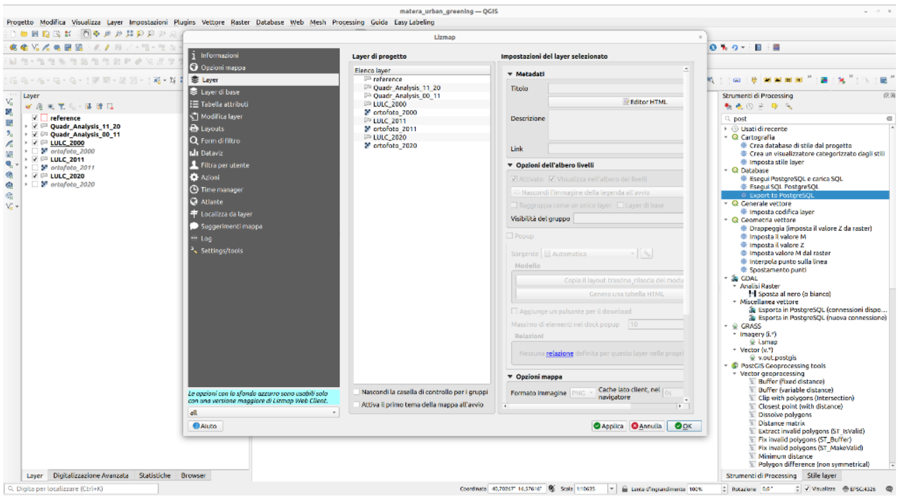


Figure 4.23. Layers upload through PostgreSQL.

It was also possible to define which layers should be updated, modified, and eliminated (Figure 4.24). In this case, the author loaded the geospatial data of the built-up area and vegetation cover imported and vectorized in GIS after the classification and segmentation tasks performed through the AI-GIS informatics platform, the layer with population retrieved from ISTAT and the layers containing the quadrant zones employed to perform the quadrant analysis.

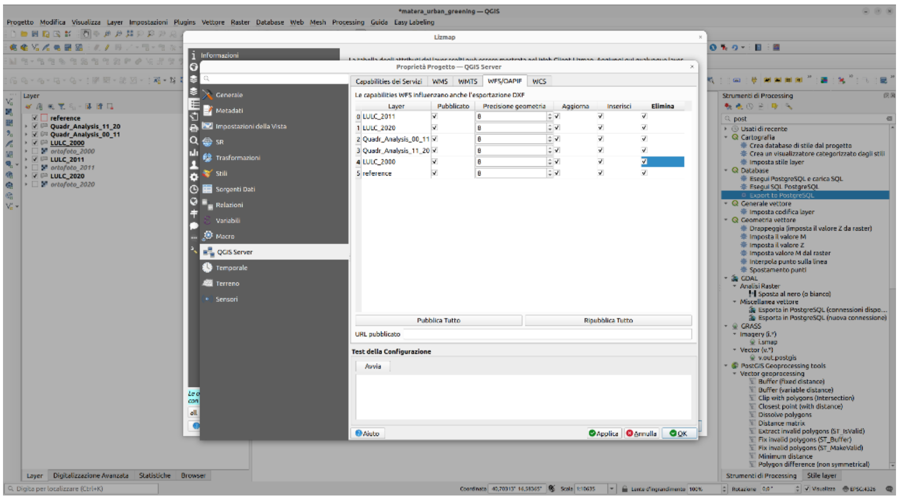


Figure 4.24. Setup of layers for upload into the WebGIS platform.

Authorized and non-authorized users can also obtain statistical information about the geometries loaded into the WebGIS prototype. For example, considering the layers on built-up area and vegetation cover, non-authorized and authorized users can retrieve statistical information by land use land cover data by applying selection and intersection functions. In this way, as shown in Figure 4.25 and Figure 4.26, statistical information about urban and greening coverage can be obtained.

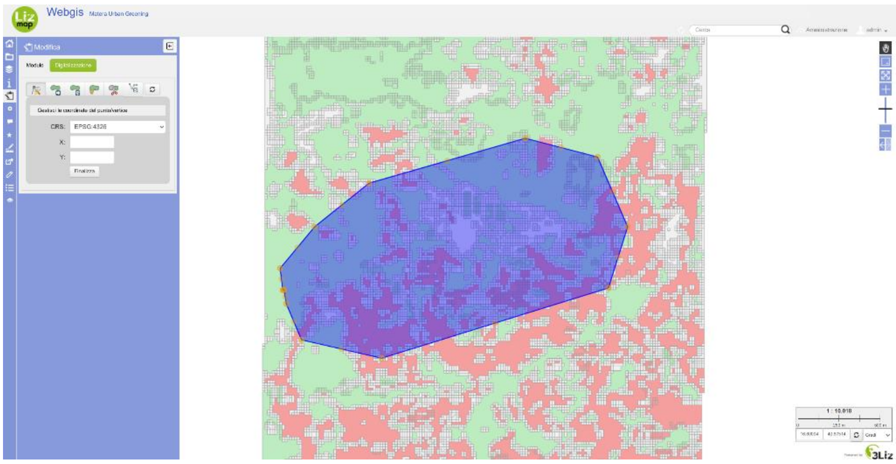


Figure 4.25. Selection functions example on urban and greening layer.

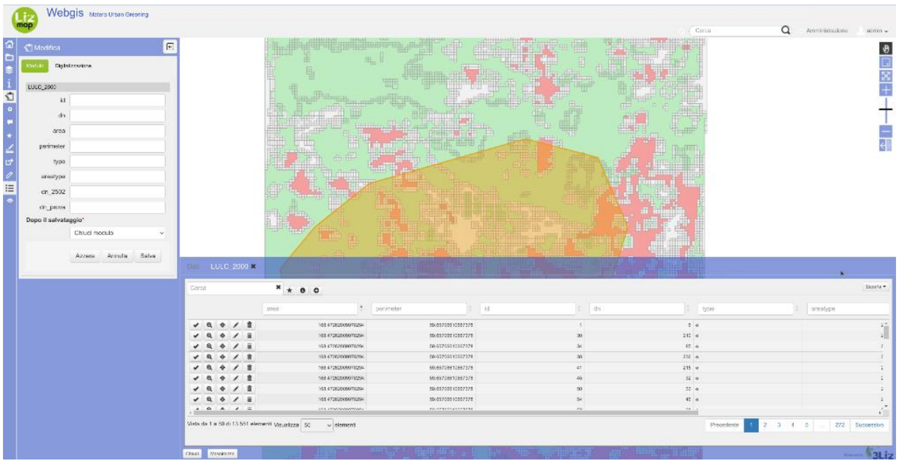


Figure 4.26. Table of attributes from selection function for urban and greening layer.

By using the functions currently available in the Web-GIS prototype, the quadrant analysis can be performed, and the results can be questioned (Figure 4.27).

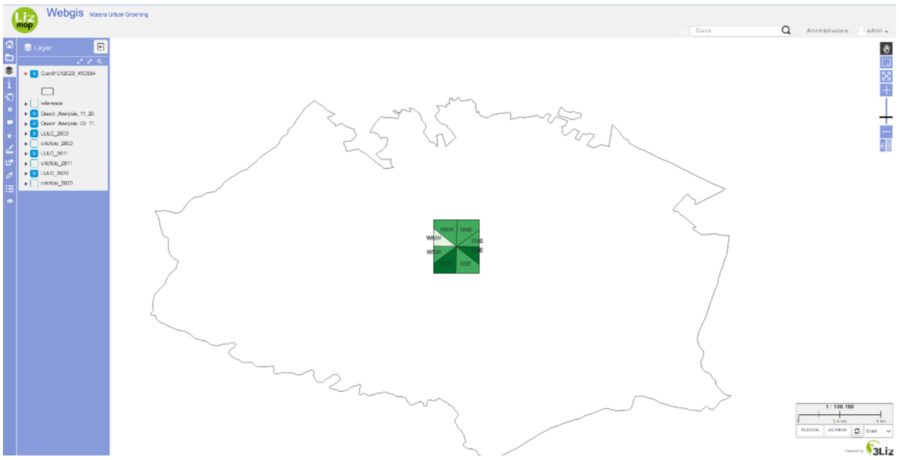


Figure 4.27. Co-relation of urban, greening and population dynamics results overview on WebGIS platform.

Users can query the layers obtaining information regarding the attribute tables. Indeed, in this case, the values of USDMI and GSDMI for each quadrant can be assessed by users by selecting the preferred geometry and questioning the attribute table (Figure 4.28).

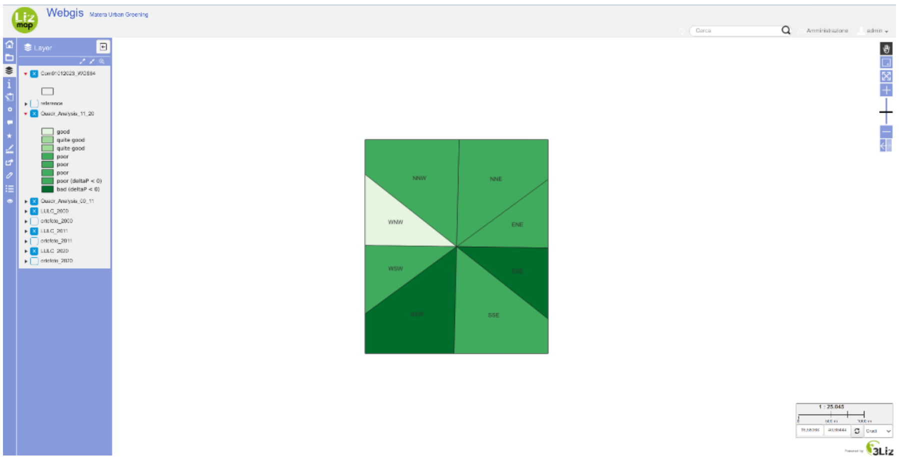


Figure 4.28. Detailed zoom on co-relation of urban, greening and population dynamics results overview on WebGIS platform.

Authorized users can also update the results about urban and greening changes with population dynamics results by modifying the input data. For example, if authorized users performed more analysis on the urban and greening data as well as on population data, these layers could be modified and updated by authorized users, in particular.

For example, Figure 4.29 presents how it is possible to modify and update information for urban and greening cover within the WebGIS prototype platform. After modifying or adding geometries, the quadrant analysis can be reworked and new results in terms of USDMI and GSDMI can be obtained.

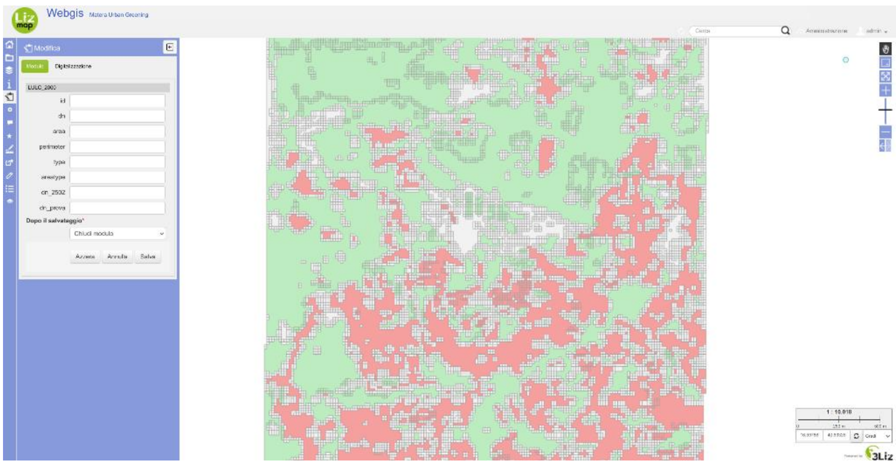


Figure 4.29. Creation of a new geometry in the urban and greening layer.

3.2. Testing the usability of the proposed WebGIS prototype for assessing the densification and/or greening potential of urban areas

As described in the previous Section, data for assessing the densification and/or greening potential of urban areas is uploaded into the WebGIS prototype platform (Figure 4.30).

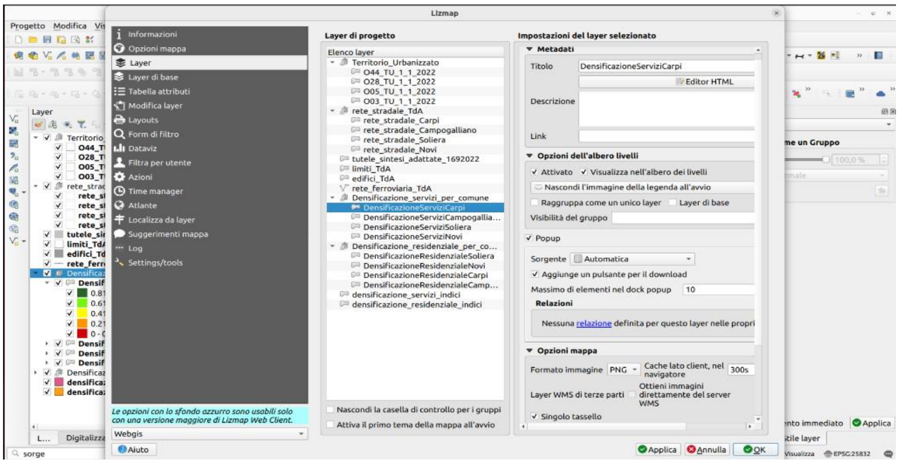


Figure 4.30. Upload of layers on the WebGIS prototype platform for assessing the densification and/or greening potential of urban areas.

The WebGIS prototype platform consents to visualize and query the results. For example, Figure 4.31 shows the results for densification potential. Users can query each grid cell to have information about the densification potential.

Figure 4.31. Overview of the obtained results into the WebGIS platform.

The grid cells can be selected and a pop-up with the information about the id number, the value of each thematic index and the score for the densification will appear (Figure 4.32).

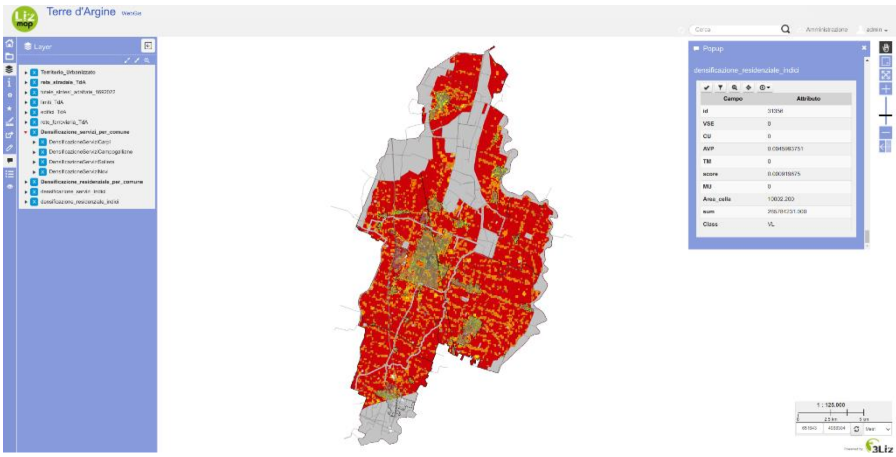


Figure 4.32. Selection and statistics analysis functions.

