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Landscape Impacts of Renewable Energy Systems on Ecosystem Services: An Integrated Assessment Framework for Sustainable Spatial Planning in Basilicata, Southern Italy.
A Multi-Method Approach Combining Expert Knowledge, GIS-Based Multi-Criteria Analysis, and Unsupervised Machine Learning.

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Nel nome della vita e della saggezza,

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With heartfelt greetings to the gentle and cultured land of Italy, which welcomed me as a guest, became my home, and gave love a whole new meaning in my life.

I dedicate the results of this scientific journey to all the brave and devoted souls of Iran. To the courageous men, women, and children who would not endure humiliation against the human spirit, who took to the streets for freedom, fought oppression with empty hands, and became immortal.

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به نام خداوند جان و خرد،

به خاک مقدس میسم، ایران، دود می فرستم؛ سرزمینی که مرا در آغوش مهربان و نجیب خود پرورش داد و خواندن، نوشتن و زیستن را به من آموخت.

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ثمره ی این مسیر علمی را به تمامی جان های شجاع و وفادار ایران تقدیم می کنم؛

به مردان، زنان و کودکانی که در برابر تحقیر روح انسانی سر فرود نیاوردند، برای آزادی به خیابان ها آمدند، با دستانی خالی در برابر ظلم ایستادند و با شجاعت خود جاودانه شدند.

پیمودن این راه دشوار و پر آشوب، بدون مادر ممکن نبود؛ زنی که معنای حقیقی استقامت را به من آموخت. مادر عزیزم، تو باید امروز در کنارم می بودی، اما تقدیر و مرزها ما را از هم جدا کردند. با این حال بدان که بدون عشق تو، هیچ چیز ممکن نبود. امروز بیش از هر زمان دیگری حضور تو را در کنار خود احساس می کنم و دختر کوچک تو اگر افتخاری کسب می کند، می خواهم بدانی که همه ی اعتبار آن را مدیون تو ست.

پدر عزیزم، سپاس من از تو بی پایان است. دستان پرتلاش و صبوری بی اندازه ی تو، راهی را برایم ترسیم کرد و به من جسارت بخشید که بتوانم به سمت آرزوهایم گام بردارم. تو به من آموختی چگونه صبور باشم و با سختی با مدارا کنم. پدر بودن در سرزمین ما از دشوارترین مسئولیت هاست، و تو آن را با مهربانی و بردباری بی نهایت به دوش کشیدی. برای هر گامی که برداشته ام و خواهم برداشت، همواره وادار تو هستم. ای کاش امروز در کنارم بودی و این شادی را با هم تقسیم می کردیم.

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به آنای عزیزم، زنی والا و آموزگاری دلسوز، که با از خودگذشتگی مرا همراهی کرد. از او نه تنها شیرینی زبان ایتالیایی، بلکه معنای حقیقی انسانیت را آموختم. آشنایی با او به من توان ادامه دادن و پیوند با دیگران را بخشید. رد مهربانی‌اش تا همیشه در وجودم باقی خواهد ماند.

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از استاد راهبنای گرامی‌ام، پروفیسور بنیامینو مورگانته، صمیمانه سپاسگزارم؛ برای راهبنایی‌های ارزشمند و سخاوتمندانه‌اش. حمایت و دانش او چراغ راه این مسیر علمی بود و شاگردی ایشان برای من همواره یکی از بزرگ‌ترین افتخارات علمی‌ام خواهد بود.

همچنین از استاد گرامی، پروفیسور فرانچسکو اسکورزا، برای حمایت‌ها و دانشی که با من به اشتراک گذاشتند، صمیمانه قدردانی می‌کنم. راهبنایی‌های ایشان نقشی کلیدی در گشودن مسیر پیشرفت علمی و حرفه‌ای من داشت.

و در پایان تشکر می‌کنم از تمام دوستان، همکاران و اساتیدی که در این سفر مرا بزرگوارانه همراهی کردند و به من فرصت دادند در کنار آن‌ها رشد کنم و از آن‌ها بیاموزم.

در پایان، از خودم بابت قدرت، پشتکار و اراده‌ای که مرا تا رسیدن به این نقطه همراهی کردند، سپاسگزارم. با وجود دشواری‌ها و لحظات تردید و نااطمینانی، هرگز از باور به ارزش این مسیر دست نکشیدم. این پایان‌نامه حاصل تلاش، رشد فردی و توانایی من در ادامه دادن مسیر با شجاعت و تعهد است.

بهار دوهزار دویست بیست و شش میلادی، پوتنزا، ایتالیا

Executive Summary

The global transition toward renewable energy systems (RES) has become a central pillar of climate change mitigation and sustainable development strategies. Driven by international agreements, European climate policies, and national energy targets, the deployment of renewable energy technologies such as wind and solar power is accelerating worldwide. While these technologies play a critical role in reducing greenhouse gas emissions and enhancing energy security, their rapid expansion is increasingly transforming landscapes and generating new environmental, ecological, and social challenges. Renewable energy infrastructure requires substantial land resources and may affect ecosystem services, biodiversity, agricultural productivity, visual landscape quality, and public acceptance. Consequently, there is an urgent need for integrated assessment approaches capable of supporting sustainable energy planning while minimizing unintended environmental impacts.

This dissertation addresses this challenge by developing an integrated assessment framework for evaluating the interactions between renewable energy systems and ecosystem services within the context of landscape planning and territorial decision-making. The research focuses on the Basilicata region in Southern Italy, a territory characterized by significant renewable energy development, valuable natural and cultural landscapes, and increasing pressures associated with the energy transition. The overarching aim of the study is to support sustainable spatial planning by improving the understanding of how renewable energy systems influence landscape dynamics and ecosystem service provision.

The research is guided by three main questions: (i) which spatial, environmental, and social indicators are most suitable for investigating the relationship between renewable energy systems and ecosystem services; (ii) which tools and methods are most effective for assessing the impacts of renewable energy development on landscapes and ecosystem services; and (iii) how these tools can be integrated into a comprehensive framework capable of supporting evidence-based planning and decision-making.

To address these questions, the dissertation adopts a multi-method approach that combines expert knowledge, GIS-based spatial analysis, multi-criteria decision-making techniques, ecosystem service assessment models, and unsupervised machine learning. The proposed framework integrates both human and ecological dimensions through a set of complementary indicators. The geospatial dimension evaluates landscape fragmentation, scenic quality, and renewable energy visibility, while the ecosystem service dimension examines habitat quality, carbon storage, crop production, and crop pollination. Together, these indicators provide a comprehensive assessment of landscape sustainability in areas affected by renewable energy development.

The first component of the research investigates the aesthetic and visual impacts of wind energy installations. Using expert-based evaluation methods and the Scenic Quality model implemented within the InVEST software, the study assesses the influence of existing and planned wind turbines on landscape value in a highly developed area of Basilicata. The results demonstrate that future wind energy expansion is likely to increase the proportion of landscapes experiencing high and very high visual impacts. The findings highlight the importance of incorporating visual quality and social perception into environmental assessments and confirm the continued relevance of local expert knowledge in evaluating landscape change.

The second component focuses on the spatial planning of green hydrogen infrastructure. As green hydrogen emerges as a strategic technology for industrial decarbonization, the research applies GIS-based Spatial Multi-Criteria Analysis integrated with the Analytic Hierarchy Process (AHP) to identify suitable locations for hydrogen production, storage, and distribution facilities. The methodology is tested through a real-world case study involving an energy-intensive steel industry in Basilicata. By integrating technical, environmental, economic, and social criteria into a transparent decision-support framework, the study demonstrates how spatial analysis can guide sustainable infrastructure planning while reducing environmental conflicts and maximizing operational efficiency.

The third component represents the methodological synthesis of the dissertation. Building upon the expert-based approaches developed in the previous chapters, this research integrates unsupervised machine learning through Self-Organizing Maps (SOM) to reduce subjectivity and enhance analytical robustness. The study combines spatial indicators related to renewable energy infrastructure with ecosystem service indicators to evaluate sustainability patterns across the Basilicata region. By comparing expert-weighted assessments with data-driven classifications, the analysis identifies distinct landscape typologies characterized by varying levels of ecological sensitivity, agricultural productivity, and renewable energy pressure. The results demonstrate that expert-based and machine-learning approaches are highly complementary, providing consistent spatial patterns while revealing additional relationships that may not be apparent through expert judgment alone.

The principal contribution of this dissertation lies in the development of an integrated and transferable framework that bridges the gap between traditional expert-based assessment and emerging data-driven methodologies. Rather than treating these approaches as competing paradigms, the research demonstrates their complementary value in addressing the complexity of renewable energy planning. The framework provides decision-makers with practical tools for evaluating trade-offs between renewable energy expansion and ecosystem

service conservation, while supporting transparent, reproducible, and evidence-based planning processes.

Beyond its methodological contributions, the dissertation advances the broader understanding of landscape sustainability within the energy transition. The findings emphasize that renewable energy planning should not be evaluated solely through technical or economic criteria but must also consider ecological integrity, cultural landscape values, and ecosystem service preservation. By integrating these dimensions into a unified assessment framework, the research contributes to the development of more balanced and sustainable approaches to territorial planning.