Furthermore, users can select a cluster of cells and obtain the information about the grid cell identification number, the value of the various thematic indexes and the densification potential score. Using this functionality, for instance, it is possible to select all the cells characterized by a specific level of potential (very low, low, medium, high and very high) and analyze the attributes related to them. Figure 4.33 shows an example of this functionality.

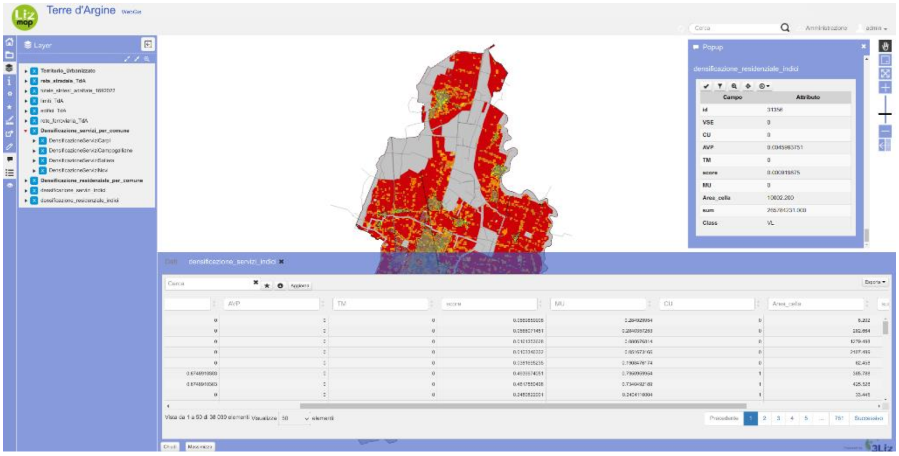


Figure 4.33. Selection and attribute table analysis.

Moreover, through the selection operations and toolbox, a popup containing the information on scores appears. From that, it is possible to identify the total values, the maximum, the minimum and the average values of densification potential scores (Figure 4.34).

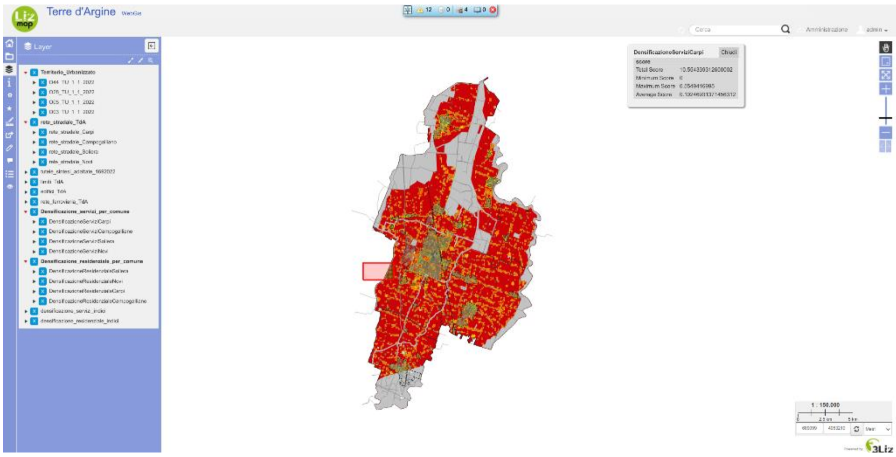


Figure 4.34. Selection operations and toolbox for statistical analysis functions.

Moreover, authorized users have also the possibility to create new layers or update the information of the various existing layers and rework the analysis for obtaining new results. This functionality is interesting in the case of a scenario-modeling approach for assessing the potential for densification interventions of urban areas.

3.3. *Discussion of the results*

The two applications show that the proposed Web-GIS prototype represents a valid decision support tool for urban planning decision-making. The proposed case study applications reflect the usefulness of these web-based decision support systems (DSS).

According to the bottom-up approach, the authorized users can operate within the proposed Web-GIS platform by creating new layers and defining new attributes and geometry, which will be loaded online after the local planning authorities make a final decision. Stakeholders interested in urban planning can query the different urban planning layers and obtain information about specific layers and their attributes. It promotes more shared and informed urban decision-making processes, as demonstrated by the proposed Web-GIS application.

Concerning the two applications tested within the proposed WebGIS platform prototype, urban planners and policymakers can benefit from the Web-GIS platform for developing and implementing planning policies for a more sustainable use of land and soil.

The proposed application shows how top-down and bottom-up Web-GIS platforms can share and assess information on urban planning processes with stakeholders. Through this application, the author demonstrates that web-based decision support systems containing urban planning-related data, such as the proposed Web-GIS platform, help to share information about urban planning and management processes with stakeholders and the interested public. Moreover, thanks to its modular organization, it is an effective tool for storing data and has an updated basis of urban planning information. It represents an opportunity to employ it in various urban planning applications and operations. Moreover, its replicability and scalability allow for its use in other urban contexts.

Through the bottom-up paradigm, local stakeholders, in general, can actively identify the impacts of land use policies and propose solutions. The platform can facilitate this by making complex data accessible and understandable to non-experts. Involving local insights for the tested application can enhance the effectiveness of urban planning solutions aimed at more sustainable land use and promoting sustainability and liveability.

The proposed platform is particularly suitable for integrating data from local (bottom-up) and governmental (top-down) sources through the top-down paradigm, enhancing the overall understanding of planning strategies.

Moreover, the top-down paradigm allows for tailoring urban planning solutions to each ambit's specific needs, informed by local input and broader strategic objectives. Making data and planning processes transparent, the platform builds trust and ensures accountability in decision-making.

In summary, the innovation in using the proposed platform in urban planning bridges the gap between local knowledge and expertise (bottom-up) and strategic, overarching urban planning goals (top-down). This integrated approach enhances the effectiveness and precision of urban planning, fosters community engagement, and ensures a more resilient and adaptive urban development model.

The proposed platform prototype represents a valid DSS and a proper tool for detailed urban and territorial planning, management, control, environmental monitoring, and emergency scenarios management. Its design paradigm adapts both top-down and bottom-up participatory planning approaches.

The Web-GIS is adapted for urban and territorial planning, supporting all the interested stakeholders in the choice step of the decision-making process to select between available strategic choices. Such a system guarantees analytic and deliberative components that can be included simultaneously in the participatory decision-making process, making it possible for stakeholders at various levels to contribute, access, and exchange information related to planning policies and strategies. The analytical functions allow all participants and local authorities to use a spatial decision analysis tool.

The proposed Web-GIS platform prototype applications demonstrate how it is essential to make environmental information more widely accessible through the World Wide Web. The applied methodology is configured to support three planning functions: pre-application advice, development control, and strategic planning. According to their permissions, all urban and territorial planning stakeholders can interact by uploading and querying information through the platform.

Future developments of the proposed institutional Web-GIS platform will also be oriented to define specific interfaces to allow authorized technicians and local administrators to upload technical layers. The bottom-up side of the proposed Web-GIS platform will be strengthened by implementing more functions to promote the stakeholders' engagement in urban planning decision-making. Moreover, future developments of the proposed Web-GIS platform prototype will allow it to be interfered with remotely and in real-time with innovative telemetric and photogrammetric survey instruments, such as global positioning system (GPS) receivers and mobile devices. Such a feature would allow for the automation of several processes that are currently performed manually by users.

Conclusions

1. Summarization of the main research findings

The development of this research work starts from the assumption that managing urban growth and greening interventions in cities to guarantee sustainability and liveability to urban dwellers is an urgent need for sustainable urban development. Frameworks and tools to manage urban growth and greening interventions are lacking within the scientific literature. Moreover, employing innovative technologies, including artificial intelligence and advanced geospatial techniques, also available via the web, represents valuable systems to reach this aim.

Starting from these assumptions, the overall aims of this research work are to clarify the complex relationship between urban growth and greening development, explore the role and the potentialities of information and communication technologies for supporting sustainable urban development, define an innovative methodological framework to manage urban growth and greening goals towards sustainable urban development, test the proposed methodological framework on case studies and show the potentialities of making the defined framework and the obtained results shared via an information technology platform for geospatial analysis.

First, the new and consolidated practices to assess the complex relationship between urban growth and greening goals are analyzed to reach these multiple aims within Chapter 1. Specifically, this analysis is performed to give the theoretical background on urban growth and greening goals concepts as well as on the complex relationship between these two urban planning paradigms and to identify the tools and frameworks available within the scientific literature to assess and manage the relationship between urban growth and greening goals for sustainable and liveable urban development. This analysis consented to delineating the main concepts and definitions related to urban growth and greening goals and identifying that managing urban growth processes, compact or dispersed, while ensuring sustainable, liveable, and resilient conditions through environmental protection actions is difficult. This becomes more difficult because of the lack of suitable decision support systems to manage and assess this complex relationship and support sustainable urban planning.

Building on these assumptions, the spreading of innovative methodologies and tools in the era of information technology to support sustainable urban planning is analyzed in Chapter 2. Specifically, the author examined the role of integrating artificial intelligence models with geographic information systems and WebGIS informatics platforms in supporting sustainable urban planning and development. The author found that artificial intelligence models have a promising potential to significantly impact urban planning by providing innovative solutions, optimizing processes, and enhancing decision-making. Artificial intelligence models integrated with geographic information systems, which refer to Geospatial Artificial Intelligence (GeoAI), consent to analyze, interpret, and derive insights for various applications in the sustainable urban planning field. It is demonstrated through the systematic literature review performed in Chapter 2 to identify the most recent GeoAI applications in the context of sustainable urban planning. The systematic literature review revealed that the topic is very recent in urban planning research and practice and needs further exploration. However, five key research areas of GeoAI applications for sustainable urban planning are identified, namely AI-GIS integration for disaster management planning, AI-GIS integration for land use land cover and urban features detection, AI-GIS integration for land use land cover change prediction, AI-GIS integration for environmental quality assessment, and AI-GIS integration for spatial planning tasks. The in-depth analysis of these applications demonstrated that GeoAI offers powerful tools to enhance decision-making, optimize resource allocation, and address complex spatial challenges. Subsequently, a specific focus on WebGIS systems as tools for accessing, analyzing, and visualizing spatial data over the web is done. After defining the main characteristics and operational workflow of WebGIS, an analysis of Italian WebGIS platforms is carried out. This analysis provided valuable insights into the strengths and weaknesses of such systems. This analysis revealed that WebGIS at the national level lacks functionalities for supporting bottom-up and top-down urban planning approaches.

Based on these research findings, the author analyzed the possibility of assessing and managing the complex relationship between urban growth and greening policies through innovative models, tools, and geospatial analysis by proposing an innovative methodological framework to support sustainable urban planning and use of land in Chapter 3.

The proposed methodological workflow integrates artificial intelligence models and geospatial techniques, also shared via the web, for assessing and managing the complex relationship between urban growth and greening goals. Indeed, the proposed methodological framework is based on three key steps.

The first consists of analyzing, evaluating, quantifying, and monitoring the co-relationship between urban growth, greening development, and population changes toward urban sustainability levels over time. In this phase of the methodological approach, the author aimed to identify the co-relation between urban growth, greening development, and population dynamics over time by combining innovative remote sensing methodologies, artificial intelligence technologies, and geospatial techniques. First, the author detected urban and greening features with a high level of detail through an AI-GIS informatics platform programmed and developed in-house to remote sensing data. Then, the effects of the interaction between urban and greening changes and population dynamics on urban sustainability levels are determined by performing a quadrant analysis and using quantitative indicators. The indicators that assess the co-relation between urban growth, greening changes, and population dynamics are based on the mismatch between the supply of built-up areas and UGAs, represented by their provision in the study area, and their demand, linked to population needs and current law requirements.

Then, a multi-criteria framework is defined to assess the potentiality of urban areas to undergo dense urban growth processes or greening interventions. This method aims to quantify and spatially identify urban areas' densification and/or greening potential. The proposed method is based on different criteria identified according to specific thematic areas in a literature review on densification and greening development.

Finally, the last part of the proposed methodological framework aimed at developing a WebGIS platform prototype for visualizing, managing, and mapping the results obtained by the previous steps of the methodological framework.

Chapter 4 tests the proposed methodological approach through specific case study applications.

First, the method for assessing the correlation between urban growth processes, greening, and population dynamics toward urban sustainability is tested by considering Matera as a case study. Matera was selected as a suitable case study for this application because of its notable cultural interest at the national and international levels. The results of this application demonstrated that during the observation period, which coincided with 2000-2020, the case study showed a poor co-relation between urban growth, greening development, and population dynamics. In terms of urban and greening changes, the obtained results from the AI-GIS informatics platform indicate that significant urban and greening cover changes happened from 2000 to 2020.

Over 20 years, the study area experienced an 8.28% increase in built-up area density and a 5.13% decrease in vegetation cover density. These changes were primarily driven by establishing new residential areas and urban services in the northern part of the area and completing industrial/productive zones in the west. The development of residential buildings and associated urban services followed planned policies between the urban core and peri-urban areas, while industrial areas aligned with existing enterprises. The overall pattern indicates decentralized planning, leading to a sprawl in urban development at the periphery. Unfortunately, the loss of vegetation cover outside the urban core was not offset by creating new green spaces. The study reveals that while planning policies aimed at integrating core and peripheral areas enhance efficiency through urban and territorial services, they also deplete vegetation cover, negatively impacting ecosystem services. Increased urban development beyond the city center correlates with higher consumption of natural resources and vegetation. This trend puts pressure on vegetation cover, adversely affecting the livability and sustainability of urban and territorial areas. Furthermore, the analysis indicates a relatively good sustainable coexistence period in certain quadrants between 2000 and 2011, but overall, sustainable coexistence was poor or bad. Between 2011 and 2020, the situation worsened, with only the WNW quadrant showing good sustainable coexistence. The study employs a valuable methodology, utilizing deep learning algorithms on remote sensing data to assess the interaction between urban growth, urban green areas (UGAs), and population changes. Decision-makers can use this information to shape urban land use policies, promote compact and mixed-use development, implement green infrastructure, protect existing UGAs, employ intelligent growth principles, and monitor the effectiveness of planning decisions at a large scale.

Then, the framework for assessing and quantifying the potential of urban areas for densification and/or greening interventions is applied to the union of municipalities of Terre d'Argine (Emilia Romagna, Italy). Terre d'Argine comprises four municipalities, namely Campogalliano, Carpi, Novi di Modena and Soliera. This case study was selected because of its similarities with other Italian contexts and Emilia Romagna's interest in defining urban planning performance-based frameworks to limit and contrast soil consumption. The proposed methodology is an indicator-based approach to assess the potential of urban areas to accommodate urban densification interventions or, on the other side, greening interventions. It reflects the key urban aspects for densification and/or greening interventions, such as socioeconomic vulnerability, urban morphology, urban complexity, urban green areas, and transportation and mobility. It aims to provide an innovative methodological approach for quantifying and identifying densification and greening interventions' spatial patterns distribution.

Analyzing Terre d'Argine's potential reveals a generally deficient level of densification potential for residential demand satisfaction, with the urbanized area showing low to very low potential and some areas having medium potential. Novi di Modena has the highest densification potential in the urbanized area, particularly near the city center and primary services. Carpi exhibits low densification potential for new residential areas, with medium potential near key services and infrastructures. Soliera's urbanized areas also have low densification potential, mainly around provided services. Campogalliano's urbanized areas mostly feature low densification potential, with some areas showing medium potential.

Concerning the potential for densifying urban services, Novi di Modena generally exhibits a medium densification potential, with some areas having a high potential, particularly near the primary urban center. The highest suitability is observed in lots with blocks or isolated buildings. In Carpi, high densification potential for urban services is mainly found near significant infrastructures and the city center, gradually decreasing to medium potential farther from the center and reaching low and very low potential in primarily residential areas. Campogalliano demonstrates the highest percentage of high densification potential for new urban services, particularly within the historical part of the city, emphasizing the strategic importance of urban services development in this context. Soliera shares a similar situation, characterized by a lack of urban services and lower values of built-up area density.

The findings indicate that the potential for densification interventions is generally higher in the consolidated parts of urban areas, where accessibility to services, infrastructure, and job opportunities is greater. Areas lacking these services exhibit lower potential, while moderate situations are predominantly situated on the fringes between well-served and underserved areas in each municipality, although variations exist. The municipalities showed a notable potential for densification only in cases involving the development of urban services, particularly when considering the adverse impact of urban complexity indicators. This is justified by the results related to residential demand satisfaction, revealing a deficiency in urban services and infrastructure within the study area. The results underscore the significance of integrating these contexts, both physically and immaterially, with a focus on urban services and infrastructure integration as a vital strategy to strengthen their strengths and opportunities.

Finally, an innovative WebGIS platform prototype is developed to integrate the defined frameworks and visualize, manage, and map the obtained results by providing an innovative tool to support sustainable urban planning. The WebGIS platform prototype's usability is tested first to assess the relationship between urban growth, greening development, and population dynamics and then to assess the densification and/or greening potential of urban areas. Through these applications, the author demonstrated that web-based decision support systems containing urban planning-related data, such as the proposed Web-GIS platform, help to share information about urban planning and management processes with stakeholders and the interested public. Moreover, thanks to its modular organization, it is an effective tool for storing data and has an updated basis of urban planning information. It represents an opportunity to employ it in various urban planning applications and operations. Moreover, its replicability and scalability allow for its use in other urban contexts.

The research work developed within this study made it possible to answer the research questions in the Introduction section. The first research question was, “How can innovative artificial intelligence techniques and geospatial analysis contribute to a better understanding of urban growth patterns and urban greening planning policies implementation?”. To respond to this research question, the author first identified the state of the art on the combined use of artificial intelligence and geographic information systems for sustainable urban planning through a systematic literature review (Chapter 2). Then, based on the obtained results, recognizing the utility of the combined use of these technologies for land use land cover and urban feature detection, the author proposed an innovative informatics platform based on AI-GIS integration for urban and greening features at a very high-resolution classification and segmentation.

In the direction of answering the second research question of this research work, namely “How can these methods support urban planners and decision-makers in managing the complex relationship between these two policies and, therefore, define sustainable urban growth and greening policies?”, the author investigated the usability of these methods and tools for supporting sustainable urban planning, investigating the relationship between urban growth and greening goals, by integrating the AI-GIS informatics platform with spatial quadrant analysis and defining data-driven approach to investigate the relationship between urban growth, greening goals and population demand and to assess the potential of urban areas to be subjected to dense urban growth processes and/or greening interventions, respectively.

Finally, based on the third research question of this work, "How can information about urban growth and greening policies be shared with different stakeholders and make them accessible and consultable?", the author proposed an innovative WebGIS platform prototype to make the methods and results available and consultable with stakeholders and, therefore, promoting a more shared and informed decision-making processes, which in the cases analyzed in this work assumes great significance.

2. Future research perspectives

Going forward to the main objectives of this research work, considering the many novelties introduced within the urban planning research and practice regarding the assessment and management of the complex relationship between urban growth and greening goals, further work would advance the understanding of these policies in the context of urban planning towards sustainability.

Future research developments are recommended for each of the phases developed and addressed within this work, both for better defining each phase and ensuring their integration.

Regarding the co-relation analysis between urban growth, greening goals, and population dynamics, this study looked exclusively at a small area within the municipality of Matera, excluding larger areas characterized by even more significant urban growth, greening changes, and population dynamics and processes. Therefore, the first direction to which future research should point is the analysis of such dynamics in large areas, such as cities and or metropolitan areas. For such a direction of study, a substantial need for further research is needed to analyze interactions along the interface between rural and urban areas. As this framework is only applied to the case study of Matera, much research can also be carried out to identify specific threshold values, as growth patterns worldwide differ severely in both their magnitude and shape. The author, therefore, recommends adding thresholds for future studies based on the growth or shrinkage patterns adapted to the given setting and data. Furthermore, as the co-relation quantification and analysis between urban growth, greening goals, and population dynamics is based on urban and greening classification and segmentation through an AI-GIS informatics platform, the proposed research work may be improved by testing other deep learning architectures that are more accurate to reach better performance in building and vegetation cover prediction. Qualitative information on the type and quality of urban and greening changes is also missing. Possibilities that should be considered to overcome this limitation would be adding qualitative information about urban and greening cover from remote sensing or including urban and vegetation configuration as determinants of green growth performance as essential planning considerations. Moreover, the proposed analysis based on integrating deep learning and GIS technologies may be deepened by introducing socioeconomic and environmental indicators to analyze the drivers and the impacts of urban and greening development over time and space. Ultimately, conducting more comprehensive fieldwork would contribute valuable insights. Integrating the unparalleled quantitative capabilities of Earth observation with qualitative methodologies holds significant promise for advancing urban research. This approach has the potential to yield robust, openly accessible, and easily applicable results, thereby enhancing the planning of improved cities through collaborative and multi-stakeholder efforts.

To assess urban areas' densification and/or greening potential, additional research can be pursued in subsequent studies to improve and expand the current analysis. The factors and criteria for densification and/or greening potential evaluation can be integrated with information about buildings, urban services, infrastructure, and land use/land cover to better comprehend the potential for densification and/or greening in already urbanized areas. Another element that can be further examined in subsequent research is the allocation of weights to criteria. First, a sensitivity analysis is essential to assess the stability of the proposed method and warrants additional scrutiny. Second, it may prove beneficial, for example, to incorporate the perceptions and considerations of decision-makers. Involving diverse stakeholders such as residents, businesses, and government agencies for input and feedback on proposed densification plans and comparing their judgments or results could be valuable. Community engagement could be facilitated by developing web-based applications for interactive mapping and visualization. This approach would help combine the densification suitability analysis outcomes with stakeholders' input, facilitating informed decisions regarding where and how to densify urban areas. Additionally, this interactive process enables planners and decision-makers to continuously monitor the impacts of densification, evaluating whether the anticipated benefits and challenges are being realized. Planners can adapt and refine plans and policies based on such analyses and observed outcomes.

Moreover, the suggested approach can be incorporated into scenario-based modeling to simulate the potential for densification and greening. Various densification and/or greening scenarios can be formulated by adjusting factors, such as building height, density, land use mix, and urban green areas, to evaluate the effects of each scenario on the criteria and the overall potential for urban densification and/or greening.

Furthermore, although the findings presented in this study offer valuable insights for urban planners, as illustrated in the case study, it is crucial to prioritize further research that tests the proposed methodology in other kinds of cities. This will enable the assessment of its effectiveness in quantifying and evaluating the densification potential of urban areas. Moving from the territorial scale considered within this study (the union of municipalities of Terre d'Argine), it would be interesting to apply the proposed methodology in big cities or metropolitan areas to understand if and to what extent it can be employed for such kinds of contexts. Subsequent investigations should be conducted in this domain to evaluate the continued relevance of the suggested approach in big cities. Indeed, the applicability of the approach in big cities should be explored. The findings may indicate whether further customization is necessary to address the diverse needs of these specific contexts.

Looking at the defined WebGIS platform prototype, the forthcoming advancements of the envisioned institutional Web-GIS platform will also focus on establishing specific interfaces. These interfaces will enable authorized technicians and local administrators to upload technical layers effortlessly. To enhance the grassroots aspect of the proposed Web-GIS platform, additional functionalities will be integrated to foster stakeholder engagement in the urban planning decision-making process. Furthermore, future iterations of the Web-GIS platform prototype will enable remote and real-time interaction with cutting-edge telemetric and photogrammetric survey instruments, including global positioning system (GPS) receivers and mobile devices. This capability is poised to automate various processes users carry out manually.

To this latter possibility, the proposed innovative and integrated framework for assessing and managing the complexity of urban growth and greening interactions aims to point out becoming an opportunity for managing urban growth processes while promoting and protecting natural ecosystems through innovative urban planning approaches and tools to make human and urban development truly sustainable.

References

Abdullah, A. Y. M., Law, J., Butt, Z. A., & Perlman, C. M. (2021). Understanding the differential impact of vegetation measures on modeling the association between vegetation and psychotic and non-psychotic disorders in Toronto, Canada. *International Journal of Environmental Research and Public Health*, *18*(9), 4713. https://doi.org/10.3390/ijerph18094713

Abdullahi, S., Pradhan, B., & Jebur, M. N. (2015). GIS-based sustainable city compactness assessment using integration of MCDM, Bayes theorem and RADAR technology. *Geocarto International*, *30*(4), 365-387. https://doi.org/10.1080/10106049.2014.911967

Abid, S. K., Sulaiman, N., Chan, S. W., Nazir, U., Abid, M., Han, H., Ariza-Montes, A., & Vega-Muñoz, A. (2021). Toward an Integrated Disaster Management Approach: How Artificial Intelligence Can Boost Disaster Management. *Sustainability*, *13*(22), 12560. https://doi.org/10.3390/su132212560

Ahmed, B., Rahman, M. S., Islam, R., Sammonds, P., Zhou, C., Uddin, K., & Al-Hussaini, T. M. (2018). Developing a dynamic Web-GIS based landslide early warning system for the Chittagong Metropolitan Area, Bangladesh. *ISPRS International Journal of Geo-Information*, *7*(12), 485. https://doi.org/10.3390/ijgi7120485

Akylbekov, O., Al Said, N., Martínez-García, R., & Gura, D. (2022). ML models and neural networks for analyzing 3D data spatial planning tasks: Example of Khasansky urban district of the Russian Federation. *Advances in Engineering Software*, *173*, 103251. https://doi.org/10.1016/j.advengsoft.2022.103251

Al-Darwish, Y., Ayad, H., Taha, D., & Saadallah, D. (2018). Predicting the future urban growth and it's impacts on the surrounding environment using urban simulation models: Case study of Ibb city–Yemen. *Alexandria Engineering Journal*, *57*(4), 2887-2895. https://doi.org/10.1016/j.aej.2017.10.009

Alexander, D. E. (2002). Principles of emergency planning and management. Harpenden, U.K.: Terra.

Alexander, D. E. (2005). Towards the development of a standard in emergency planning. *Disaster Prevention and Management*, 14(2), 158–175. https://doi.org/10.1108/09653560510595164

Alexander, D. E. (2013). Emergency and disaster planning. In A. López-Carresi, M. Fordham, B. Wisner, I. Kelman, & J. C. Gallard (Eds.), Disaster management: International lessons in risk reduction, response and recovery (pp. 125–141). London: Routledge.

Alicandro, M., Zollini, S., Oxoli, D., Pascucci, N., Dominici, D., & Brescia, D. (2022). Design and Implementation of AN Open-Source Web-Gis to Manage the Public Works of Abruzzo Region: AN Example Towards the Digitalization of the Management Process of Public Administrations. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *48*, 21-26. https://doi.org/10.5194/isprs-archives-XLVIII-4-W1-2022-21-2022

Allam, Z., & Dhunny, Z. A. (2019). On big data, artificial intelligence and smart cities. *Cities*, *89*, 80-91. https://doi.org/10.1016/j.cities.2019.01.032

Almenar, J. B., Elliot, T., Rugani, B., Philippe, B., Gutierrez, T. N., Sonnemann, G., & Geneletti, D. (2021). Nexus between nature-based solutions, ecosystem services and urban challenges. *Land Use Policy*, *100*, 104898. https://doi.org/10.1016/j.landusepol.2020.104898

Amiri, S. S., Mueller, M., & Hoque, S. (2023). Investigating the application of a commercial and residential energy consumption prediction model for urban Planning scenarios with Machine Learning and Shapley Additive explanation methods. *Energy and Buildings*, *287*, 112965. https://doi.org/10.1016/j.enbuild.2023.112965

Andersson, E., Barthel, S., Borgström, S., Colding, J., Elmqvist, T., Folke, C., & Gren, Å. (2014). Reconnecting cities to the biosphere: stewardship of green infrastructure and urban ecosystem services. *Ambio*, *43*, 445-453. https://doi.org/10.1007/s13280-014-0506-y

Aram, F., García, E. H., Solgi, E., & Mansournia, S. (2019). Urban green space cooling effect in cities. *Heliyon*, *5*(4). https://doi.org/10.1016/j.heliyon.2019.e01339

Aria, M., & Cuccurullo, C. (2017). bibliometrix: An R-tool for comprehensive science mapping analysis. *Journal of Informetrics*, *11*(4), 959-975. https://doi.org/10.1016/j.joi.2017.08.007

Ariluoma, M., Ottelin, J., Hautamäki, R., Tuhkanen, E. M., & Mänttäri, M. (2021). Carbon sequestration and storage potential of urban green in residential yards: A case study from Helsinki. *Urban Forestry & Urban Greening*, *57*, 126939. https://doi.org/10.1016/j.ufug.2020.126939

Arsanjani, J. J., Helbich, M., & de Noronha Vaz, E. (2013). Spatiotemporal simulation of urban growth patterns using agent-based modeling: The case of Tehran. *Cities*, *32*, 33-42. https://doi.org/10.1016/j.cities.2013.01.005

Artmann, M. (2013). Spatial dimensions of soil sealing management in growing and shrinking cities—A systemic multi-scale analysis in Germany. *Erdkunde*, 249-264. https://www.jstor.org/stable/23597155

Artmann, M., Inostroza, L., & Fan, P. (2019). Urban sprawl, compact urban development and green cities. How much do we know, how much do we agree? *Ecological Indicators*, *96*, 3-9. https://doi.org/10.1016/j.ecolind.2018.10.059

Artmann, M., Kohler, M., Meinel, G., Gan, J., & Ioja, I. C. (2019). How smart growth and green infrastructure can mutually support each other—A conceptual framework for compact and green cities. *Ecological Indicators*, *96*, 10-22. https://doi.org/10.1016/j.ecolind.2017.07.001

Ayo-Odifiri, O. S., Fasakin, J. O., & Henshaw, F. O. (2017). Road connectivity approach to eased traffic congestion on market roads in Benin metropolis, Nigeria. *American Journal of Engineering Research*, *6*(6), 41-48. https://api.semanticscholar.org/CorpusID:212607887

Bai, H., Li, Z., Guo, H., Chen, H., & Luo, P. (2022). Urban green space planning based on remote sensing and geographic information systems. *Remote Sensing*, 14(17), 4213. https://doi.org/10.3390/rs14174213

Balikçi, S., Giezen, M., & Arundel, R. (2022). The paradox of planning the compact and green city: Analyzing land-use change in Amsterdam and Brussels. *Journal of Environmental Planning and Management*, *65*(13), 2387-2411. https://doi.org/10.1080/09640568.2021.1971069

Barlow, H. B. (1989). Unsupervised learning. *Neural Computation*, *1*(3), 295-311. https://doi.org/10.1162/neco.1989.1.3.295

Bendib, A., Hadda, D., & Mahdi, K. (2016). Application of Webgis in the development of interactive interface for urban management in Batna City. *Journal of Engineering and Technology Research*, *8*(2), 13-20. https://doi.org/10.5897/JETR2015.0579

Berke, P. R., Godschalk, D. R., Kaiser, E. J., & DA, R. (2006). What makes a good plan?. *Urban Land Use Planning*, 5, 59-83.