Although the study is grounded in the specific context of Basilicata, the proposed framework is sufficiently flexible to be adapted to other regions experiencing similar energy transition challenges. The research therefore provides both a regional contribution to sustainable planning in Southern Italy and a broader methodological contribution to international discussions on renewable energy, ecosystem services, and landscape governance.

Contents

1. Introduction.....	15
1.1. Global context: Energy transition and land-use change	15
1.2. Landscape-scale assessment and decision-support systems	20
1.3. Ecosystem services as a framework for sustainability assessment	21
1.4. Expert-based approaches in environmental planning	21
1.5. Data-driven and machine-learning approaches for spatial analysis.....	22
2. Research goal and questions.....	24
3. Structure of the Thesis	25
4. List of Publications	27
CHAPTER 2.....	29
Predicting the Aesthetic Impact of Wind Turbines and Their Influence on Landscape Value	30
2.1. Introduction	31
2.2. Methodology	33
2.2.1. Input Data.....	34
2.2.2. Literature Review.....	35
Expert Involvement in Landscape Assessment	35
2.2.3. Case study	38
2.2.4. Definition of the Visual Impact Area	39
VP calculation	40
VI calculation	45
2.3. Result	48
2.4. Conclusion and discussion.....	49
CHAPTER 3.....	51
Spatial multi-criteria Analysis for identifying suitable locations for Green Hydrogen Infrastructure: a case study of an Energy-Intensive Industry	52
3.1. Introduction	53
3.1.1. Literature review.....	56
Green hydrogen technology	58

3.2. Methodology	59
3.2.1. Analytic Hierarchy Process	61
3.2.2. Spatial Multi-Criteria Analysis	64
Definition of criteria and sub-criteria.....	65
Constraining criteria	65
Weighted criteria	66
Slope.....	71
Solar radiation.....	71
Road accessibility	72
Accessibility to industry	73
Distance of RES.....	73
Distance of GAS Pipelines	73
Land use.....	74
3.2.3. Case studies.....	74
Application of the methodology for the “Siderpotenza” steel plant.....	74
Stability of Criterion Rankings.....	76
One-at-a-Time Sensitivity and Tornado Analysis	77
3.2.4. Elaboration of criteria maps	78
3.2.5. Land suitability map	86
3.2.6. Elaboration of three alternative scenarios	88
3.3. Discussion.....	94
3.4. Conclusion	96
CHAPTER 4.....	98
Renewable Energy Sustainability Assessment in Basilicata: From Expert-Based to Data-Driven Approach	99
4.1. Introduction	100
4.1.1. Expert Knowledge and Data-Driven Methods in Landscape-Scale Renewable Energy Impact Assessment	101
4.1.2. The main objective of the present study	103
4.2. Material and Method	104

4.2.1. Study Area	104
4.2.2. Methodological framework	107
4.2.3. Geo-spatial indicators	108
Sprinkling Index	109
Visual index	110
4.2.4. Ecosystem-services indicators	110
Land Cover Future Predictions	111
Habitat quality	112
Carbon Storage	113
Crop pollination	113
Crop production	113
4.2.5. Self-Organizing Maps	114
4.3. Results	115
4.3.1. Relative impact of the indicators	115
4.3.2. Spatial characteristics and ecological implications of RES deployments	126
Expert-based scenarios	127
Data-driven clusters	128
4.4. Discussions	132
4.5. Conclusion	133
CHAPTER 5	135
Conclusion	135
References	145
List of Figures	155
List of Tables	156
Appendix	158

1. Introduction

Energy has always been one of the fundamental needs of human beings. Natural energy sources, now commonly referred to as renewable resources, have long existed and therefore do not represent a recent phenomenon. The use of renewable energy dates back to early human history, particularly to the discovery and controlled use of fire. In contemporary terms, the energy obtained from burning dried plants and wood is classified as bioenergy. The ability to harness this form of energy represented a significant milestone in human development, providing warmth and light, protection from predators, and the ability to cook food, all of which contributed to major transformations in human societies.

There are numerous historical examples of the use of natural energy sources. One notable illustration is the so-called heat ray attributed to Archimedes. A wall painting in the Stanza delle Matematiche of the Uffizi Gallery depicts the Greek mathematician Archimedes using mirrors to concentrate solar radiation to burn Roman military ships. The artwork, painted around 1600, reflects the long-standing interest in harnessing natural forces such as solar energy. The earliest recorded uses of wind power date to around 3200 BC, when ancient Egyptians utilized wind energy to navigate sailing vessels along the Nile River. By approximately 200 BC, simple wind-powered devices were employed for water pumping in regions of China and the Middle East, representing some of the earliest technological applications of wind as a source of mechanical energy. In antiquity, the Ancient Romans used solar and geothermal heat to warm buildings and public baths. The Ancient Greeks developed some of the earliest waterwheels, harnessing hydropower to grind wheat into flour, and the windcatcher in Persian architecture is a traditional architectural element used to create cross ventilation and passive cooling in buildings.

However, the naming of these energies and their growing importance became clearer to us when we realized that we could harness them on a large scale and use them whenever we needed.

1.1. Global context: Energy transition and land-use change

The emergence of renewable energy sources in the modern era represents a clear response to climate change challenges and energy security concerns (Bashir et al., 2025). The concept of energy security emerged in response to the energy price shocks of the 1970s and has since evolved to encompass a broader range of concerns, including emerging energy-related risks and the assessment of energy affordability, accessibility, and consumption patterns. According to the International Energy Agency (IEA), energy security is defined as “the uninterrupted availability of energy at an affordable price” (Cherp and Jewell, 2014). Academic attention to energy security declined in the late 1980s and 1990s following oil price stabilization and a reduced risk of political embargoes. The topic regained prominence in the 2000s amid rising

energy demand in Asia, recurring gas supply disruptions in Europe, and mounting policy pressure to decarbonize energy systems (Hancock and Vivoda, 2014). However, there is an important difference between the classic and modern definitions of energy security. Although in the 1970s and 1980s, the concept of energy security centered on ensuring a stable supply of inexpensive oil against the backdrop of embargo risks and price manipulation by oil-exporting nations (E W Colglazier Jr and Deese, 1983), In contrast, recently energy security has evolved to become closely linked with broader energy policy challenges, including equitable access to modern energy and climate change mitigation (Goldthau, 2011).

The importance of RES became increasingly evident following the oil shocks in 1970, which highlighted the vulnerabilities of dependence on fossil fuels. In particular, the 1973–74 OPEC oil shock sharply increased energy costs, triggered global inflation, and led to a severe economic recession, while also causing a long-term reduction in measured productive capacity (Louis, 1977). COP 3, which was held in Kyoto in 1997, resulted in the Kyoto Protocol, the first international treaty to establish binding greenhouse gas (GHG) reduction targets for industrialized countries. The agreement introduced flexible, market-based mechanisms and committed signatories to a 5% reduction in emissions relative to 1990 levels for the period 2008–2012 (Gerden, 2018). In 2001, one of the earliest European Union directives aimed at promoting electricity generation from renewable energy sources across the internal energy market established indicative national targets for member states (*Directive 2001/77/EC of the European Parliament and of the Council of 27 September 2001 on the promotion of electricity produced from renewable energy sources in the internal electricity market*, 2001)

Later, the Paris Agreement, adopted at COP21 in 2015, is widely regarded as a turning point in global climate governance. It established the first near-universal climate agreement, under which almost all countries committed to actions aimed at limiting global warming while also linking climate policy with broader objectives related to development and poverty reduction. The agreement established a long-term temperature objective of keeping global warming well below 2 °C above pre-industrial levels while pursuing efforts to limit it to 1.5 °C. It also called for a global peak in greenhouse gas emissions as soon as possible and the achievement of net-zero emissions in the second half of the century (Kinley, 2017).

The year 2019 represents another key milestone, marked by the introduction of the European Green Deal. This initiative comprises a comprehensive set of policy measures designed to place the European Union on a pathway toward a green transition, with the overarching objective of achieving climate neutrality by 2050. The vision underpinning the European Green Deal includes transforming the EU into the first climate-neutral region globally, while reducing pollution and restoring a balanced and resilient relationship with natural systems and ecosystems (*COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT*,

THE EUROPEAN COUNCIL, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS A Green Deal Industrial Plan for the Net-Zero Age, 2023). In the following year (2020), to ensure that offshore renewable energy can help reach the EU's ambitious energy and climate targets for 2030 and 2050, the Commission published a dedicated EU strategy on offshore renewable (COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS *An EU Strategy to harness the potential of offshore renewable energy for a climate neutral future*, 2020). Later in May 2022, in response to disruptions in global energy markets following the Russian invasion of Ukraine, the European Commission introduced the REPowerEU plan to progressively reduce and ultimately eliminate dependence on fossil fuel imports from Russia (COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE EUROPEAN COUNCIL, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS *REPowerEU Plan*, 2022). Finally, Italy submitted its updated National Energy and Climate Plan (PNIEC) for the 2021–2030 period to the European Commission on 1 July 2024. The plan sets a target of 39.4% of total energy consumption from renewable sources, including 63.4% in the electricity sector, by 2030, reflecting a transition pathway centered on the expansion of solar and wind energy alongside infrastructure development (“Commission Assessment of the Final Updated National Energy and Climate Plan of Italy - European Commission,” 2024)

Over recent decades, the European Union has implemented robust climate policies, leading to a reduction of more than 37% in greenhouse gas emissions by 2023 relative to 1990 levels. This decline has been driven primarily by the expanded deployment of renewable energy and a reduced reliance on carbon-intensive fossil fuels (Shukla et al., 2022). Still, several questions remain unresolved, including whether the expansion of renewable energy contributes effectively to energy security and why, despite years of implementing renewable energy strategies, the European Union has not fully achieved its stated objectives.