Bernard, L., Kanellopoulos, I., Annoni, A., & Smits, P. (2005). The European geoportal—one step towards the establishment of a European Spatial Data Infrastructure. *Computers, Environment and Urban Systems*, *29*(1), 15-31. https://doi.org/10.1016/j.compenvurbsys.2004.05.009

Bhat, P. A., ul Shafiq, M., Mir, A. A., & Ahmed, P. (2017). Urban sprawl and its impact on landuse/land cover dynamics of Dehradun City, India. *International Journal of Sustainable Built Environment*, *6*(2), 513-521. https://doi.org/10.1016/j.ijsbe.2017.10.003

Bhavsar, P., Safro, I., Bouaynaya, N., Polikar, R., & Dera, D. (2017). Machine learning in transportation data analytics. In *Data analytics for intelligent transportation systems* (pp. 283-307). Elsevier: Amsterdam, Netherlands.

Birkhofer, K., Diehl, E., Andersson, J., Ekroos, J., Früh-Müller, A., Machnikowski, F., ... & Smith, H. G. (2015). Ecosystem services—current challenges and opportunities for ecological research. *Frontiers in Ecology and Evolution*, *2*, 87. https://doi.org/10.3389/fevo.2014.00087

Boughorbel, S., Jarray, F., & El-Anbari, M. (2017). Optimal classifier for imbalanced data using Matthews Correlation Coefficient metric. *PloS ONE*, 12(6), e0177678. https://doi.org/10.1371/journal.pone.0177678

Breheny, M. (1992). The compact city: an introduction. *Built Environment*, 18(4), 241. https://www.proquest.com/docview/1292634075?pq-origsite=gscholar&fromopenview=true&imgSeq=1

Breheny, M.J. (1992). *Sustainable Development and Urban Form*. Pion.

Breuste, J., Haase, D., & Elmqvist, T. (2013). Urban landscapes and ecosystem services. In S. D. Wratten, H. Sandhu, R. Cullen, & R. Costanza (Eds.), *Ecosystem* *services in agricultural and urban landscapes* (pp. 83-104). Wiley-Blackwell. https://doi.org/10.1002/9781118506271.ch6

Brinkman, J. C. (2016). Congestion, agglomeration, and the structure of cities. *Journal of Urban Economics*, *94*, 13-31. https://doi.org/10.1016/j.jue.2016.05.002

Brown, D. G., Goovaerts, P., Burnicki, A., & Li, M. Y. (2002). Stochastic simulation of land-cover change using geostatistics and generalized additive models. *Photogrammetric Engineering and Remote Sensing*, *68*(10), 1051-1062. https://api.semanticscholar.org/CorpusID:11171011

Building Regulations of Matera (2021). Retrieved March 23, 2023, from https://www.comune.matera.it/images/amm_trasp/pianificazione_e_governo_del_territorio/regolamento_2021/RU_P1_Relazione_appr_giugno2021.pdf.

Burchfield, M., Overman, H. G., Puga, D., & Turner, M. A. (2006). Causes of sprawl: A portrait from space. *The Quarterly Journal of Economics*, *121*(2), 587-633. https://doi.org/10.1162/qjec.2006.121.2.587

Burkhard, B., Kroll, F., Nedkov, S., & Müller, F. (2012). Mapping ecosystem service supply, demand, and budgets. *Ecological Indicators*, *21*, 17-29. https://doi.org/10.1016/j.ecolind.2011.06.019

Burton, E. (2000). The compact city: just or just compact? A preliminary analysis. *Urban Studies*, *37*(11), 1969-2006. https://doi.org/10.1080/00420980050162184

Burton, E. (2002). Measuring urban compactness in UK towns and cities. *Environment and planning B: Planning and Design*, *29*(2), 219-250. https://doi.org/10.1068/b2713

Büttner G., Kosztra B., 2011, *Manual of CORINE Land Cover changes*. Copenhagen: European Environment Agency.

Cabrera-Jara, N., Orellana, D., & Hermida, M. A. (2017). Assessing sustainable urban densification using geographic information systems. *International Journal of Sustainable Building Technology and Urban Development*, *8*(2), 237-243. https://doi.org/10.12972/susb.20170021

Cao, Y., Kong, L., Zhang, L., & Ouyang, Z. (2021). The balance between economic development and ecosystem service value in the process of land urbanization: A case study of China's land urbanization from 2000 to 2015. *Land Use Policy*, *108*, 105536. https://doi.org/10.1016/j.landusepol.2021.105536

Capolupo, A., Monterisi, C., Saponieri, A., Addona, F., Damiani, L., Archetti, R., & Tarantino, E. (2021). An interactive WebGIS framework for coastal erosion risk management. *Journal of Marine Science and Engineering*, *9*(6), 567. https://doi.org/10.3390/jmse9060567

Carlucci, S., De Simone, M., Firth, S. K., Kjærgaard, M. B., Markovic, R., Rahaman, M. S., ... & Van Treeck, C. (2020). Modeling occupant behavior in buildings. *Building and Environment*, *174*, 106768. https://doi.org/10.1016/j.buildenv.2020.106768

Chang, H. S., & Chen, T. L. (2016). Examine sustainable urban space based on compact city concept. *Global Journal of Human-Social Science: B Geography, Geo-Sciences, Environmental Science & Disaster Management*, *16*(4), 2-12.

Chen, Q., Zhang, Z., Chen, S., Wen, S., Ma, H., & Xu, Z. (2022). A self-attention based global feature enhancing network for semantic segmentation of large-scale urban street-level point clouds. *International Journal of Applied Earth Observation and Geoinformation*, *113*, 102974. https://doi.org/10.1016/j.jag.2022.102974

Chen, X., Xiang, S., Liu, C. L., & Pan, C. H. (2014). Vehicle detection in satellite images by hybrid deep convolutional neural networks. *IEEE Geoscience and Remote Sensing Letters*, 11(10), 1797-1801. https://doi.org/10.1109/LGRS.2014.2309695

Chinchor, N., & Sundheim, B. M. (1993). MUC-5 evaluation metrics. *Proceedings of the Fifth Message Understanding Conference (MUC-5)*, Baltimore, Maryland, 25-27 August 1993. https://aclanthology.org/M93-1007.pdf

Churchman, A. (1999). Disentangling the concept of density. *Journal of Planning Literature*, *13*(4), 389-411. https://doi.org/10.1177/08854129922092478

Cilliers, P., van Vuuren, J. H., & van Heerden, Q. (2021). A framework for modelling spatio-temporal informal settlement growth prediction. *Computers, Environment and Urban Systems*, 90, 101707. https://doi.org/10.1016/j.compenvurbsys.2021.101707

Corine Land Cover (2018). Retrieved March 18, 2022, from https://land.copernicus.eu/pan-european/corine-land-cover/clc2018.

Coetzee, S., Ivánová, I., Mitasova, H., & Brovelli, M. A. (2020). Open geospatial software and data: A review of the current state and a perspective into the future. *ISPRS International Journal of Geo-Information*, *9*(2), 90. https://doi.org/10.3390/ijgi9020090

Cohen-Shacham, E., Walters, G., Janzen, C., & Maginnis, S. (2016). Nature-based solutions to address global societal challenges. *IUCN: Gland, Switzerland*, *97*, 2016-2036. http://dx.doi.org/10.2305/IUCN.CH.2016.13.en

Conticelli, E., De Luca, C., & Tondelli, S. (2020). Assessing the balance between urban developmentand densification: consolidated practices and new challenges. *BDC*, *2*(20), 231-240. https://dx.doi.org/10.6092/2284-4732/7553

Costanza, R., d'Arge, R., De Groot, R., Farber, S., Grasso, M., Hannon, B., ... & Van Den Belt, M. (1997). The value of the world's ecosystem services and natural capital. N*ature*, *387*(6630), 253-260. https://doi.org/10.1038/387253a0

Curran, S. R., & de Sherbinin, A. (2004). Completing the picture: the challenges of bringing “consumption” into the population–environment equation. *Population and Environment*, *26*, 107-131. https://doi.org/10.1007/s11111-004-0837-x

Daneshpour, A., & Shakibamanesh, A. (2011). Compact city; dose it create an obligatory context for urban sustainability. *International Journal of Architectural Engineering & Urban Planning*, *21*(2), 110-118.

Daniel, R. (2018). *Analytic Hierarchy Process: Advances in Research and Applications*. Nova Science Publishers.

Dantzig, G. B., & Saaty, T. L. (1973). *Compact city: a plan for a liveable urban environment.* W.H. Freeman and Co.

Darabi, H., Choubin, B., Rahmati, O., Haghighi, A. T., Pradhan, B., & Kløve, B. (2019). Urban flood risk mapping using the GARP and QUEST models: A comparative study of machine learning techniques. *Journal of Hydrology*, *569*, 142-154. https://doi.org/10.1016/j.jhydrol.2018.12.002

Darabi, H., Rahmati, O., Naghibi, S. A., Mohammadi, F., Ahmadisharaf, E., Kalantari, Z., ... & Tien Bui, D. (2022). Development of a novel hybrid multi-boosting neural network model for spatial prediction of urban flood. *Geocarto International*, *37*(19), 5716-5741. https://doi.org/10.1080/10106049.2021.1920629

Das, T., Jana, A., Mandal, B., & Sutradhar, A. (2021). Spatio-temporal pattern of land use and land cover and its effects on land surface temperature using remote sensing and GIS techniques: A case study of Bhubaneswar city, Eastern India (1991–2021). *GeoJournal*, 1-31. https://doi.org/10.1007/s10708-021-10541-z

Corine Land Cover (2018). Retrieved March 18, 2022, from https://land.copernicus.eu/pan-european/corine-land-cover/clc2018.

National Synthesis Database (2022). Retrieved January 27, 2022, from https://www.igmi.org/it/dbsn-database-di-sintesi-nazionale.

Topographic Database of Emilia Romagna Region. (2022). Retrieved March, 10, 2022, from https://geoportale.regione.emilia-romagna.it/approfondimenti/database-topografico-regionale.

De Carvalho, R. M., & Szlafsztein, C. F. (2019). Urban vegetation loss and ecosystem services: The influence on climate regulation and noise and air pollution. *Environmental Pollution*, *245*, 844-852. https://doi.org/10.1016/j.envpol.2018.10.114

De la Barrera, F., Reyes-Paecke, S., & Banzhaf, E. (2016). Indicators for green spaces in contrasting urban settings. *Ecological Indicators*, *62*, 212-219. https://doi.org/10.1016/j.ecolind.2015.10.027

De Luca, C., Libetta, A., Conticelli, E., & Tondelli, S. (2021). Accessibility to and Availability of Urban Green Spaces (UGS) to support Health and Wellbeing during the COVID-19 Pandemic-The case of Bologna. *Sustainability*, *13*(19), 11054. https://doi.org/10.3390/su131911054

De Roo, G. (2000). Environmental conflicts in compact cities: complexity, decisionmaking, and policy approaches. *Environment and Planning B: Planning and Design*, *27*(1), 151-162. https://doi.org/10.1068/b2614

De Roo, G., & Miller, D. (2000). *Compact Cities and Sustainable Urban Development: A Critical Assessment of Policies and Plans from an International Perspective* (1st ed.). Routledge. https://doi.org/10.4324/9781315189369

Deal, B., & Schunk, D. (2004). Spatial dynamic modeling and urban land use transformation: a simulation approach to assessing the costs of urban sprawl. *Ecological Economics*, *51*(1-2), 79-95. https://doi.org/10.1016/j.ecolecon.2004.04.008.

Dempsey, N. (2010). Revisiting the compact city? *Built Environment*, *36*, 5–8. http://dx.doi.org/10.2148/benv.36.1.5

Demuzere, M., Orru, K., Heidrich, O., Olazabal, E., Geneletti, D., Orru, H., ... & Faehnle, M. (2014). Mitigating and adapting to climate change: Multi-functional and multi-scale assessment of green urban infrastructure. *Journal of Environmental Management*, *146*, 107-115. https://doi.org/10.1016/j.jenvman.2014.07.025

Deng, G., Chen, H., Xie, B., & Wang, M. (2022). Risk Assessment and Prediction of Air Pollution Disasters in Four Chinese Regions. *Sustainability*, *14*(5), 3106. https://doi.org/10.3390/su14053106

Denyer, D., & Tranfield, D. (2009). Producing a systematic review. In D. A. Buchanan & A. Bryman (Eds.), *The Sage handbook of organizational research methods* (pp. 671–689). Sage Publications Ltd.

Denyer, D., Tranfield, D., & Van Aken, J. E. (2008). Developing Design Propositions through Research Synthesis. *Organization Studies*, *29*(3), 393-413. https://doi.org/10.1177/0170840607088020

DM 1444/1968 (1968). Retrieved 18 March, 2022, from https://www.gazzettaufficiale.it/eli/id/1968/04/16/1288Q004/sg

Dong, S., Wang, X., Yin, H., Xu, S., & Xu, R. (2013). Semantic enhanced WebGIS approach to visualize Chinese historical natural hazards. *Journal of Cultural Heritage*, *14*(3), 181-189. https://doi.org/10.1016/j.culher.2012.06.009

Dzhambov, A. M., & Dimitrova, D. D. (2014). Urban green spaces′ effectiveness as a psychological buffer for the negative health impact of noise pollution: A systematic review. *Noise and Health*, *16*(70), 157-165. https://www.noiseandhealth.org/text.asp?2014/16/70/157/134916

EEA Briefing. (2012). GMES land monitoring service. http://www.eea.europa.eu/themes/landuse/

Eggermont, H., Balian, E., Azevedo, J. M. N., Beumer, V., Brodin, T., Claudet, J., ... & Le Roux, X. (2015). Nature-based solutions: new influence for environmental management and research in Europe. *GAIA-Ecological Perspectives for Science and Society*, *24*(4), 243-248. https://doi.org/10.14512/gaia.24.4.9

Eggimann, S., Wagner, M., Ho, Y. N., Züger, M., Schneider, U., & Orehounig, K. (2021). Geospatial simulation of urban neighbourhood densification potentials. *Sustainable Cities and Society*, *72*, 103068. https://doi.org/10.1016/j.scs.2021.103068

Eini, M., Kaboli, H. S., Rashidian, M., & Hedayat, H. (2020). Hazard and vulnerability in urban flood risk mapping: Machine learning techniques and considering the role of urban districts. *International Journal of Disaster Risk Reduction*, *50*, 101687. https://doi.org/10.1016/j.ijdrr.2020.101687

Elkin, T., McLaren, D., & Hillman, M. (1991). *Reviving the City: Towards Sustainable Urban Development*. Friends of the Earth with Policy Studies Institute.

Elmqvist, T., Bai, X., Frantzeskaki, N., Griffith, C., Maddox, D., McPhearson, T., Parnell, S., Romero-Lankao, P., Simon, D., & Watkins, M. (2018). *The Urban Planet: Knowledge towards Sustainable Cities.* Cambridge University Press. https://doi.org/10.1017/9781316647554

Emilia-Romagna Region Urbanistic Law 24/2017 (2017). Retrieved 10 September, 2022, from https://demetra.regione.emilia-romagna.it/al/articolo?urn=er:assemblealegislativa:legge:2017;24

Eom, S. J., Choi, N., & Sung, W. (2016). The use of smart work in government: Empirical analysis of Korean experiences. *Government Information Quarterly*, *33*(3), 562-571. https://doi.org/10.1016/j.giq.2016.01.005

Erick, S. Ã., & Sosa, M. R. (2017). Spatial suitability for urban sustainable densification in a borderland city. *Journal of Geography and Regional Planning*, *10*(10), 266-277. https://doi.org/10.5897/JGRP2017.0648

European Commission (2006), Comunicazione della Commissione al Consiglio, al Parlamento europeo, al Comitato economico e sociale europeo e al Comitato delle regioni. Strategia tematica per la protezione del suolo, COM(2006) 231.

European Commission (2011). Mapping Guide for a European Urban Atlas.

European Commission (2016). Nature-based solutions webpage. http://publications.europa.eu/resource/cellar/fb117980-d5aa-46df-

European Commission (2020). OPEN SOURCE SOFTWARE STRATEGY 2020 – 2023 Think Open. https://commission.europa.eu/system/files/2023-02/en_ec_open_source_strategy_2020-2023.pdf

European Commission. Directorate-General for Research and Innovation. (2015). Towards an EU research and innovation policy agenda for Nature-Based Solutions & Re-Naturing Cities. Final Eeport of the Horizon 2020 expert group on “Nature-based solutions and re-naturing cities”. https://op.europa.eu/en/publication-detail/-/publication/fb117980-d5aa-46df-8edc-af367cddc202

European Environment Agency. (2016). Urban Sprawl in Europe. Joint EEA-FOEN Report. https://www.eea.europa.eu/publications/urban-sprawl-in-europe

Ewing, R. (1997). Is Los Angeles-style sprawl desirable?. *Journal of the American Planning Association*, *63*(1), 107-126. https://doi.org/10.1080/01944369708975728

Fago, P., Pignatelli, C., Piscitelli, A., Milella, M., Venerito, M., Sansò, P., & Mastronuzzi, G. (2014). WebGIS for Italian tsunami: A useful tool for coastal planners. *Marine Geology*, *355*, 369-376. https://doi.org/10.1016/j.margeo.2014.06.012

Fan, R., Feng, R., Han, W., & Wang, L. (2021). Urban functional zone mapping with a bibranch neural network via fusing remote sensing and social sensing data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *14*, 11737-11749. https://doi.org/10.1109/JSTARS.2021.3127246

Faravelli, M., Bozzoni, F., Zuccolo, E., Di Meo, A., Quaroni, D., Polli, D., ... & Lai, C. G. (2023). A WebGIS platform for managing the seismic risk at regional scale: the case study of the Emilia-Romagna Region. *Procedia Structural Integrity*, *44*, 43-50. https://doi.org/10.1016/j.prostr.2023.01.007

Fashae, O. A., Adagbasa, E. G., Olusola, A. O., & Obateru, R. O. (2020). Land use/land cover change and land surface temperature of Ibadan and environs, Nigeria. *Environmental Monitoring and Assessment*, *192*, 1-18. https://doi.org/10.1007/s10661-019-8054-3

Feltynowski, M. (2015). Spatial information systems–a tool supporting good governance in spatial planning processes of green areas. *Journal of Urban and Regional Analysis*, *7*(1), 69-82. https://doi.org/10.37043/JURA.2015.7.1.5

Feng, Y., & Qi, Y. (2018). Modeling patterns of land use in Chinese cities using an integrated cellular automata model. *ISPRS International Journal of Geo-Information*, *7*(10), 403. https://doi.org/10.3390/ijgi7100403

Fietkiewicz, K. J., Mainka, A., & Stock, W. G. (2017). eGovernment in cities of the knowledge society. An empirical investigation of Smart Cities' governmental websites. *Government Information Quarterly*, *34*(1), 75-83. https://doi.org/10.1016/j.giq.2016.08.003

Fistola, R., Gallo, M., La Rocca, R. A., & Russo, F. (2020). The effectiveness of urban cycle lanes: From dyscrasias to potential solutions. *Sustainability*, *12*(6), 2321. https://doi.org/10.3390/su12062321

Francini, M., Salvo, C., & Vitale, A. (2023). Combining Deep Learning and Multi-Source GIS Methods to Analyze Urban and Greening Changes. *Sensors*, 23(8), 3805. https://doi.org/10.3390/s23083805

Francini, M., Salvo, C., Viscomi, A., & Vitale, A. (2022). A Deep Learning-Based Method for the Semi-Automatic Identification of Built-Up Areas within Risk Zones Using Aerial Imagery and Multi-Source GIS Data: An Application for Landslide Risk. *Remote Sensing*, *14*(17), 4279. https://doi.org/10.3390/rs14174279

Freitas, F., Berreth, T., Chen, Y. C., & Jhala, A. (2023). Characterizing the perception of urban spaces from visual analytics of street-level imagery. *AI & Society*, *38*(4), 1361-1371. https://doi.org/10.1007/s00146-022-01592-y

Galster, G., Hanson, R., Ratcliffe, M. R., Wolman, H., Coleman, S., & Freihage, J. (2001). Wrestling sprawl to the ground: defining and measuring an elusive concept. *Housing Policy Debate*, *12*(4), 681-717. https://doi.org/10.1080/10511482.2001.9521426

Gasparatos, A. (2010). Embedded value systems in sustainability assessment tools and their implications. *Journal of Environmental Management*, *91*(8), 1613-1622. https://doi.org/10.1016/j.jenvman.2010.03.014

Gaur, S., & Singh, R. (2023). A comprehensive review on land use/land cover (LULC) change modeling for urban development: current status and future prospects. *Sustainability*, *15*(2), 903. https://doi.org/10.3390/su15020903

Geneletti, D., & Zardo, L. (2016). Ecosystem-based adaptation in cities: An analysis of European urban climate adaptation plans. *Land Use Policy*, *50*, 38-47. https://doi.org/10.1016/J.LANDUSEPOL.2015.09.003

Geneletti, D., Cortinovis, C., Zardo, L., & Esmail, B. A. (2020). *Planning for Ecosystem Services in Cities*. Springer Cham. https://doi.org/10.1007/978-3-030-20024-4

Geoportale Regione Basilicata. (n.d.). Retrieved April 8, 2023, from https://rsdi.regione.basilicata.it/ppr/

Geoportale Regione Calabria. (n.d.). Retrieved April 8, 2023, from http://geoportale.regione.calabria.it/

Geoportale Regione Emilia Romagna. (n.d.). Retrieved March 18, 2022, from https://geoportale.regione.emilia-romagna.it

Geoportale Regione Lazio. (n.d.). Retrieved April 8, 2023, from https://geoportale.regione.lazio.it/

Geoportale Regione Lombardia. (n.d.). Retrieved April 8, 2023, https://www.geoportale.regione.lombardia.it/

Geoportale Regione Puglia. (n.d.). Retrieved April 8, 2023, from https://pugliacon.regione.puglia.it/freegis/RR242005/

Geoportale Regione Sicilia. (n.d.). Retrieved April 8, 2023, from https://www.sitr.regione.sicilia.it/geoportale

Geoportale Regione Toscana. (n.d.). Retrieved April 8, 2023, from https://www.regione.toscana.it/-/geoscopio

Geoportale Regione Umbria. (n.d.). Retrieved April 8, 2023, from http://www.umbriageo.regione.umbria.it/pagine/geoportale-000

Geoportale Regione Veneto. (n.d.). Retrieved April 8, 2023, from https://idt2.regione.veneto.it/

Gil-Garcia, J. R., Zhang, J., & Puron-Cid, G. (2016). Conceptualizing smartness in government: An integrative and multi-dimensional view. *Government Information Quarterly*, *33*(3), 524-534. https://doi.org/10.1016/j.giq.2016.03.002

Goddard, M. A., Dougill, A. J., & Benton, T. G. (2010). Scaling up from gardens: biodiversity conservation in urban environments. *Trends in Ecology & Evolution*, *25*(2), 90-98. https://doi.org/10.1016/j.tree.2009.07.016

Gómez-Baggethun, E., & Barton, D. N. (2013). Classifying and valuing ecosystem services for urban planning. *Ecological Economics*, *86*, 235-245. https://doi.org/10.1016/j.ecolecon.2012.08.019

Gong, F. Y., Zeng, Z. C., Zhang, F., Li, X., Ng, E., & Norford, L. K. (2018). Mapping sky, tree, and building view factors of street canyons in a high-density urban environment. *Building and Environment*, *134*, 155-167. https://doi.org/10.1016/j.buildenv.2018.02.042

Goodchild, M. F. (2012). The future of digital earth. *Annals of GIS*, *18*(2), 93-98. https://doi.org/10.1080/19475683.2012.668561

Goodchild, M. F. (2018). Reimagining the history of GIS. *Annals of GIS*, *24*(1), 1-8. https://doi.org/10.1080/19475683.2018.1424737

Goodchild, M. F., Fu, P., & Rich, P. (2007). Sharing geographic information: an assessment of the Geospatial One-Stop. *Annals of the Association of American Geographers*, *97*(2), 250-266. https://doi.org/10.1111/j.1467-8306.2007.00534.x

Goodchild, M. F., Guo, H., Annoni, A., Bian, L., De Bie, K., Campbell, F., ... & Woodgate, P. (2012). Next-generation digital earth. *Proceedings of the National Academy of Sciences*, *109*(28), 11088-11094. https://doi.org/10.1073/pnas.1202383109

Goodwill, J., & Hendricks, S. J. (2002). *Building transit oriented development in established communities*. Tampa: National Center for Transit Research, Center for Urban Transportation Research, University of South Florida.

Grunewald, K., Richter, B., Meinel, G., Herold, H., & Syrbe, R. U. (2017). Proposal of indicators regarding the provision and accessibility of green spaces for assessing the ecosystem service "recreation in the city" in Germany. *International Journal of Biodiversity Science, Ecosystem Services & Management*, *13*(2), 26-39. https://doi.org/10.1080/21513732.2017.1283361

Guo, T., Dong, J., Li, H., & Gao, Y. (2017, March). Simple convolutional neural network on image classification. In *2017 IEEE 2nd International Conference on Big Data Analysis (ICBDA)* (pp. 721-724). IEEE. https://doi.org/10.1109/ICBDA.2017.8078730

Guo, Z., Leitao, J. P., Simões, N. E., & Moosavi, V. (2021). Data-driven flood emulation: Speeding up urban flood predictions by deep convolutional neural networks. *Journal of Flood Risk Management*, *14*(1), e12684. https://doi.org/10.1111/jfr3.12684

Gupta, K., Kumar, P., Pathan, S. K., & Sharma, K. P. (2012). Urban Neighborhood Green Index–A measure of green spaces in urban areas. *Landscape and Urban Planning*, *105*(3), 325-335. https://doi.org/10.1016/j.landurbplan.2012.01.003

Haaland, C., & van Den Bosch, C. K. (2015). Challenges and strategies for urban green-space planning in cities undergoing densification: A review. *Urban forestry & Urban Greening*, *14*(4), 760-771. https://doi.org/10.1016/j.ufug.2015.07.009

Haase, D., Kabisch, N., & Haase, A. (2013). Endless urban growth? On the mismatch of population, household and urban land area growth and its effects on the urban debate. *PloS one*, *8*(6), e66531. https://doi.org/10.1371/journal.pone.0066531

Hagenauer, J., & Helbich, M. (2012). Mining urban land-use patterns from volunteered geographic information by means of genetic algorithms and artificial neural networks. *International Journal of Geographical Information Science*, *26*(6), 963-982. https://doi.org/10.1080/13658816.2011.619501

Haines-Young, R., & Potschin, M. (2012). Common International classification of ecosystem services. *Nottingham: Centre for Environmental Management, University of Nottingham*. http://www.cices.eu

Hamad, R., Balzter, H., & Kolo, K. (2018). Predicting land use/land cover changes using a CA-Markov model under two different scenarios. *Sustainability*, *10*(10), 3421. https://doi.org/10.3390/su10103421

Hamid, B., Massinissa, B., & Nabila, G. (2023). Landslide susceptibility mapping using GIS-based statistical and machine learning modeling in the city of Sidi Abdellah, Northern Algeria. *Modeling Earth Systems and Environment*, *9*(2), 2477-2500. https://doi.org/10.1007/s40808-022-01633-x

Han, M., Wang, Z., & Zhang, X. (2021). An Approach to Data Acquisition for Urban Building Energy Modeling Using a Gaussian Mixture Model and Expectation-Maximization Algorithm. *Buildings*, *11*(1), 30. https://doi.org/10.3390/buildings11010030

Hansen, R., Olafsson, A. S., Van Der Jagt, A. P., Rall, E., & Pauleit, S. (2019). Planning multifunctional green infrastructure for compact cities: What is the state of practice?. *Ecological Indicators*, *96*, 99-110. https://doi.org/10.1016/j.ecolind.2017.09.042

Hassan, M. M. (2017). Monitoring land use/land cover change, urban growth dynamics and landscape pattern analysis in five fastest urbanized cities in Bangladesh. *Remote Sensing Applications: Society and Environment*, 7, 69-83. https://doi.org/10.1016/j.rsase.2017.07.001

He, T., Huang, W., Qiao, Y., & Yao, J. (2016). Text-attentional convolutional neural network for scene text detection. *IEEE Transactions on Image Processing*, 25(6), 2529-2541. https://doi.org/10.1109/TIP.2016.2547588

He, X., & He, S. Y. (2023). Using open data and deep learning to explore walkability in Shenzhen, China. *Transportation research part D: transport and environment*, *118*, 103696. https://doi.org/10.1016/j.trd.2023.103696

Holden, E., & Norland, I. T. (2005). Three challenges for the compact city as a sustainable urban form: household consumption of energy and transport in eight residential areas in the greater Oslo region. *Urban studies*, *42*(12), 2145-2166. https://doi.org/10.1080/00420980500332064

Huang, C., Hu, T., Duan, Y., Li, Q., Chen, N., Wang, Q., Zhou, M. & Rao, P. (2022). Effect of urban morphology on air pollution distribution in high-density urban blocks based on mobile monitoring and machine learning. *Building and Environment*, *219*, 109173. https://doi.org/10.1016/j.buildenv.2022.109173

Huang, C., Zhao, D., Liao, Q., & Xiao, M. (2023). Linking landscape dynamics to the relationship between water purification and soil retention. *Ecosystem Services*, *59*, 101498. https://doi.org/10.1016/j.ecoser.2022.101498

Huang, J., Tang, Z., Liu, D., & He, J. (2020). Ecological response to urban development in a changing socio-economic and climate context: Policy implications for balancing regional development and habitat conservation. *Land Use Policy*, *97*, 104772. https://doi.org/10.1016/j.landusepol.2020.104772

Huang, M., Chen, N., Du, W., Wen, M., Zhu, D., & Gong, J. (2021). An on-demand scheme driven by the knowledge of geospatial distribution for large-scale high-resolution impervious surface mapping. *GIScience & Remote Sensing*, 58(4), 562-586. https://doi.org/10.1080/15481603.2021.1909304

Huu, C. N., Van, C. N., & My, T. N. N. (2022). Modeling land-use changes using logistic regression in Western Highlands of Vietnam: A case study of Lam Dong province. *Agriculture and Natural Resources*, *56*(5), 935-944. https://doi.org/10.34044/j.anres.2022.56.5.08

Inostroza, L. (2017). Informal urban development in Latin American urban peripheries. Spatial assessment in Bogotá, Lima and Santiago de Chile. *Landscape and Urban Planning*, *165*, 267-279. https://doi.org/10.1016/j.landurbplan.2016.03.021

Inostroza, L., Baur, R., & Csaplovics, E. (2013). Urban sprawl and fragmentation in Latin America: A dynamic quantification and characterization of spatial patterns. *Journal of environmental management*, *115*, 87-97. https://doi.org/10.1016/j.jenvman.2012.11.007

ISTAT (2001) 14° Censimento generale della Popolazione e delle Abitazioni. http://dawinci.istat.it/, last accessed 2023/03/23.