Despite the potential of renewable energy technologies, projects frequently encounter significant challenges across their life cycles. Failures may arise during the planning, design, construction, operation, or decommissioning phases. In many cases, the underlying causes are multifactorial, encompassing technical deficiencies, financial miscalculations, regulatory misalignment, and organizational weaknesses. A systematic examination of these failures is essential to inform improved project design, implementation, and long-term performance. Failures in renewable energy systems can be classified into several interconnected categories. Technical failures involve hardware or software malfunctions that reduce system functionality, cause unscheduled downtime, or lead to catastrophic breakdowns. Economic failures occur when projects fail to achieve financial sustainability due to poor economic modeling, cost

overruns, or the withdrawal of subsidies. Regulatory and permitting failures arise when projects are delayed, hindered, or canceled because of conflicts with environmental regulations, zoning restrictions, or strong community opposition. Management and human factor failures stem from poor decision-making, inadequate oversight, or organizational fragmentation that undermines project implementation. Finally, environmental and geotechnical failures result from inappropriate site selection, exposure to natural hazards, or climate-related stressors that compromise the long-term viability of renewable energy installations.

All of these challenges arise because the effectiveness of such policies depends on coordinated action, technological progress, and careful attention to socio-economic conditions, while low-income countries continue to face persistent barriers to capturing these benefits (Elkhatat and Al-Muhtaseb, 2024)

Additional challenges emerge as RES technologies drive transformations in land use and territorial organization. Research indicates that although the current land footprint of energy systems is relatively limited, future low-carbon energy infrastructures could substantially reshape landscapes, particularly as global energy demand is expected to double by 2050 and electrification extends across multiple sectors (Scheidel and Sorman, 2012). The land-use impacts of the energy transition are strongly dependent on the context. Evidence from case studies in Vietnam, New Zealand, and Finland demonstrates that national energy strategies frequently insufficiently account for spatial constraints and land availability, thereby increasing the risk of conflicts and inefficiencies. In densely populated or agriculturally intensive regions, including India and parts of Europe, the expansion of renewable energy can intensify competition for land and enhance social tensions (Tran and Egermann, 2022)(Kiesecker et al., 2023) . In the following part, there is some evidence that shows how RES installations have changed the use of land in European countries.

In the Region of Murcia, which is located in Spain, more than 5,300 renewable energy facilities are currently in operation, the majority of which are solar photovoltaic installations. Notably, 12 out of the 45 municipalities account for over two-thirds of these facilities (71.53%) and a comparable share of the total installed capacity (77.57%), indicating a marked spatial concentration of renewable energy development. The expansion of solar photovoltaic projects in the Region of Murcia has led to significant land-use changes, contributing to the emergence of new landscape configurations. These developments are primarily located on former rain-fed herbaceous and woody croplands (60%), as well as on scrubland, esparto grasslands, and marginal lands (30%), and to a lesser extent on irrigated horticultural areas and both citrus and non-citrus orchards (10%). Such projects tend to prioritize proximity to major transportation routes and access to the electricity grid, thereby reshaping the structure and visual character of rural landscapes (Martínez-Medina et al., 2025).

In Italy, only a few studies have proposed an actual measure of the land consumed by renewable energies. (Ferrari et al., 2021) proposed a study to determine the soil footprint of agricultural anaerobic digestion plants in Italy based on aerial imagery. In the referenced study, the soil footprint was defined as the total area occupied by the anaerobic digestion facility, including the footprint of plant structures (e.g., anaerobic digesters and cogeneration units), newly constructed access roads, and additional operational areas such as manoeuvring spaces. The result of the work that is done by (Cogato et al., 2023a), shows that 75.8% of photovoltaic installations were located on previously cultivated agricultural land, predominantly arable fields. A further 12.1% were established on areas formerly used as permanent meadows, while 3% were situated on land previously covered by natural forests. The remaining 9.1% were installed on land classified under other categories. Before the development of photovoltaic systems, many of these sites were uncultivated, including abandoned or unused land or areas already occupied by other infrastructure. For instance, one installation was located within the premises of a hydroelectric facility. The second analysis examined the extent of additional land required for permanent infrastructure, such as roads and buildings. The results indicate that 34.8% of the new photovoltaic systems required the construction of new infrastructure, including access roads, operational areas, and built structures. A further 26.1% involved the development of new road networks without additional buildings, while 39.1% did not require any new infrastructure.

In the Ostrobothnia region in Finland, wind farms are predominantly located in forested areas (81%) and transitional woodland (11%), resulting in deforestation rates approximately six times higher than those observed in control areas. Moreover, micro-siting practices often fail to avoid mature forest stands. These findings indicate that the deployment of wind energy in forested areas leads to deforestation levels significantly exceeding background levels associated with conventional construction activities. Habitat loss attributable to infrastructure ranged from 1.4% to 6.0% of the project area, while the extent of road networks varied substantially (1–67 km). Despite this variability, habitat fragmentation remained relatively consistent across sites, with an average distance of 202 m between locations without infrastructure and the nearest point of disturbance (Balotari-Chiebáo and Byholm, 2024). In Germany and Austria, wind energy development is predominantly concentrated on agricultural land (up to 86%). However, forested areas are increasingly being targeted as suitable sites become more limited (Franz and Dumke, 2025). In the United Kingdom, solar farms currently occupy approximately 0.06–0.07% of the total land area, predominantly converted from arable land or improved grassland. Projections suggest that this share could increase to around 0.72% by 2050 under ambitious deployment scenarios (Blaydes et al., 2025). In Eastern Europe, the case of Poland illustrates that, although national-scale impacts remain relatively limited (with land occupation below 2%), local-scale transformations can be substantial where utility-scale photovoltaic

installations replace arable land. In such contexts, reductions in wheat yields per megawatt of installed capacity have been documented (Pelczar, 2025).

1.2. Landscape-scale assessment and decision-support systems

Due to the complexity and uncertainty of the issues that are mentioned in the previous parts, the focus must be on the assessment phase and improving the decision support system (DSS) by guiding smarter and more sustainable planning decisions. Firstly, DSS can identify optimal locations for renewable energy installations by integrating multiple spatial and non-spatial datasets, including land-use and land-cover maps to assess suitability and availability of space, environmental constraints such as protected areas and biodiversity hotspots to avoid ecological conflicts, socio-economic factors like agricultural value and proximity to settlements to minimize social and economic impacts, and technical potential indicators such as solar radiation, wind speed, and access to the power grid to ensure efficient and feasible energy production (Barzehkar et al., 2021). Furthermore, DSS enables planners to conduct scenario analysis by testing various “what-if” situations before implementation, such as comparing different layouts or capacities of wind and solar projects, evaluating centralized versus distributed energy installations, and assessing rooftop or brownfield development against greenfield sites. By analyzing and comparing the outcomes of these scenarios, decision-makers can identify options that minimize land-use change, reduce environmental and social conflicts, and support more sustainable planning decisions (Kazak et al., 2021). Additionally, DSS-based assessments can support multifunctional land use by promoting co-existence strategies that integrate renewable energy development with existing land functions. Such strategies include agrivoltaic systems that combine solar energy production with agricultural activities, wind energy installations located within already industrialized areas or along infrastructure corridors, and solar projects developed on degraded or abandoned land. By prioritizing these approaches, DSS can reduce the need for additional land conversion while enhancing both energy generation and overall land-use efficiency (Garegnani et al., 2015).

When used together, Decision Support Systems (DSS) and landscape assessment form a strong preventive planning framework that helps guide sustainable land-use decisions. Early spatial screening through DSS reduces the risk of unplanned land conversion, while multi-criteria evaluation helps avoid conflicts with agriculture and biodiversity. Landscape sensitivity mapping addresses potential visual and cultural landscape degradation, and transparent, evidence-based decision-making processes help reduce public opposition. Together, these tools support adaptive and reversible planning approaches, minimizing the risk of irreversible land-use change while balancing energy development with environmental and social considerations.

1.3. Ecosystem services as a framework for sustainability assessment

According to the Millennium Ecosystem Services Assessment, ecosystem services (ES) are the goods and services offered by ecosystems to help and support people's well-being (Millennium Ecosystem Assessment (Program), 2005), explicitly differentiating ecosystem stocks from service flows and highlighting the importance of long-term sustainability (Bateman et al., 2011). Moreover, ES are closely aligned with the Sustainable Development Goals, particularly those related to biodiversity, food, water, climate, and urban sustainability. Yet current monitoring efforts remain largely focused on biophysical supply, with limited data available on service use, demand, and governance (Meraj et al., 2022). Ecosystem service assessment encompasses the valuation of ecological, economic, and socio-cultural dimensions and can enhance environmental decision-making by supporting the sustainable allocation of services to promote human well-being (Kenter, 2016).

Reversing ecosystem degradation while meeting rising demands for ecosystem services remains a major challenge. Nevertheless, three of the four Millennium Ecosystem Assessment scenarios demonstrate that substantial reforms in policies, institutions, and management practices could alleviate many of the negative impacts of increasing ecosystem pressures, although such transformations have yet to be realized (Millennium Ecosystem Assessment (Program), 2005). Although substantial knowledge is available to inform actions that support ecosystem conservation and human well-being, significant information gaps persist. Knowledge remains limited regarding the likelihood of nonlinear ecosystem dynamics and the thresholds at which such changes may occur. Moreover, fundamental global data on the extent and temporal trends of ecosystem types and land use remain unexpectedly scarce. Existing models used to project future environmental and economic conditions also have a limited capacity to incorporate ecological feedbacks, including nonlinear ecosystem responses.

The context of decision-making about ecosystems is changing rapidly. The new challenge to decision-making is to make effective use of information and tools in this changing context in order to improve the decision. Scenario analysis serves to examine the implications of alternative assumptions concerning key uncertainties in the behavior of coupled human-ecological systems. In this regard, scenarios provide a systematic means of addressing uncertainty in the assessment of response options. The relevance, credibility, and influence of scenario outcomes ultimately depend on the actors and institutions engaged in their formulation.

1.4. Expert-based approaches in environmental planning

Environmental planners and engineers play a critical role in evaluating the implications of decision-making processes, while the development and adoption of advanced technologies and methodologies in environmental planning enhance the capacity to safeguard long-term

environmental sustainability (Wright et al., 1993). Expert-based approaches in environmental planning encompass decision-making frameworks grounded in the professional judgment, experiential knowledge, and disciplinary expertise of specialists, enabling the evaluation of environmental conditions, the establishment of planning criteria, and the formulation of planning outcomes, particularly in contexts marked by limited data availability or elevated system complexity. Expert approaches rely on generalized public preferences for specific landscape features, drawing on foundational research related to landscape perception and visual amenities, expert judgment, and legal frameworks. The main benefit of expert-based assessment is the capacity to generate timely insights in data-scarce contexts; the integration of ecological, social, and political dimensions; cost-effective preliminary assessments; and support for adaptive management processes.

Effective ecosystem management commonly depends on place-based knowledge, encompassing a detailed understanding of the specific characteristics and historical context of individual ecosystems. While formal scientific research represents an important source of such knowledge, traditional and practitioner knowledge held by local resource managers can be equally, or in some cases more, valuable. Despite its relevance, this knowledge is often underrepresented in broader decision-making processes and is frequently undervalued or dismissed. To sum up, expert-based approaches play a central role in contemporary environmental planning, supporting applications ranging from modelling and threat assessment to green infrastructure and marine spatial planning. Their effectiveness is greatest when expertise is broadly defined, elicitation processes are structured and transparent, and expert judgment is integrated with empirical evidence and local knowledge. Recent literature emphasizes a shift away from reliance on single, ostensibly neutral experts toward pluralistic and rigorously designed expert processes that explicitly address uncertainty and power dynamics (Di Febbraro et al., 2018).

1.5. Data-driven and machine-learning approaches for spatial analysis

Although classic expert-based or statistical methods offer superior interpretability, control, and, in some cases, smoother maps, data-driven spatial approaches generally enhance predictive accuracy and scalability. These approaches often outperform linear or simple interpolation methods in interpolation and exposure modelling, particularly in the presence of nonlinear relationships and a large number of predictors (Y. Wang et al., 2025). For example, in soil and rainfall interpolation, data-driven methods have been shown to improve prediction efficiency by approximately 60% and to achieve higher accuracy than inverse distance weighting (IDW) techniques (Nobrega and Barroca Filho, 2025), or in air pollution modeling, nonlinear data-driven approaches reduced the root mean square error (RMSE) by 10–40% compared with linear land-use regression (LUR) models (Ren et al., 2020). Overall, reviews indicate that data-driven approaches typically achieve higher classification accuracy than

parametric or rule-based methods in land-cover mapping and urban land-use studies. A further advantage of data-driven methods is that spatial machine-learning approaches more readily integrate diverse data sources, including satellite imagery, LiDAR data, sensor measurements, and socio-economic layers, compared with traditional modeling techniques (Casali et al., 2022).

In an aim to have a more holistic understanding of landscape systems, this study adopts an integrated methodological framework to assess the impacts of RES on ES (Figure 1). The framework combines expert-based evaluation with data-driven unsupervised learning, enabling a multidimensional analysis. The assessment is structured around two complementary groups of indicators. The geospatial dimension captures the societal and spatial characteristics of RES deployment and includes three indicators: spatial index, scenic quality, and solar visibility. In parallel, the ecosystem services dimension provides an ecological perspective on RES interactions with environmental functions and comprises four indicators: habitat quality, carbon stock, crop production, and crop pollination. The integration of these indicator sets ensures that both human and ecological dimensions are systematically incorporated into the analysis.

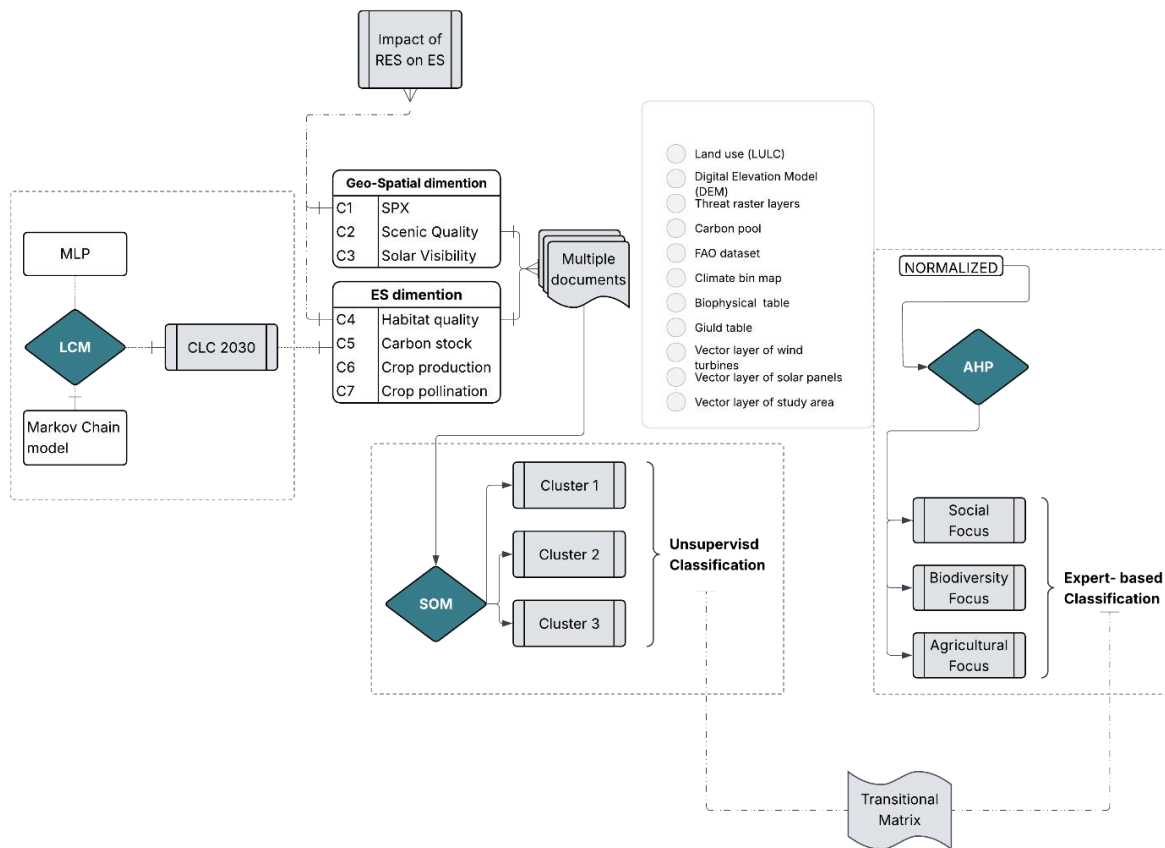


Fig.1. The general framework of the core of study.

2. Research goal and questions

Despite the growing number of studies on renewable energy systems and ecosystem services, the existing literature remains fragmented. Research methods vary widely, and studies are distributed inconsistently across energy technologies, ecosystem service categories, and geographic regions. The lack of common indicators and standardized assessment approaches limits comparison between studies and makes it difficult to identify long-term and cumulative impacts at the landscape scale. In addition, the limited use of before-and-after impact study designs reduces confidence in linking observed ecological changes directly to renewable energy development. These limitations, together with a strong focus on hydropower and provisioning services and a concentration of studies in a small number of regions, highlight the need for more integrated and transferable assessment approaches. To address these gaps, a coherent framework is required that links indicators, assessment tools, and spatial analysis to support robust planning and decision-making. This PhD research aims to contribute to the development of such a framework, so the main goal of this PhD research is:

Monitoring the impacts of RES on landscape and ecosystem services to support sustainable energy planning in Basilicata.