ISTAT (2011) 15° Censimento della Popolazione e delle Abitazioni. http://www.istat.it/it/censimento-popolazione/censimento-popolazione-2011.

ISTAT. Available online: https://www.istat.it/it/dati-analisi-e-prodotti/open-data (Accessed on 10 March 2022)

Ito, K., & Biljecki, F. (2021). Assessing bikeability with street view imagery and computer vision. *Transportation research part C: emerging technologies*, *132*, 103371. https://doi.org/10.1016/j.trc.2021.103371

Jenks, M., & Burgess, R. (Eds.). (2000). *Compact cities: Sustainable urban forms for developing countries*. Taylor & Francis.

Jenks, M., Burton, E., & Williams, K. (1996). Compact cities and sustainability: an introduction. The Compact City: a sustainable urban form, 11-12. (book)

Jenks, M., Burton, E., Williams, K., & Symes, M. (1996). The Compact City: A sustainable urban form?. *Land Use Policy*, *14*(3), 215.

Jha, A. K., Ghimire, A., Thapa, S., Jha, A. M., & Raj, R. (2021, January). A review of AI for urban planning: Towards building sustainable smart cities. In *2021 6th International Conference on Inventive Computation Technologies (ICICT)* (pp. 937-944). IEEE. https://ieeexplore.ieee.org/abstract/document/9358548

Jim, C. Y. (2004). Green-space preservation and allocation for sustainable greening of compact cities. *Cities*, *21*(4), 311-320. https://doi.org/10.1016/j.cities.2004.04.004

Jim, C. Y. (2013). Sustainable urban greening strategies for compact cities in developing and developed economies. *Urban Ecosystems*, *16*, 741-761. https://doi.org/10.1007/s11252-012-0268-x

Jim, C. Y., & Chen, W. Y. (2008). Assessing the ecosystem service of air pollutant removal by urban trees in Guangzhou (China). *Journal of environmental management*, *88*(4), 665-676. https://doi.org/10.1016/j.jenvman.2007.03.035

Jin, J., Gergel, S. E., Lu, Y., Coops, N. C., & Wang, C. (2020). Asian cities are greening while some North American cities are browning: long-term greenspace patterns in 16 cities of the Pan-Pacific region. *Ecosystems*, *23*, 383-399. https://doi.org/10.1007/s10021-019-00409-2

Kabisch N., Bosch M. A. V. D. (2017), "Urban Green Spaces and the Potential for Health Improvement and Environmental Justice in a Changing Climate", in Kabisch N., Korn H., Stadler J., Bonn A. (ed.), Nature-Based Solutions to Climate Change Adaptation in Urban Areas, Springer, Cham, pp. 207-220.

Kabisch, N., Haase, D., & Annerstedt van den Bosch, M. (2016). Adding natural areas to social indicators of intra-urban health inequalities among children: A case study from Berlin, Germany. *International journal of environmental research and public health*, *13*(8), 783. https://doi.org/10.3390/ijerph13080783

Kabisch, N., Strohbach, M., Haase, D., & Kronenberg, J. (2016). Urban green space availability in European cities. *Ecological indicators*, *70*, 586-596. https://doi.org/10.1016/j.ecolind.2016.02.029

Khorrami, B., Heidarlou, H. B., & Feizizadeh, B. (2021). Evaluation of the environmental impacts of urbanization from the viewpoint of increased skin temperatures: a case study from Istanbul, Turkey. Applied Geomatics, 13, 311-324. https://doi.org/10.1007/s12518-020-00350-3

Khoshkar, S., Balfors, B., & Wärnbäck, A. (2018). Planning for green qualities in the densification of suburban Stockholm–opportunities and challenges. *Journal of Environmental Planning and Management*, *61*(14), 2613-2635. https://doi.org/10.1080/09640568.2017.1406342

Kim, D., Jung, S., & Jeong, Y. (2021). Theft Prediction Model Based on Spatial Clustering to Reflect Spatial Characteristics of Adjacent Lands. *Sustainability*, *13*(14), 7715. https://doi.org/10.3390/su13147715

Kingma, D.P., & Ba, J.L. Adam: A method for stochastic optimization. In Proceedings of the 3rd International Conference for Learning Representations (ICLR), San Diego, CA, USA, 7–9 May 2015

Kotharkar, R., Bahadure, P., & Sarda, N. (2014). Measuring compact urban form: A case of Nagpur City, India. *Sustainability*, *6*(7), 4246-4272. https://doi.org/10.3390/su6074246

Koutra, S., & Ioakimidis, C. S. (2022). Unveiling the Potential of Machine Learning Applications in Urban Planning Challenges. *Land*, *12*(1), 83. https://doi.org/10.3390/land12010083

Krishna, K., & Murty, M. N. (1999). Genetic K-means algorithm. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, *29*(3), 433-439. https://doi.org/10.1109/3477.764879

Krüger, T., Meinel, G., & Schumacher, U. (2013). Land-use monitoring by topographic data analysis. *Cartography and Geographic Information Science*, *40*(3), 220-228. https://doi.org/10.1080/15230406.2013.809232

Kulawiak, M., Kulawiak, N., Sulima, M., & Sikorska, K. (2022). A novel architecture of Web-GIS for mapping and analysis of echinococcosis in Poland. *Applied Geomatics*, *14*(2), 181-198. https://doi.org/10.1007/s12518-022-00447-x

Kumar, S., Radhakrishnan, N., & Mathew, S. (2014). Land use change modelling using a Markov model and remote sensing. *Geomatics, Natural Hazards and Risk*, *5*(2), 145-156. https://doi.org/10.1080/19475705.2013.795502

Kuo, C. C. J. (2016). Understanding convolutional neural networks with a mathematical model. *Journal of Visual Communication and Image Representation*, *41*, 406-413. https://doi.org/10.1016/j.jvcir.2016.11.003

Kushwaha, K., Singh, M. M., Singh, S. K., & Patel, A. (2021). Urban growth modeling using earth observation datasets, Cellular Automata-Markov Chain model and urban metrics to measure urban footprints. *Remote Sensing Applications: Society and Environment*, 22, 100479. https://doi.org/10.1016/j.rsase.2021.100479

Larondelle, N., & Lauf, S. (2016). Balancing demand and supply of multiple urban ecosystem services on different spatial scales. *Ecosystem Services*, *22*, 18-31. https://doi.org/10.1016/j.ecoser.2016.09.008

Larondelle, N., Haase, D., & Kabisch, N. (2014). Mapping the diversity of regulating ecosystem services in European cities. *Global Environmental Change*, *26*, 119-129. https://doi.org/10.1016/j.gloenvcha.2014.04.008

LeCun, Y., & Bengio, Y. (1995). Convolutional networks for images, speech, and time series. *The handbook of brain theory and neural networks*, *3361*(10), 1995. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=e26cc4a1c717653f323715d751c8dea7461aa105

Lee, J., Kurisu, K., An, K., & Hanaki, K. (2015). Development of the compact city index and its application to Japanese cities. *Urban Studies*, *52*(6), 1054-1070. https://doi.org/10.1177/0042098014536786

Li, F., Li, Z., Chen, H., Chen, Z., & Li, M. (2020). An agent-based learning-embedded model (ABM-learning) for urban land use planning: A case study of residential land growth simulation in Shenzhen, China. *Land Use Policy*, *95*, 104620. https://doi.org/10.1016/j.landusepol.2020.104620

Li, H., Xu, E., & Zhang, H. (2021). High-resolution assessment of urban disaster resilience: a case study of Futian District, Shenzhen, China. *Natural hazards*, *108*, 1001-1024. https://doi.org/10.1007/s11069-021-04717-6

Li, X., Cheng, S., Lv, Z., Song, H., Jia, T., & Lu, N. (2020). Data analytics of urban fabric metrics for smart cities. *Future Generation Computer Systems*, *107*, 871-882. https://doi.org/10.1016/j.future.2018.02.017

Li, Z., Fan, Z., & Shen, S. (2018). Urban green space suitability evaluation based on the AHP-CV combined weight method: A case study of Fuping county, China. *Sustainability*, *10*(8), 2656. https://doi.org/10.3390/su10082656

Liberati, A., Altman, D. G., Tetzlaff, J., Mulrow, C., Gøtzsche, P. C., Ioannidis, J. P., Mike Clarke, B.A., Devereaux, P. J., Kleijnen, J., & Moher, D. (2009). The PRISMA Statement for Reporting Systematic Reviews and Meta-Analyses of Studies That Evaluate Health Care Interventions: Explanation and Elaboration. *Annals of Internal Medicine*, *151*(4), W-65. https://doi.org/10.7326/0003-4819-151-4-200908180-00136

Liu, C. C., Lin, T. C., Yuan, K. Y., & Chiueh, P. T. (2022). Spatio-temporal prediction and factor identification of urban air quality using support vector machine. *Urban Climate*, *41*, 101055. https://doi.org/10.1016/j.uclim.2021.101055

Liu, P., & Biljecki, F. (2022). A review of spatially-explicit GeoAI applications in Urban Geography. *International Journal of Applied Earth Observation and Geoinformation*, *112*, 102936. https://doi.org/10.1016/j.jag.2022.102936

Maes, J., Egoh, B., Willemen, L., Liquete, C., Vihervaara, P., Schägner, J. P., ... & Bidoglio, G. (2012). Mapping ecosystem services for policy support and decision making in the European Union. *Ecosystem services*, *1*(1), 31-39. https://doi.org/10.1016/j.ecoser.2012.06.004

Maes, J., Liquete, C., Teller, A., Erhard, M., Paracchini, M. L., Barredo, J. I., ... & Lavalle, C. (2016). An indicator framework for assessing ecosystem services in support of the EU Biodiversity Strategy to 2020. *Ecosystem services*, *17*, 14-23. https://doi.org/10.1016/J.ECOSER.2015.10.023

Majidizadeh, A., Hasani, H., & Jafari, M. (2023). Semantic Segmentation of Uav Images Based on U-Net in Urban Area. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 10, 451-457. https://doi.org/10.5194/isprs-annals-X-4-W1-2022-451-2023

Mandal, J., Patel, P. P., & Samanta, S. (2022). Examining the expansion of Urban Heat Island effect in the Kolkata Metropolitan Area and its vicinity using multi-temporal MODIS satellite data. *Advances in Space Research*, 69(5), 1960-1977. https://doi.org/10.1016/j.asr.2021.11.040

Mao, T., Liu, Y., Chen, W. Q., Li, N., Dong, N., & Shi, Y. (2022). Quantifying spatiotemporal dynamics of urban building and material metabolism by combining a random forest model and GIS-based material flow analysis. *Frontiers in Earth Science*, *10*, 944865. https://doi.org/10.3389/feart.2022.944865

Martnez-Harms, M. J., & Balvanera, P. (2012). Methods for mapping ecosystem service supply: A review. *International Journal of Biodiversity Science, Ecosystem Services and Management,* *8*(1–2), 17–25. https://doi.org/10.1080/21513732.2012.663792

Matsugu, M., Mori, K., Mitari, Y., & Kaneda, Y. (2003). Subject independent facial expression recognition with robust face detection using a convolutional neural network. *Neural Networks*, *16*(5-6), 555-559. https://doi.org/10.1016/S0893-6080(03)00115-1

Maurya, N. K., Rafi, S., & Shamoo, S. (2023). Land use/land cover dynamics study and prediction in jaipur city using CA markov model integrated with road network. *GeoJournal*, *88*(1), 137-160. https://doi.org/10.1007/s10708-022-10593-9

McCarty, D., Lee, J., & Kim, H. W. (2021). Machine Learning Simulation of Land Cover Impact on Surface Urban Heat Island Surrounding Park Areas. *Sustainability*, *13*(22), 12678. https://doi.org/10.3390/su132212678

Mell, I. C. (2009, March). Can green infrastructure promote urban sustainability?. In *Proceedings of the institution of civil engineers-engineering sustainability* (Vol. 162, No. 1, pp. 23-34). Thomas Telford Ltd.

Michalik, A., & Zwirowicz-Rutkowska, A. (2023). A Geoportal Supporting Spatial Planning in Poland: Concept and Pilot Version. *Geomatics and Environmental Engineering*, *17*(2), 5-30. https://doi.org/10.7494/geom.2023.17.2.5

Middel, A., Lukasczyk, J., Maciejewski, R., Demuzere, M., & Roth, M. (2018). Sky View Factor footprints for urban climate modeling. *Urban Climate*, *25*, 120-134. https://doi.org/10.1016/j.uclim.2018.05.004

Middel, A., Lukasczyk, J., Zakrzewski, S., Arnold, M., & Maciejewski, R. (2019). Urban form and composition of street canyons: A human-centric big data and deep learning approach. *Landscape and Urban Planning*, *183*, 122-132. https://doi.org/10.1016/j.landurbplan.2018.12.001

Millennium Ecosystem Assessment. (2005). *Ecosystems and Human Well-being. General Synthesis: a Report of the Millennium Ecosystem Assessment*. Island Press.

Miller, M. D. (2012). The impacts of Atlanta's urban sprawl on forest cover and fragmentation. *Applied Geography*, *34*, 171-179. https://doi.org/10.1016/j.apgeog.2011.11.010

Mitchell, T. M. (1997). Machine learning.

Mobasheri, A., Mitasova, H., Neteler, M., Singleton, A., Ledoux, H., & Brovelli, M. A. (2020). Highlighting recent trends in open source geospatial science and software. *Transactions in GIS*, *24*(5), 1141-1146. https://doi.org/10.1111/tgis.12703

Montero, E.; Wolvelaer, J.V.; Garzón, A. The European Urban Atlas. In Land Use and Land Cover Mapping in Europe. Remote Sensing and Digital Image Processing; Manakos, I., Braun, M., Eds.; Springer: Dordrecht, The Netherlands, 2014; Volume 18, pp. 115–124.

Moon, T. K. (1996). The expectation-maximization algorithm. *IEEE Signal Processing Magazine*, *13*(6), 47-60. https://doi.org/10.1109/79.543975

Motta, M., de Castro Neto, M., & Sarmento, P. (2021). A mixed approach for urban flood prediction using Machine Learning and GIS. *International Journal of Disaster Risk Reduction*, *56*, 102154. https://doi.org/10.1016/j.ijdrr.2021.102154

Mudassir, G., Howard, E. E., Pasquini, L., Arbib, C., Clementini, E., Di Marco, A., & Stilo, G. (2021). Toward Effective Response to Natural Disasters: A Data Science Approach. *IEEE Access*, *9*, 167827-167844. https://doi.org/10.1109/ACCESS.2021.3135054

Munafò, M. (Ed.). (2019). *Consumo di suolo, dinamiche territoriali e servizi ecosistemici* (p. 224). Roma, Italy: ISPRA.