Therefore, the main objective of this PhD research is to develop an integrated assessment framework for evaluating the relationships between renewable energy systems and ecosystem services in the context of landscape planning and decision-making. Specifically, the study aims to identify the most appropriate spatial, environmental, and social indicators for analysing how different RES technologies interact with and influence ecosystem services. In addition, the research seeks to evaluate and compare existing tools and methods used to assess the impacts of RES on landscapes and ES, with particular attention to their effectiveness, applicability, and limitations. Building on this analysis, the study addresses how selected tools can be systematically integrated into a comprehensive assessment framework to support informed planning and policy decisions. These objectives are addressed through three core research questions:

- Which **indicators** (spatial, environmental, and social) are most suitable for investigating the relationship between Renewable Energy Systems and Ecosystem Services?
- Which **tools and methods** are most effective for assessing the impacts of RES on landscape and ES?
- How can selected tools be integrated into a comprehensive **assessment framework** to support evidence-based planning and decision-making?

3. Structure of the Thesis

This research study is structured as a thesis by publication and consists of a collection of three main research articles. These articles represent original research conducted during the doctoral study and have been either published in or submitted for publication to internationally recognized peer-reviewed journals. Each article addresses a specific research objective while collectively contributing to the overarching aims and central research questions of the thesis. The articles are thematically interconnected and together provide a coherent and comprehensive investigation of the research problem. To ensure clarity and continuity, the thesis includes introductory and concluding chapters that contextualize the individual studies within a unified theoretical and methodological framework.

The introductory chapter outlines the background, motivation, research objectives, and overall structure of the thesis, while also situating the included articles within the broader scholarly literature. The final chapter synthesizes the key findings of the three studies, discusses their collective contributions to the field, highlights theoretical and practical implications, and suggests directions for future research.

Chapter 2

Chapter 2 presents the outcomes of applied research conducted in collaboration with *F4 Engineering S.P.A* during the initial stage of the PhD program. This chapter focuses on the implementation of a landscape assessment framework within a real-world professional context. The research is grounded in expert-based supervision and applied practice, where specialist knowledge is systematically employed to evaluate landscape and environmental impacts. The work integrates professional expertise with structured assessment procedures to support evidence-based environmental decision-making. Expert judgment is operationalized through field investigations, analytical evaluation, and compliance with environmental assessment standards, thereby demonstrating the practical application of technical knowledge in responding to landscape-related environmental assessment requirements.

This chapter is based on the article:

Rahmani S., Pierri V., Zuccaro L., & Murgante B. (2024). Predicting the aesthetic impact of wind turbines and their influence on landscape value. *Journal of Land use, Mobility and Environment (TeMA)*. <https://doi.org/10.6093/1970-9870/12572>.

Chapter 3

This chapter is based on a peer-reviewed research article that applies a GIS-based Spatial Multi-Criteria Analysis integrated with the Analytic Hierarchy Process (AHP) to identify suitable locations for green hydrogen infrastructure in an urban–industrial context.

While Chapter 2 focuses on professional practice and expert supervision in environmental and landscape assessment, Chapter 3 formalizes expert knowledge into a structured methodological approach. Technical, economic, and environmental criteria are translated into spatial indicators and weighted through AHP evaluation, enabling transparent, reproducible, and scenario-based land suitability analysis. The methodology is tested through a real-world case study of an energy-intensive steel industry (*Siderpotenza S.p.A., Italy*), demonstrating how spatial analysis can support environmental planning and industrial decarbonization strategies.

This chapter is based on the article:

Rahmani S., Scorzelli R., Fattoruso G., Annunziata A., D'Angola A. & Murgante. Spatial multi-criteria Analysis for identifying suitable locations for Green Hydrogen Infrastructure: a case study of an Energy-Intensive Industry. *Energy Reports* (submitted)

Chapter 4

Chapter 4 represents the methodological and conceptual consolidation of the thesis by extending the expert-based and GIS-driven approaches developed in Chapters 2 and 3 into a hybrid expert–data-driven assessment framework. While Chapter 2 focuses on applied professional practice and expert-led landscape assessment, and Chapter 3 formalizes expert judgment through a GIS-based multi-criteria decision analysis (AHP), Chapter 4 advances the research by integrating unsupervised machine learning techniques to reduce subjectivity and enhance analytical robustness.

This chapter evaluates the sustainability of renewable energy development at the landscape scale by coupling expert-based spatial indicators with a Self-Organizing Map (SOM) approach. The methodology combines geo-spatial indicators related to renewable energy infrastructure (e.g., landscape fragmentation and visual impact) with ecosystem service indicators, including habitat quality, carbon storage, crop pollination, and crop production. By comparing expert-weighted AHP scenarios with data-driven SOM clusters, the chapter enables a systematic exploration of spatial patterns and trade-offs that are not fully captured by expert judgment. Applied to the Basilicata region in southern Italy, Chapter 4 demonstrates how the integration of expert knowledge and machine learning can support transparent, reproducible, and evidence-based spatial planning. The results identify distinct landscape typologies characterized by varying levels of ecological sensitivity, agricultural productivity, and exposure to renewable energy infrastructure. In doing so, the chapter provides a robust decision-support framework for balancing renewable energy expansion with ecosystem service preservation, marking a progression from practice-oriented assessment toward advanced analytical and policy-relevant insights. A part of this chapter is the result of collaboration with the University of Lausanne (UNIL) during my visiting research period.

This chapter is based on the article:

Rahmani S., Tonini M., & Murgante B. Renewable Energy Sustainability Assessment in Basilicata: From Expert-Based to Data-Driven Approach. Energy Reports (submitted)

4. List of Publications

Furthermore, the chapters included in this thesis are drawn from a selection of papers published during the Ph.D. program.

- Contributo “Green Hydrogen Infrastructure: valutazione dell’idoneità dei suoli” in: Munafò, M. (a cura di), 2023. Consumo di suolo, dinamiche territoriali e servizi ecosistemici. Edizione 2023. Report SNPA 37/23
- Scorzelli, R., Rahmani, S., Telesca, A., Fattoruso, G., & Murgante, B. (2023, June). Spatial Multi-criteria Analysis for Identifying Suitable Locations for Green Hydrogen Infrastructure. In International Conference on Computational Science and Its Applications (pp. 480-494). Cham: Springer Nature Switzerland.
- Castellaneta, B., Dastoli, P. S., Corrado, S., Gatto, R., Scorzelli, R., Rahmani, S., & Scorza, F. (2023, June). Strategic Development Scenarios in Inland Areas: Logical Framework Approach Preparing Collaborative Design. In International Conference on Computational Science and Its Applications (pp. 138-151). Cham: Springer Nature Switzerland.
- Lacerenza, A., Terminio, V., Lacidogna, V., Parente, V., Gatto, R., Scorzelli, R., Rahmani, S., & Scorza, F. (2023, June). “Back to the Villages”: Design Sustainable Development Scenarios for In-Land Areas. In International Conference on Computational Science and Its Applications (pp. 162-176). Cham: Springer Nature Switzerland.
- Rahmani, S., Scorzelli, R., Murgante, B., & D’Angola, A. (2023). Spatial Multi-criteria Analysis for Identifying Suitable Locations for Green Hydrogen Infrastructure: Three Case Studies of Energy-intensive Industries. In Renewable and Sustainable Energy Reviews journal
- Rahmani, S., Scorzelli, R., Ragone, F., Fattoruso, G., & Murgante, B. (2023). Utilizing Spatial Multi-Criteria Analysis to determine optimal sites for Green Hydrogen

Infrastructure deployment”. In Innovation in Urban and Regional Planning: Proceedings of INPUT 2023 - Volume 2. Cham: Springer Nature Switzerland AG.

- Scorzelli, R., Rahmani, S., Delfino, M., Fattoruso, G., Annunziata, A., Murgante, B. (2024). Spatial Multi-criteria Analysis for the Planning of Green Hydrogen Infrastructure: The Case Study of the Industrial Area of Viggiano.

In: Gervasi, O., Murgante, B., Garau, C., Tanar, D.,

C. Rocha, A.M.A., Faginas Lago, M.N. (eds) Computational Science and Its Application – ICCSA 2024 Workshops. ICCSA 2024. Lecture Notes in Computer Science, vol 14819. Springer, Cham. https://doi.org/10.1007/978-3-031-65282-0_22

- Murgante, B., Rahmani, S., Scorzelli, R., Fattoruso, G., Annunziata, A. (2024). Optimizing Agrivoltaic Integration: Spatial Analysis and AHP Assessment. In: Gervasi, O., Murgante, B., Garau, C., Tanar, D., C. Rocha, A.M.A., Faginas Lago, M.N. (eds) Computational Science and Its Applications – ICCSA 2024 Workshops. ICCSA 2024. Lecture Notes in Computer Science, vol 14825. Springer, Cham. https://doi.org/10.1007/978-3-031-65343-8_22

- Contributo in: Munafò, M. (a cura di), 2024. Consumo di suolo, dinamiche territoriali e servizi ecosistemici. Edizione 2024.

- Rahmani, S., Murgante, B. (2025) Renewable Energy and Landscape Transformation: A GIS-Based Ecosystem Services Assessment. Computational Science and Its Applications – ICCSA 2025 Workshops. ICCSA 2025.

CHAPTER 2

Predicting the Aesthetic Impact of Wind Turbines and Their Influence on Landscape Value

Abstract

The growing reliance on renewable energy sources is a direct response to global challenges such as climate change and the limited availability of fossil fuels. Due to their low costs and scale suitability for applications, wind turbines and solar panels are among the most widely adopted RES technologies for electricity generation. Their benefits are generally considered to outweigh the disadvantages. However, despite their image as green alternatives, these technologies face opposition due to concerns about noise, visual impact, and possible negative effects on ecosystem services. Following the EU Green Deal and its goal of achieving climate neutrality by 2050, the adoption of green energy technologies requires immediate implementation beyond legislation. The Basilicata region in Italy is among the most affected areas, having the highest percentage of wind farms and experiencing notable territorial fragmentation due to their installation. This study aims to assess not only the environmental impacts of wind turbines but also their social and aesthetic effects. Expert-based assessments and spatial analyses will be conducted, followed by the Scenic Quality Model within InVEST to evaluate visual impacts. The findings provide valuable insights for policymakers, planners, and researchers involved in sustainable land management and renewable energy planning.

Keywords: InVEST Model, Sustainable Land Management, Scenic Quality, Renewable Energy Planning, Environmental Assessment.

2.1. Introduction

Rising global demand for energy represents one of the most urgent and complex issues of the 21st century (Codemo et al., 2021). To address climate change, we need to reduce our reliance on fossil fuels. One of the direct solutions that was proposed to us is to increase the use of renewable energy sources (RES), such as wind and solar energy (Bhatti et al., 2024) (“World Energy Outlook,” 2023). The use of RES, especially in European countries, intensified in November 2019 when the European Parliament adopted a plan known as the Green Deal. This plan aims to produce 100% of electricity from renewable sources by 2050 and achieve climate neutrality in Europe (Bäckstrand, 2022). Given that the shift toward renewable energy must be prioritized to overcome this challenge and to move toward sustainability, which is a global necessity, it is crucial to conduct environmental assessments in a critical and systematic manner because it is closely linked to land-use change and its environmental implications (Kishore et al., 2025). Italy is one of the countries that has actively participated in this plan until now, and it has taken on a prominent role as a leader in advancing it. The Basilicata region in southern Italy is one of the provinces that has been heavily impacted by the establishment of RES (Scorza et al., 2020b).

Regarding the data available on the official website of the Basilicata region (“Catalogo RSDI,” 2018), In addition to the wind farms that have been established currently (around 2,100), there are currently 780 structures under development, and there are 230 wind turbines that are awaiting final authorization. Environmental assessments become crucial for the Basilicata region, especially since this region, due to its low population and the gaps in its urban planning frameworks, has become somewhat marginalized. Additionally, it’s important to consider that Italy and the Basilicata region are rich in cultural and natural resources, which must be preserved (Gizzi et al., 2019). The Basilicata region is a unique combination of environmental, geological, and cultural heritage. This area includes national and regional parks, notable archaeological sites such as the UNESCO World Heritage city of Matera, and the abandoned town of Craco, which showcases a remarkable intersection of natural and human-made features, as well as the region’s global significance (Bentivenga et al., 2024). The region also hosts 113 geosites of remarkable educational, scientific, and touristic importance, strengthening its reputation as an “open-air laboratory” for research, environmental education, and geotourism (Pilogallo et al., 2019).

This historical and natural heritage requires a comprehensive environmental assessment. However, given the aesthetic impacts that wind structures, in particular, have on the landscape, this aspect has always been a focal point in environmental evaluations. Therefore, in this research, our goal is to focus on the impact that wind energy facilities have on the landscape aesthetics of the Basilicata region. The case study focuses on a cluster of seven municipalities in the Basilicata region: Livello, Montemilone, Venosa, Maschito, Palazzo San Gervasio, Banzi, and Forenza. These areas were selected based on the concentration of authorized RES. Furthermore, given that environmental assessments require ultimate data and a comprehensive understanding of the study area, the initial phase of the methodology involved extensive data collection and preliminary analyses conducted in collaboration with domain local experts. Subsequently, the Scenic Quality Model within the InVEST software was employed to evaluate the aesthetic impacts of wind turbine installations, considering both the current conditions and the proposed developments in the near future. The research findings, in addition to providing a more realistic perspective on renewable energy, can also highlight the importance of local experts and position Basilicata as a model for European cities. It will demonstrate how the integration and implementation of RES in the region can have environmental implications. The originality of this research lies in the fact that, until now, methods used to assess visual impact have typically relied on conventional approaches, such as viewshed analysis. However, in this study, we employed a newer and more advanced method.

2.2. Methodology

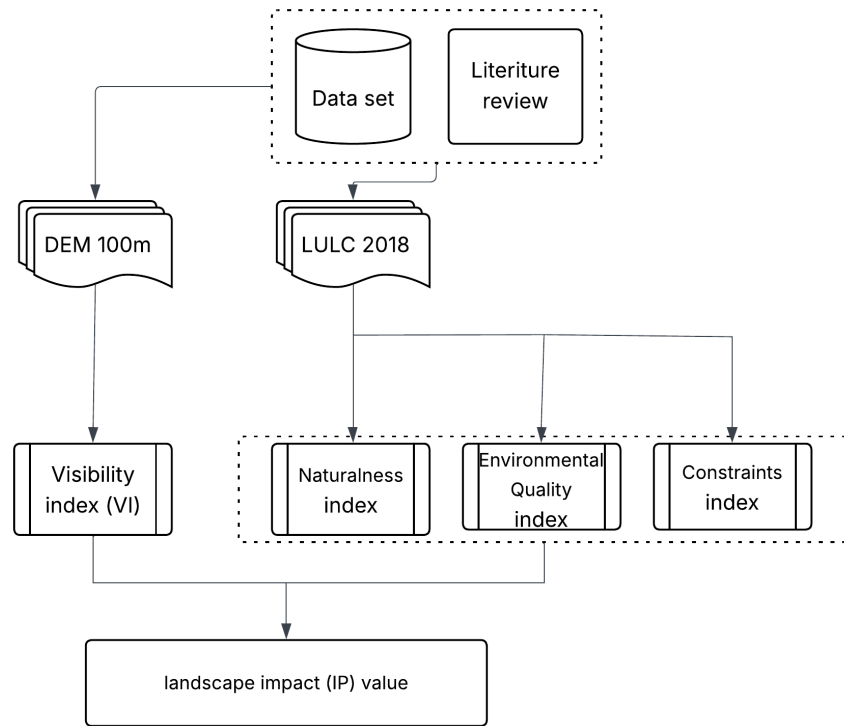


Fig.2. Methodology framework

In the methodology section, as outlined in Figure 2, it is generally divided into three parts. In the first part, we review the theoretical framework, emphasizing the importance of expert opinions and expert-based methods for local and regional projects, as well as identifying gaps and shortcomings in the evaluation methods for the visual impact of wind energy facilities. In the second part, to calculate the landscape value, we employ an expert-based approach. This was carried out during the training period at the *F4 s.r.l* company, which consists of around seventy specialists in architecture, agricultural engineering, environmental science, technicians, legal experts, consultants, and researchers. They collaborated in designing the questionnaires, and the industry specialists, including geologists, have spent about ten years working on environmental bases for projects related to water, energy, and aquatic environments. In the third part, the focus is on calculating the visual impact of wind facilities on the environment, using the InVEST software and the Scenic Quality Model.

2.2.1. Input Data

In the process of selecting indicators for the assessments, careful attention was given to aligning them with upper-level plans and relevant national, international, and European frameworks, such as the Basilicata energy plan (“World Energy Outlook,” 2023). Regarding this plan, we can understand what restrictions exist during the selection of indicators, considering the specific characteristics of the study, which factors are more significant in environmental assessments, and the protocols we need to consider at both local and national levels. Corine Land Cover data of Copernicus for the year 2018, which is the most recent available land use data, is going to be applied as the base of analysis in this work. To map the location of wind turbines within the study area, vector point layers were primarily obtained from the official website of the Basilicata region and the GSE website, the primary resource for renewable energy information in Italy. These layers were later updated through orthophotography and Google Maps, additionally, using data from F4, a professional company actively involved in local and regional environmental assessments of renewable energy projects in the area. The current number of wind facilities in the case study sample is 279, and this number is going to increase to 327 according to the regional plan. In summary, Table 1 outlines the data used for this research, including both data formats and sources.

Tab.1 Input data information.