Mushonga, H. T., Banda, F., & Mulolwa, A. (2017). Development of a web based GIS for health facilities mapping, monitoring and reporting: A case study of the Zambian Ministry of health. *South African Journal of Geomatics*, *6*(3), 321-332. https://doi.org/10.4314/sajg.v6i3.4

Nadeem, M., Aziz, A., Al-Rashid, M. A., Tesoriere, G., Asim, M., & Campisi, T. (2021). Scaling the potential of compact city development: The case of Lahore, Pakistan. *Sustainability*, *13*(9), 5257. https://doi.org/10.3390/su13095257

Nero, B. F., Callo-Concha, D., Anning, A., & Denich, M. (2017). Urban green spaces enhance climate change mitigation in cities of the global south: the case of Kumasi, Ghana. *Procedia engineering*, *198*, 69-83. https://doi.org/10.1016/j.proeng.2017.07.074

Nesshöver, C., Assmuth, T., Irvine, K. N., Rusch, G. M., Waylen, K. A., Delbaere, B., ... & Wittmer, H. (2017). The science, policy and practice of nature-based solutions: An interdisciplinary perspective. *Science of the total environment*, *579*, 1215-1227. https://doi.org/10.1016/j.scitotenv.2016.11.106.

Neuman, M. (2005). The compact city fallacy. *Journal of planning education and research*, *25*(1), 11-26. https://doi.org/10.1177/0739456X04270466

Newman P. W. G., & Kenworthy, J. R. (1989). Gasoline consumption and cities: A comparison of U.S. cities with a global survey". *Journal of the American Planning Association*, *55*(1), pp. 24–37. https://doi.org/10.1080/01944368908975398

Newman, P. G., & Kenworthy, J. R. (1989). *Cities and automobile dependence: An international sourcebook*.

Nguyen, L. T., Vo, B., Hong, T. P., & Thanh, H. C. (2013). CAR-Miner: An efficient algorithm for mining class-association rules. *Expert Systems with Applications*, *40*(6), 2305-2311. https://doi.org/10.1016/j.eswa.2012.10.035

Niemelä, J. (1999). Ecology and urban planning. *Biodiversity & Conservation*, *8*, 119-131. https://doi.org/10.1023/A:1008817325994

Niemelä, J. (2014). Ecology of urban green spaces: The way forward in answering major research questions. *Landscape and urban planning*, *125*, 298-303. https://doi.org/10.1016/j.landurbplan.2013.07.014

Nuissl, H., Haase, D., Lanzendorf, M., & Wittmer, H. (2009). Environmental impact assessment of urban land use transitions—A context-sensitive approach. *Land Use Policy*, *26*(2), 414-424. https://doi.org/10.1016/j.landusepol.2008.05.006

OECD. (2012). *Compact City Policies: A Comparative Assessment*. OECD Green Growth Studies, OECD Publishing, Paris. https://doi.org/10.1787/9789264167865-en

Ongsulee, P. (2017, November). Artificial intelligence, machine learning and deep learning. In 2017 15th *International Conference on ICT and Knowledge Engineering (ICT&KE)* (pp. 1-6). IEEE. 10.1109/ICTKE.2017.8259629

Opdam, P. (2010). Learning science from practice. *Landscape Ecology*, *25*, 821-823. https://doi.org/10.1007/s10980-010-9485-y

Open Geospatial Consortium, 2023. GeoPackage Encoding Standard.

Ostadabbas, H., Merz, H., & Weippert, H. (2021). Integration of Urban Spatial Data Management and Visualization with Enterprise Applications Using Open-

Source Software. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *43*, 307-312. https://doi.org/10.5194/isprs-archives-XLIII-B4-2021-307-2021

Ostadabbas, H., Weippert, H., & Behr, F. J. (2019). Database Transformation, Cadastre Automatic Data Processing in Qgis and Implementation in Web GIS. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *42*, 175-178. https://doi.org/10.5194/isprs-archives-XLII-4-W14-175-2019

O'Toole, R. (2009). The myth of the compact city: Why compact development is not the way to reduce carbon dioxide emissions. *Cato Policy Analysis Series*, (653). https://dx.doi.org/10.2139/ssrn.1543980

Ouma, Y. O., & Tateishi, R. (2014). Urban flood vulnerability and risk mapping using integrated multi-parametric AHP and GIS: methodological overview and case study assessment. *Water*, *6*(6), 1515-1545. https://doi.org/10.3390/w6061515

Oxoli, D., Cannata, M., Terza, V., & Brovelli, M. A. (2019). Natural heritage management and promotion through free and open source software: A preliminary system design for the Insubriparks Project. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *42*, 179-183. https://doi.org/10.5194/isprs-archives-XLII-4-W14-179-2019

Pan, H., Page, J., Cong, C., Barthel, S., & Kalantari, Z. (2021). How ecosystems services drive urban growth: Integrating nature-based solutions. *Anthropocene*, *35*, 100297. https://doi.org/10.1016/j.ancene.2021.100297

Pan, H., Page, J., Cong, C., Barthel, S., & Kalantari, Z. (2021). How ecosystems services drive urban growth: Integrating nature-based solutions. *Anthropocene*, *35*, 100297. https://doi.org/10.1016/j.ancene.2021.100297

Pandey, G., Sharma, V. K., Chaudhary, P., Chowdary, V. M., & Udayraj. (2021). Integration of Texture and Spectral Response with AI Techniques for Buildings Footprint Identification Using High-Resolution Satellite Images. *Journal of the Indian Society of Remote Sensing*, *49*, 1439-1452. https://doi.org/10.1007/s12524-021-01322-9

Park, J., & Yang, B. (2020). GIS-enabled digital twin system for sustainable evaluation of carbon emissions: A case study of Jeonju city, south Korea. *Sustainability*, *12*(21), 9186. https://doi.org/10.3390/su12219186

Park, J., Yoo, S. (2023). Evolution of the smart city: three extensions to governance, sustainability, and decent urbanisation from an ICT-based urban solution. *International Journal of Urban Sciences*, *27*(sup1), 10-28. https://doi.org/10.1080/12265934.2022.2110143

Pauleit, S. (2003). Perspectives on urban greenspace in Europe. *Built Environment (1978-)*, *29*(2), 88-93. https://doi.org/10.2148/benv.29.2.89.54470

Peng, J., Tian, L., Liu, Y., Zhao, M., & Wu, J. (2017). Ecosystem services response to urbanization in metropolitan areas: Thresholds identification. *Science of the Total Environment*, *607*, 706-714. https://doi.org/10.1016/j.scitotenv.2017.06.218

Pont, M. B., Haupt, P., Berg, P., Alstäde, V., & Heyman, A. (2021). Systematic review and comparison of densification effects and planning motivations. *Buildings and Cities*, *2*(1), 378-401. https://doi.org/10.5334/bc.125

Population Trend Matera 2001-2021. Available online: https://www.tuttitalia.it/basilicata/73-matera/statistiche/popolazione-andamento-demografico/ (accessed on 26 January 2023).

PRG Carpi. Piano Regolatore Generale di Carpi. Available online at: https://prg.carpidiem.it/

PRG Novi. Piano Regolatore Generale di Novi. Available online at: https://www.comune.novi.mo.it/aree-tematiche/urbanistica/669-piano-regolatore-generale

PSC Campogalliano. Piano Strutturale Comunale di Campogalliano. Available online at: https://www.comune.campogalliano.mo.it/servizi-al-cittadino/edilizia-sportello-unico-edilizia-sue/351-psc-poc-rue

PSC Soliera. Piano Strutturale Comunale di Soliera. Available online at: https://www.comune.soliera.mo.it/servizi-al-cittadino/sue/348-psc-poc-rue

PTCP Modena. Piano Territoriale di Coordinamento Provinciale di Modena. Available online at: http://www.sistemonet.it/sistemonet/viewSections-action.do?sectionId=6382

PUG TdA. Piano Urbanistico Generale Unione dei Comuni delle Terre d'Argine.

PUMS Carpi. Piano Urbano della Mobilità Sostenibile di Carpi. Available online at: https://www.comune.carpi.mo.it/aree-tematiche/trasporti-e-viabilita/13528-pums-carpi-piano-urbano-della-mobilita-sostenibile/84637-pums-carpi-piano-urbano-della-mobilita-sostenibile

QGIS. (2023). QGIS User Guide. Available online: https://docs.qgis.org/3.22/it/docs/user_manual/ (accessed on 10 November 2023).

Randall, M., Fensholt, R., Zhang, Y., & Bergen Jensen, M. (2019). Geographic object based image analysis of worldview-3 imagery for urban hydrologic modelling at the catchment scale. *Water*, *11*(6), 1133. https://doi.org/10.3390/w11061133

Randazzo, G., Italiano, F., Micallef, A., Tomasello, A., Cassetti, F. P., Zammit, A., ... & Muzirafuti, A. (2021). WebGIS Implementation for dynamic mapping and visualization of coastal geospatial data: A case study of BESS project. *Applied Sciences*, *11*(17), 8233. https://doi.org/10.3390/app11178233

Rizeei, H. M., Pradhan, B., & Saharkhiz, M. A. (2019). Allocation of emergency response centres in response to pluvial flooding-prone demand points using integrated multiple layer perceptron and maximum coverage location problem models. *International Journal of Disaster Risk Reduction*, *38*, 101205. https://doi.org/10.1016/j.ijdrr.2019.101205

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. In Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18 (pp. 234-241). Springer International Publishing.

Rosenblatt, F. (1958). The perceptron: A probabilistic model for information storage and organization in the brain. *Psychological Review*, *65*(6), 386. https://doi.org/10.1037/h0042519

Rosés, R., Kadar, C., & Malleson, N. (2021). A data-driven agent-based simulation to predict crime patterns in an urban environment. *Computers, Environment and Urban Systems*, *89*, 101660. https://doi.org/10.1016/j.compenvurbsys.2021.101660

Saaty, R. W. (1987). The analytic hierarchy process—what it is and how it is used. *Mathematical modelling*, *9*(3-5), 161-176. https://doi.org/10.1016/0270-0255(87)90473-8

Saaty, T. L. (2008). Decision making with the analytic hierarchy process. *International journal of services sciences*, *1*(1), 83-98. https://doi.org/10.1504/IJSSCI.2008.017590

Saaty, T. L., & Vargas, L. G. (1987). Uncertainty and rank order in the analytic hierarchy process. *European Journal of operational research*, *32*(1), 107-117. https://doi.org/10.1016/0377-2217(87)90275-X

Saha, A., Pal, S. C., Arabameri, A., Chowdhuri, I., Rezaie, F., Chakrabortty, R., Roy, P., & Shit, M. (2021). Optimization modelling to establish false measures implemented with ex-situ plant species to control gully erosion in a monsoon-dominated region with novel in-situ measurements. *Journal of Environmental Management*, *287*, 112284. https://doi.org/10.1016/j.jenvman.2021.112284

Saharkhiz, M. A., Pradhan, B., Rizeei, H. M., & Jung, H. S. (2020). Land Use Feature Extraction and Sprawl Development Prediction from Quickbird Satellite Imagery Using Dempster-Shafer and Land Transformation Model. *Korean Journal of Remote Sensing*, *36*(1), 15-27. https://doi.org/10.7780/kjrs.2020.36.1.2

Sameh, S., Zarzoura, F., & El-Mewafi, M. (2022). Automated Mapping of Urban Heat Island to Predict Land Surface Temperature and Land Use/Cover Change Using Machine Learning Algorithms: Mansoura City. *International Journal of Geoinformatics*, *18*(6). https://doi.org/10.52939/ijg.v18i6.2461

Sanchez, T. W., Shumway, H., Gordner, T., & Lim, T. (2023). The prospects of artificial intelligence in urban planning. *International Journal of Urban Sciences*, *27*(2), 179-194. https://doi.org/10.1080/12265934.2022.2102538

Scheider, S., & Richter, K. F. (2023). GeoAI. *KI-Künstliche Intelligenz*, *37,* 5-9. https://doi.org/10.1007/s13218-022-00797-z

Schwab, K. (2017). *The Fourth Industrial Revolution*. Currency. Available online: https://law.unimelb.edu.au/__data/assets/pdf_file/0005/3385454/Schwab-The_Fourth_Industrial_Revolution_Klaus_S.pdf (accessed on 12 November 2022).

Sejati, A. W., Buchori, I., Rudiarto, I., Silver, C., & Sulistyo, K. (2020). OPEN-SOURCE WEB GIS FRAMEWORK IN MONITORING URBAN LAND USE PLANNING: PARTICIPATORY SOLUTIONS FOR DEVELOPING COUNTRIES. *Journal of Urban & Regional Analysis*, *12*(1). https://doi.org/10.37043/JURA.2020.12.1.2

Semantic Segmentation Dataset. Available online: https://humansintheloop.org/semantic-segmentation-dataset/ (accessed on 10 January 2022).

Shafizadeh-Moghadam, H., Hagenauer, J., Farajzadeh, M., & Helbich, M. (2015). Performance analysis of radial basis function networks and multi-layer perceptron networks in modeling urban change: a case study. *International Journal of Geographical Information Science*, *29*(4), 606-623. https://doi.org/10.1080/13658816.2014.993989

Shao, Y., Yin, Y., Xue, Z., & Ma, D. (2023). Assessing and Comparing the Visual Comfort of Streets across Four Chinese Megacities Using AI-Based Image Analysis and the Perceptive Evaluation Method. *Land*, *12*(4), 834. https://doi.org/10.3390/land12040834

Shawul, A. A., & Chakma, S. (2019). Spatiotemporal detection of land use/land cover change in the large basin using integrated approaches of remote sensing and GIS in the Upper Awash basin, Ethiopia. *Environmental Earth Sciences*, *78*(5), 141. https://doi.org/10.1007/s12665-019-8154-y

Shi, L., Yang, S., & Gao, L. (2016). Effects of a compact city on urban resources and environment. *Journal of Urban Planning and Development*, *142*(4), 05016002. https://doi.org/10.1061/(ASCE)UP.1943-5444.0000324

Shryock, H. S. (2004). *The methods and materials of demography* (p. 693). D. Swanson, & J. S. Siegel (Eds.). California, USA: Elsevier Academic Press.