Data	Format	Source	Link
Digital Elevation Model (DEM)	Raster (100m)	TinItaly	https://tinity.pi.ingv.it/
Corin Land Cover 2018	Raster & Vector	Copernicus	https://land.copernicus.eu/en/map-viewer
Layer points of wind turbine installation for the current and future scenarios	Vector	Geoportale Basilicata	https://rsdi.regione.basilicata.it/
		GSE	https://www.gse.it/dati-e-scenari/atlaimpianti
			https://earth.google.com/web/

-UNESCO World Heritage Sites - Monumental heritage - Archaeology assets - Landscape properties - Areas included in the territorial functional ecological system the territory of the Basilicata region - Agricultural areas - Areas in hydraulic and hydrogeological disruption	Vector	Geoportale Basilicata	https://rsdi.regione.basilicata.it/
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2.2.2. Literature Review

Expert Involvement in Landscape Assessment

Environmental impact assessment (EIA) of landscapes integrates ecological, cultural, and perceptual analyses, employing quantitative and qualitative models to address the complexity of landscape changes (Medeiros et al., 2021a). Not all aspects receive equal attention. Ecological and land-use indicators typically receive the most focus due to their direct connection to habitat quality and biodiversity (Palermo et al., 2024). In contrast, cultural and socio-economic aspects, such as cultural heritage and visual aesthetic quality, often receive less consideration (Schüpbach et al., 2020a). Over the past three decades, a wide range of methods has been developed to assess landscape values (Solecka, 2019). Two fundamental approaches can be distinguished in the assessment of landscape values: the expert-driven approach and the subjectivist approach (Lothian, 1999). Expert approaches rely on generalized public preferences for specific landscape features, drawing on foundational research related to landscape perception and visual amenities, expert judgment, and legal frameworks (Dramstad et al., 2006). Such assessments are based on intersubjective values, which, while not objectively measurable, represent broadly shared preferences and are supported by a core set of common landscape values frequently cited in the literature. Existing expert assessments frequently focus on landscape aesthetic quality (LAQ), which is understood as the enjoyment derived from the aesthetic appreciation of landscapes (Solecka et al., 2022). Furthermore, stakeholder engagement and the integration of local perspectives are recognized as essential

for defining sustainability objectives, selecting appropriate indicators, and ensuring that assessments reflect both expert knowledge and community values (Dale et al., 2019a). Considering that nowadays there is a growing trend of using machine learning in decision-making, it is still important, especially for local and regional plans, to involve field experts. Since the assessment is a process rather than a one-time decision, it is crucial to engage individuals who have detailed knowledge of the plans' history and context (Gennatas et al., 2020). Additionally, because these individuals are human and interact directly with other stakeholders, their experiences can greatly contribute to the decision-making and assessment process. Moreover, these experts are often residents, and thanks to their background, they have a deep understanding of all the relevant aspects of the area (Maitland and Sammartino, 2015).

Wind Turbine Visual Impacts and Methodological Gaps

One of the critical points to consider for implementing RES installation is its aesthetic impacts on the surrounding area, especially at a local scale in Italy, as a country that keeps many historical and natural sites. One such barrier is the aesthetic impact of renewable energy facilities on the landscape (Wüstenhagen et al., 2007) . It is crucial to carefully select their locations to minimize the visual impact of RES installations and increase social acceptance. To emphasize the importance of the visual impact of RES on the landscape, we address a gap identified in the existing literature through a bibliometric summary generated using the Bibliometrix R package, based on a custom dataset of scientific publications related to RES and their aesthetic and visibility impacts on the landscape. Table 2 contains the summary of general information about the bibliometric review.

Tab.2 Main information of bibliometric analysis

MAIN INFORMATION ABOUT DATA	
Timespan	2005:2025
Sources (Journals, Books, etc)	103
Documents	174
Annual Growth Rate %	4.69
Average citations per doc	44.44
Author's Keywords (DE)	609

The dataset covers the period from 2005 to 2025 by reflecting a sustained and evolving scholarly interest in the visual and landscape impacts of RES. Comprising 174 documents, the dataset represents a relatively small but concentrated body of research that appears to be gradually expanding. The dataset draws on 103 distinct sources, including both journals and conference proceedings, indicating a moderately broad field with contributions spanning multiple disciplines such as environmental science, energy policy, landscape planning, and sustainability. The annual growth rate of 4.69% points to a steady increase in publications over time, suggesting that scholarly attention to the visibility and aesthetic dimensions of RES is gradually gaining prominence in both policy discussions and public discourse. A rich and diverse keyword set (609 keywords) reflects thematic complexity. This likely includes terms such as "landscape integration", "visual impact", "wind farms", "solar panels", "public perception", etc. Average Citations per Document (44.44) is an unusually high citation count, indicating that the field contains high-impact publications or that some seminal works are highly cited. It also reflects the growing academic and policy relevance of the visibility and aesthetic dimensions in RES deployment. The annual scientific production illustrated in Figure 9 shows steady growth in publication output over two decades, which aligns with the increased deployment of RES technologies and rising public concern over their integration into landscapes. Publication reaches its peak in 2024. Further analysis using Bibliometrix indicates that Italy and Spain are particularly active in this research area. This prominence likely reflects both the regional significance of renewable energy deployment and national priorities related to sustainable landscape planning and policy.

The thematic (Figure 3) map provides a strategic overview of the conceptual landscape within the literature on renewable energy and its connections to landscape and sustainability issues. Dominant “motor themes” underscore the increasing attention given to visual and environmental dimensions in renewable energy research. Meanwhile, the presence of themes such as ecosystem services and territorial planning in the lower-left quadrant points to areas of either emerging or waning scholarly interest, highlighting the need for longitudinal studies to better understand their developmental trajectories.

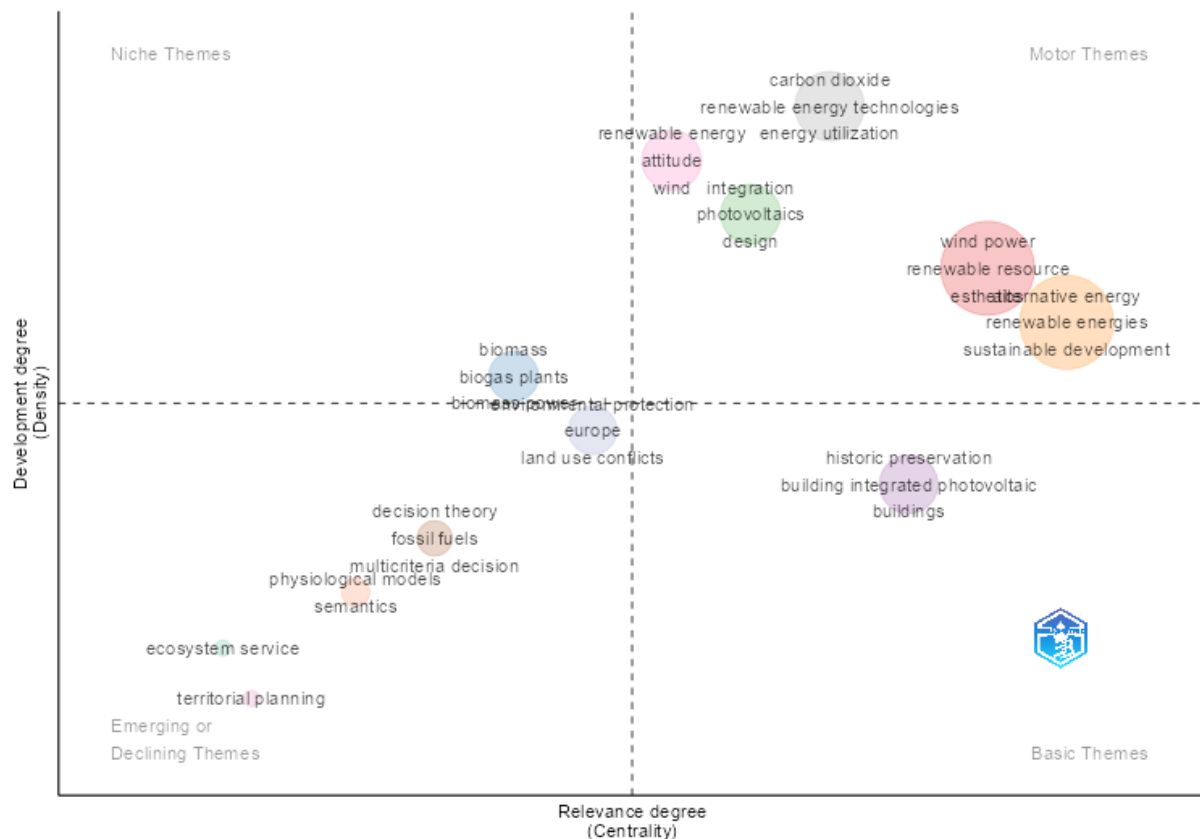


Fig.3. The thematic map offers a strategic visualization of the conceptual landscape

While visual impact emerges as one of the most frequent keywords and suggests a strong scholarly interest, there remains a lack of standardized methodologies for its assessment. The literature frequently discusses visual impacts of renewable energy installations (especially wind farms), but often relies on qualitative, case-specific, or subjective approaches rather than consistent, replicable tools. This reveals a clear gap between thematic interest and methodological maturity in the field. In this study, we aim to address this gap by employing a GIS-based methodology and by using the InVEST tool, a widely recognized and professional framework for assessing ecosystem services. Through this approach, we seek to elevate the concept of ecosystem services from an emerging or declining theme to a more central topic within the literature.