Silva, L. A., Sales Mendes, A., Sánchez San Blas, H., Caetano Bastos, L., Leopoldo Gonçalves, A., & Fabiano de Moraes, A. (2023). Active Actions in the Extraction of Urban Objects for Information Quality and Knowledge Recommendation with Machine Learning. *Sensors*, *23*(1), 138. https://doi.org/10.3390/s23010138

Simão, A., Densham, P. J., & Haklay, M. M. (2009). Web-based GIS for collaborative planning and public participation: An application to the strategic planning of wind farm sites. *Journal of Environmental Management*, *90*(6), 2027-2040. https://doi.org/10.1016/j.jenvman.2007.08.032

Simpson, J. R. (2002). Improved estimates of tree-shade effects on residential energy use. *Energy and Buildings*, *34*(10), 1067-1076. https://doi.org/10.1016/S0378-7788(02)00028-2

Singh, V. G., Singh, S. K., Kumar, N., & Singh, R. P. (2022). Simulation of land use/land cover change at a basin scale using satellite data and markov chain model. *Geocarto International*, *37*(26), 11339-11364. https://doi.org/10.1080/10106049.2022.2052976

Skokanová, H., González, I. L., & Slach, T. (2020). Mapping green infrastructure elements based on available data, a case study of the Czech Republic. *Journal of Landscape Ecology*, *13*(1), 85-103. https://doi.org/10.2478/jlecol-2020-0006

Son, T. H., Weedon, Z., Yigitcanlar, T., Sanchez, T., Corchado, J. M., & Mehmood, R. (2023). Algorithmic urban planning for smart and sustainable development: Systematic review of the literature. *Sustainable Cities and Society*, 104562. https://doi.org/10.1016/j.scs.2023.104562

Song, W., & Deng, X. (2017). Land-use/land-cover change and ecosystem service provision in China. *Science of the Total Environment*, *576*, 705-719. https://doi.org/10.1016/j.scitotenv.2016.07.078

Song, Y., & Knaap, G. J. (2004). Measuring urban form: Is Portland winning the war on sprawl?. *Journal of the American Planning Association*, *70*(2), 210-225. https://doi.org/10.1080/01944360408976371

Spasov, A., & Petrova-Antonova, D. (2021). Transferability assessment of open-source deep learning model for building detection on satellite data. In the Proceedings of the 16th GeoInfo Conference 2021, New York, NY, USA, 11–14 October 2021. https://doi.org/10.5194/isprs-archives-XLVI-4-W4-2021-107-2021

Srivastava, S., Vargas-Munoz, J. E., & Tuia, D. (2019). Understanding urban landuse from the above and ground perspectives: A deep learning, multimodal solution. *Remote Sensing of Environment*, *228*, 129-143. https://doi.org/10.1016/j.rse.2019.04.014

Stefanov, S. (2021). Visualization of Meteorological Data Sets With Open Source GIS. *International Journal of Computer Trends and Technology*, *69*(4), 15-17. https://doi.org/10.14445/22312803/IJCTT-V69I4P104

Sun, Q. C., Macleod, T., Both, A., Hurley, J., Butt, A., & Amati, M. (2021). A human-centred assessment framework to prioritise heat mitigation efforts for active travel at city scale. *Science of the Total Environment*, *763*, 143033. https://doi.org/10.1016/j.scitotenv.2020.143033

Sun, Y., Xie, S., & Zhao, S. (2019). Valuing urban green spaces in mitigating climate change: A city-wide estimate of aboveground carbon stored in urban green spaces of China's Capital. *Global change biology*, *25*(5), 1717-1732. https://doi.org/10.1111/gcb.14566

Tang, Z., Ye, Y., Jiang, Z., Fu, C., Huang, R., & Yao, D. (2020). A data-informed analytical approach to human-scale greenway planning: Integrating multi-sourced urban data with machine learning algorithms. *Urban Forestry & Urban Greening*, *56*, 126871. https://doi.org/10.1016/j.ufug.2020.126871

Tashakor, S., Chamani, A., & Moshtaghie, M. (2023). Noise pollution prediction and seasonal comparison in urban parks using a coupled GIS-artificial neural network model. *Environmental Monitoring and Assessment*, *195*(2), 303. https://doi.org/10.1007/s10661-022-10858-3

Técher, D., & Berthier, E. (2023). Supporting evidences for vegetation-enhanced stormwater infiltration in bioretention systems: a comprehensive review. *Environmental Science and Pollution Research*, *30*(8), 19705-19724. https://doi.org/10.1007/s11356-023-25333-w

TEEB. (2010). *The Economics of Ecosystems and Biodiversity: Mainstreaming the Economics of Nature: A Synthesis of the Approach, Conclusions and Recommendations of TEEB*. Progress Press.

Thayse, A., Gribomont, P., Louis, G., Snyers, D., Wodon, P., Gochet, P., Grégoire, E., Sanchez, E., & Delsarte, P. (1988). *Approche logique de l'intelligence artificielle*. Dunod Paris.

Thiebes, B., Bell, R., Glade, T., Jäger, S., Anderson, M., & Holcombe, L. (2013). A WebGIS decision-support system for slope stability based on limit-equilibrium modelling. *Engineering Geology*, *158*, 109-118. https://doi.org/10.1016/j.enggeo.2013.03.004

Thomas, L., & Cousins, W. (1996). The compact city: A successful, desirable and achievable urban form. *The compact city: a sustainable urban form*, 53-65.

Tian, Y., Jim, C. Y., & Wang, H. (2014). Assessing the landscape and ecological quality of urban green spaces in a compact city. *Landscape and urban planning*, *121*, 97-108. https://doi.org/10.1016/j.landurbplan.2013.10.001

Tzoulas, K., Korpela, K., Venn, S., Yli-Pelkonen, V., Kaźmierczak, A., Niemela, J., & James, P. (2007). Promoting ecosystem and human health in urban areas using Green Infrastructure: A literature review. *Landscape and urban planning*, *81*(3), 167-178. https://doi.org/10.1016/j.landurbplan.2007.02.001

Uhel, R., Spyropoulou, R., Breton, F., Beltrame, C., Arévalo, J., Richard, D., ... & Marin, E. (2010). Ecosystem accounting and the cost of biodiversity losses: the case of coastal Mediterranean wetlands. *European Environment Agency. Copenhagen*.

United Nations. (2015). The 2030 Agenda for Sustainable Development, Department of Economic and Social Affairs, Sustainable Development.

United Nations. (2015). *The 2030 Agenda for Sustainable Development*. United Nations.

United Nations. (2019). World Urbanization Prospects: The 2018 Revision; Technical Report; ST/ESA/SER.A/420. United Nations, New York, USA.

Ustaoglu, E., & Aydınoglu, A. C. (2020). Site suitability analysis for green space development of Pendik district (Turkey). *Urban Forestry & Urban Greening*, *47*, 126542. https://doi.org/10.1016/j.ufug.2019.126542

Uy, P. D., & Nakagoshi, N. (2008). Application of land suitability analysis and landscape ecology to urban greenspace planning in Hanoi, Vietnam. *Urban Forestry & Urban Greening*, *7*(1), 25-40. https://doi.org/10.1016/j.ufug.2007.09.002

Vacca, G., Fiorino, D. R., & Pili, D. (2017). A webgis for the knowledge and conservation of the historical buildings in Sardinia (Italy). *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *42*(4W2), 171-178. https://doi.org/10.5194/isprs-archives-XLII-4-W2-171-2017

Van den Broeck, W. A., & Goedemé, T. (2022). Combining Deep Semantic Edge and Object Segmentation for Large-Scale Roof-Part Polygon Extraction from Ultrahigh-Resolution Aerial Imagery. *Remote Sensing*, *14*(19), 4722. https://doi.org/10.3390/rs14194722

Vignoli, F., de Luca, C., & Tondelli, S. (2021). A spatial ecosystem services assessment to support decision and policy making: The case of the city of Bologna. *Sustainability*, *13*(5), 2787. https://doi.org/10.3390/su13052787

Voulodimos, A., Doulamis, N., Doulamis, A., & Protopapadakis, E. (2018). Deep Learning for Computer Vision: A Brief Review. *Computational Intelligence and Neuroscience*, *2018*. https://doi.org/10.1155/2018/7068349

Wang, L., Pijanowski, B., Yang, W., Zhai, R., Omrani, H., & Li, K. (2018). Predicting multiple land use transitions under rapid urbanization and implications for land management and urban planning: The case of Zhanggong District in central China. *Habitat International*, *82*, 48-61. https://doi.org/10.1016/j.habitatint.2018.08.007

Wang, S. C. (2003). *Interdisciplinary computing in Java programming* (Vol. 743). Springer Science & Business Media: New York.

Wang, S., Ma, H., & Zhao, Y. (2014). Exploring the relationship between urbanization and the eco-environment—A case study of Beijing–Tianjin–Hebei region. *Ecological Indicators*, *45*, 171-183. https://doi.org/10.1016/j.ecolind.2014.04.006

Wang, SC. (2003). Artificial Neural Network. In S-C. Wang (Eds.), *Interdisciplinary Computing in Java Programming* (pp. 81-100). The Springer International Series in Engineering and Computer Science, vol 743. Springer, Boston, MA. https://doi.org/10.1007/978-1-4615-0377-4_5

Wang, Y., Sun, D., Wen, H., Zhang, H., & Zhang, F. (2020). Comparison of random forest model and frequency ratio model for landslide susceptibility mapping (LSM) in Yunyang County (Chongqing, China). *International Journal of Environmental Research and Public Health*, *17*(12), 4206. https://doi.org/10.3390/ijerph17124206

Wei, Y. Q., Yang, R. H., & Liu, P. Y. (2009, August). An improved Apriori algorithm for association rules of mining. In *2009 IEEE International Symposium on IT in Medicine & Education* (Vol. 1, pp. 942-946). https://doi.org/10.1109/ITIME.2009.5236211

Wellmann, T., Lausch, A., Andersson, E., Knapp, S., Cortinovis, C., Jache, J., ... & Haase, D. (2020). Remote sensing in urban planning: Contributions towards ecologically sound policies?. *Landscape and urban planning*, *204*, 103921. https://doi.org/10.1016/j.landurbplan.2020.103921

Wellmann, T., Schug, F., Haase, D., Pflugmacher, D., & van der Linden, S. (2020). Green growth? On the relation between population density, land use and vegetation cover fractions in a city using a 30-years Landsat time series. *Landscape and Urban Planning*, *202*, 103857. https://doi.org/10.1016/j.landurbplan.2020.103857

Westerink, J., Haase, D., Bauer, A., Ravetz, J., Jarrige, F., & Aalbers, C. (2012). Expressions of the compact city paradigm in peri-urban planning across European city regions–how do planners deal with sustainability trade-offs. *European Planning Studies*, *25*, 1-25.

Williams, K., Burton, E., & Jenks, M. (1996). Achieving the compact city through intensification: An acceptable option. *The compact city: A sustainable urban form*, 83-96.

Woldesemayat, E. M., & Genovese, P. V. (2021). Monitoring urban expansion and urban green spaces change in addis ababa: Directional and zonal analysis integrated with landscape expansion index. *Forests*, 12(4), 389. https://doi.org/10.3390/f12040389

Wolff, M., & Haase, D. (2019). Mediating sustainability and liveability—turning points of green space supply in European cities. *Frontiers in Environmental Science*, *7*, 61. https://doi.org/10.3389/fenvs.2019.00061

World Commission on Environment and Development. (1987). *Our common future*, *17*(1), 1-91.

World Health Organization. (2016). *Urban green spaces and health* (No. WHO/EURO: 2016-3352-43111-60341). World Health Organization. Regional Office for Europe.

World Health Organization. (2016). Urban green spaces and health: A review of evidence. *World Health Organization: Copenhagen, Denmark*.

Wu, B., Yu, B., Shu, S., Liang, H., Zhao, Y., & Wu, J. (2021). Mapping fine-scale visual quality distribution inside urban streets using mobile LiDAR data. *Building and Environment*, *206*, 108323. https://doi.org/10.1016/j.buildenv.2021.108323

Wu, N., & Silva, E. A. (2010). Artificial intelligence solutions for urban land dynamics: a review. *Journal of Planning Literature*, *24*(3), 246-265. https://doi.org/10.1177/0885412210361571

Xu, N., Luo, J., Zuo, J., Hu, X., Dong, J., Wu, T., ... & Liu, H. (2020). Accurate suitability evaluation of large-scale roof greening based on RS and GIS methods. *Sustainability*, *12*(11), 4375. https://doi.org/10.3390/su12114375

Yagoub, M. M., Tesfaldet, Y. T., Elmubarak, M. G., & Al Hosani, N. (2022). Extraction of Urban Quality of Life Indicators Using Remote Sensing and Machine Learning: The Case of Al Ain City, United Arab Emirates (UAE). *ISPRS International Journal of Geo-Information*, *11*(9), 458. https://doi.org/10.3390/ijgi11090458

Yang, S., Xiao, W., Zhang, M., Guo, S., Zhao, J., & Shen, F. (2022) Image Data Augmentation for Deep Learning: A Survey. *Proceedings of the Computer Vision and Pattern Recognition Conference (CVPR)*, New Orleans, Louisiana, 19-24 June 2022. https://doi.org/10.1109/TPAMI.2021.3059968

Yigitcanlar, T., Desouza, K. C., Butler, L., & Roozkhosh, F. (2020). Contributions and risks of artificial intelligence (AI) in building smarter cities: Insights from a systematic review of the literature. *Energies*, *13*(6), 1473. https://doi.org/10.3390/en13061473

Yu, H., Song, G., Li, T., & Liu, Y. (2020). Spatial pattern characteristics and influencing factors of green use efficiency of urban construction land in Jilin province. *Complexity*, *2020*, 1-12. https://doi.org/10.1155/2020/5637530

Zhang, H., Jin, X., Wang, L., Zhou, Y., & Shu, B. (2015). Multi-agent based modeling of spatiotemporal dynamical urban growth in developing countries: simulating future scenarios of Lianyungang city, China. *Stochastic Environmental Research and Risk Assessment*, *29*, 63-78. https://doi.org/10.1007/s00477-014-0942-z

Zhang, R., Tang, C., Ma, S., Yuan, H., Gao, L., & Fan, W. (2011). Using Markov chains to analyze changes in wetland trends in arid Yinchuan Plain, China. *Mathematical and Computer Modelling*, *54*(3-4), 924-930. https://doi.org/10.1016/j.mcm.2010.11.017

Zhang, Z., Hörmann, G., Huang, J., & Fohrer, N. (2023). A Random Forest-Based CA-Markov Model to Examine the Dynamics of Land Use/Cover Change Aided with Remote Sensing and GIS. *Remote Sensing*, *15*(8), 2128. https://doi.org/10.3390/rs15082128

Zhou, X., & Wang, Y. C. (2011). Spatial–temporal dynamics of urban green space in response to rapid urbanization and greening policies. *Landscape and urban planning*, *100*(3), 268-277. https://doi.org/10.1016/j.landurbplan.2010.12.013

Zhou, Y., Yue, D., Liang, G., Li, S., Zhao, Y., Chao, Z., & Meng, X. (2022). Risk assessment of debris flow in a mountain-basin area, western China. *Remote Sensing*, *14*(12), 2942. https://doi.org/10.3390/rs14122942

Zhu, S., Yang, Y., Yan, Y., Causone, F., Jin, X., Zhou, X., & Shi, X. (2022). An evidence-based framework for designing urban green infrastructure morphology to reduce urban building energy use in a hot-humid climate. *Building and Environment*, *219*, 109181. https://doi.org/10.1016/j.buildenv.2022.109181

Zlatkovic, M., Zlatkovic, S., Sullivan, T., Bjornstad, J., & Shahandashti, S. K. F. (2019). Assessment of effects of street connectivity on traffic performance and sustainability within communities and neighborhoods through traffic simulation. *Sustainable Cities and Society*, *46*, 101409. https://doi.org/10.1016/j.scs.2018.12.037

Zulian, G., Marando, F., Mentaschi, L., Alzetta, C., Wilk, B., & Maes, J. (2022). Green balance in urban areas as an indicator for policy support: a multi-level application. *One Ecosystem*, *7*, 1-39. https://dx.doi.org/10.3897/oneeco.7.e72685

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