2.2.3. Case study

The case study focuses on a cluster of seven municipalities in the Basilicata region (Livello, Montemilone, Venosa, Maschito, Palazzo San Gervasio, Banzi, and Forenza). Selection of areas is based on the concentration of authorized RES installations, as identified in official data

published on the Basilicata Region's institutional website ("Catalogo Dati," 2013). Basilicata is an administrative region in Southern Italy, bordered by Campania to the west, Apulia to the north, and east ("Territorio e cartografia," 2024). Basilicata is the most mountainous region in southern Italy, with mountains covering approximately 47% of its 9,992 km² territory. The remaining area is composed of 45% hills and 8% plains. Compared to central and northern Italy regions, Basilicata presents relatively favorable spatial conditions for specific types of land use and development, particularly in relation to renewable energy installations and rural land management ("Territorio e cartografia," 2024). Furthermore, in 2018, the Basilicata Regional Authority approved a regional law entitled 'Decarbonisation and Regional Policies on Climate Change' to support the transition toward a low-carbon economy and strengthen climate resilience across the region (change, 2023).

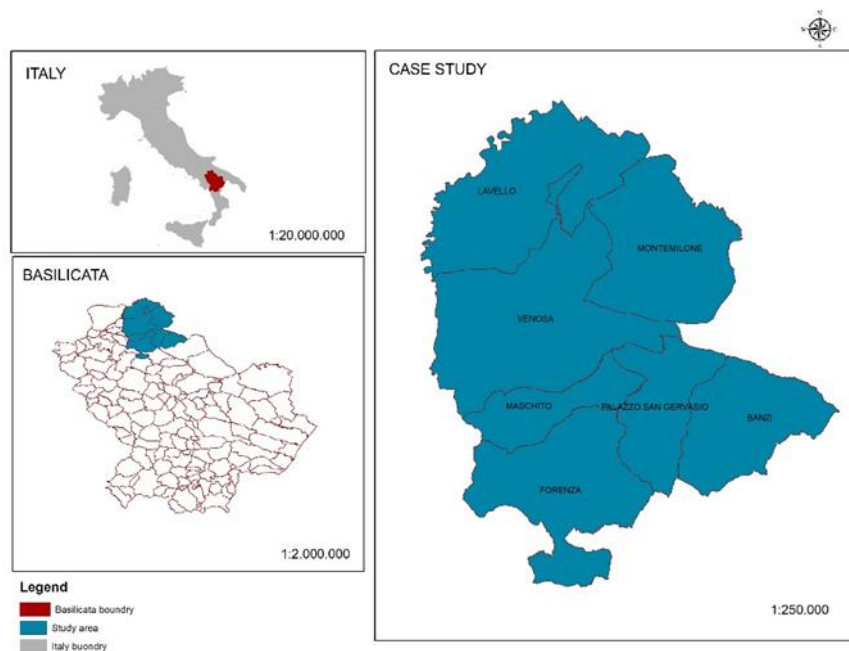


Fig.4. The location of the case study in Basilicata, Italy.

2.2.4. Definition of the Visual Impact Area

Aesthetic impacts on the landscape have long been a central source of opposition to renewable energy projects (Mazzola, 2025). Yet, the current uncertainty regarding the spatial extent and the validity of reported impacts continues to prevent the development of effective strategies for their mitigation (Ioannidis and Koutsoyiannis, 2020). In this paper, the

methodology applied for assessing the landscape visual impact of RES is based on a standardized approach that quantifies the degree of visual and contextual transformation induced by such projects, according to the following formula. A common methodological approach proposed by the University of Cagliari quantifies the landscape impact (IP) by calculating two indices: 1) VP index, representing the value of the landscape, and 2) VI index, representing the visibility of the plant (FuntanaElighe and Mncdnl, 2013). The IP, based on which decisions can be made regarding mitigation measures or system modifications that improve visual perception, is determined by the product of the two indices.

$$IP = VP * VI \quad (1)$$

The VP and the VI both expressed their opinions on a scale from 0 (no impact) to 4 (maximum impact). VP captures the intrinsic characteristics of the territory through three sub-indices: Naturalness (N), Environmental Quality (Q), and Landscape Constraints (V) according to formula 2, derived from land use data and spatial overlays of protected or regulated areas. The intervisibility analysis is conducted using DSM-based viewshed models within the Scenic quality model of InVEST software, under different scenarios (current installation and authorized for adding in the near future). The final IP raster map is obtained by multiplying the reclassified VP and VI raster maps, enabling a spatially explicit evaluation of visual impact and supporting informed decision-making for mitigation or planning purposes.

$$VP = N + Q + V \quad (2)$$

VP calculation

Evaluating the values attributed to landscapes provides essential insights that can inform landscape policy and support decision-making processes. Over the past thirty years, numerous methods have been developed to assess landscape values. Two primary approaches are commonly distinguished in this field: expert-driven and subjectivist (Lothian, 1999; Johnson et al., 2024). The following tables present the expert-based values used for calculating landscape values.

The N index was calculated based on land use data derived from the Regional Technical Map (CTR), assigning values from 1 to 10, where 1 represents highly artificial areas and 10 indicates

areas with the highest naturalness. Table 3 illustrates the N value corresponding to each land use classification used in the Basilicata region, at about 74.69%. Following that, with a significant difference, around 13.24% is dedicated to vineyards, olive groves, and orchards, all of which fall under the agricultural lands category. Close to that, about 10% is allocated to broad-leaf forests, which belong to the natural environment category. The remaining percentages are roughly similar, and each is less than 1% for our study area.

Tab.3 Index of Naturalness and classes of land use.

	Land Use	Index N
Artificially modeled territories	Industrial or commercial areas	1
	Mining areas, landfills	1
	Urban and/or tourist fabric	2
	Sports and hospitality areas	2
Agricultural lands	Arable and uncultivated land	3
	Protected crops, various types of greenhouses	2
	Vineyards, olive groves, orchards	4
Woods and semi-natural environments	Cyst areas	5
	Natural grazing areas	5
	Coniferous and mixed forests	8
	Bare rocks, cliffs, crags	8
	High, medium and low Mediterranean scrub	8
	Broadleaf forests	10
	Maritime waters	8

Like the N index, environmental quality values are assigned on a scale ranging from 1 to 6, with each value representing a distinct level of environmental quality linked to various land use typologies. Consequently, areas characterized by more ecologically beneficial or less intensive land uses (e.g., natural habitats or forests) are assigned higher scores. In contrast,

areas with more intensive or environmentally degrading uses (e.g., industrial zones or urbanized areas) receive lower scores. Table 4 included all Q values for each category.

The Q value, which can somewhat represent the habitat quality in the study area, indicates that over 87% of the area is dedicated to agricultural use. Following that, with a significant difference, about 10% of the area is assigned to maritime waters. For the remaining habitat qualities, the percentages are roughly similar, and each is less than 1%.

Tab. 4 Index of Environmental Quality.

Land Use	Q Index
Service areas, industrial areas, quarries, etc.	1
Urban fabric	2
Agricultural areas	3
Semi-natural areas (garrigues, reforestation)	4
Areas with woodland and shrub vegetation	5
Wooded areas	6
Maritime waters	5

In the Regional Energy Plan of the Basilicata region, the suitability of land for energy production is defined through a set of constraints specific to each type of renewable energy source. In this study, constraint indicators outlined in the energy plan are used, with values assigned to each category. The value scale ranges from 0 to 1, with historical and cultural heritage assigned higher values due to the extensive protection provided by various legal frameworks, although areas with hydrogeological, forest, and natural features, and municipal areas have a value of 0.5. Hydrogeologically sensitive areas, forests, natural features, and municipal zones are attributed an intermediate value of 0.5. A value of 0.25 is attributed to urban areas and river buffer zones, reflecting their comparatively lower constraint level. Areas not falling within the mentioned categories are assigned a value of 0. Table 5 presents information on the assigned constraint values for each land category.

Tab.5 Index of constraints.

Index relating to the presence of constraints	V value
---	---------

Areas with historical-archaeological constraints	1
Areas with hydrogeological constraints	0.5
Areas with forest constraints	0.5
Areas with protection of natural features (PTP)	0.5
Municipal areas	0.5
Areas of buffer (about 800m) from urban fabrics	0.25
Areas of buffer, buffers (rivers, sheep tracks, etc.)	0.25
Unconstrained areas	0

In the study area, 21.46% of the total area is subject to restrictions for the installation of these facilities due to the presence of historical and archaeological values in those areas. The largest percentage of the area, about 38.98%, is allocated to regions with no restrictions. Next, around 26.37% of the area is designated for protection due to the presence of natural features and municipal zones. Finally, the smallest percentage, approximately 13%, is allocated to buffer zones of urban fabrics, rivers, and ship tracks.

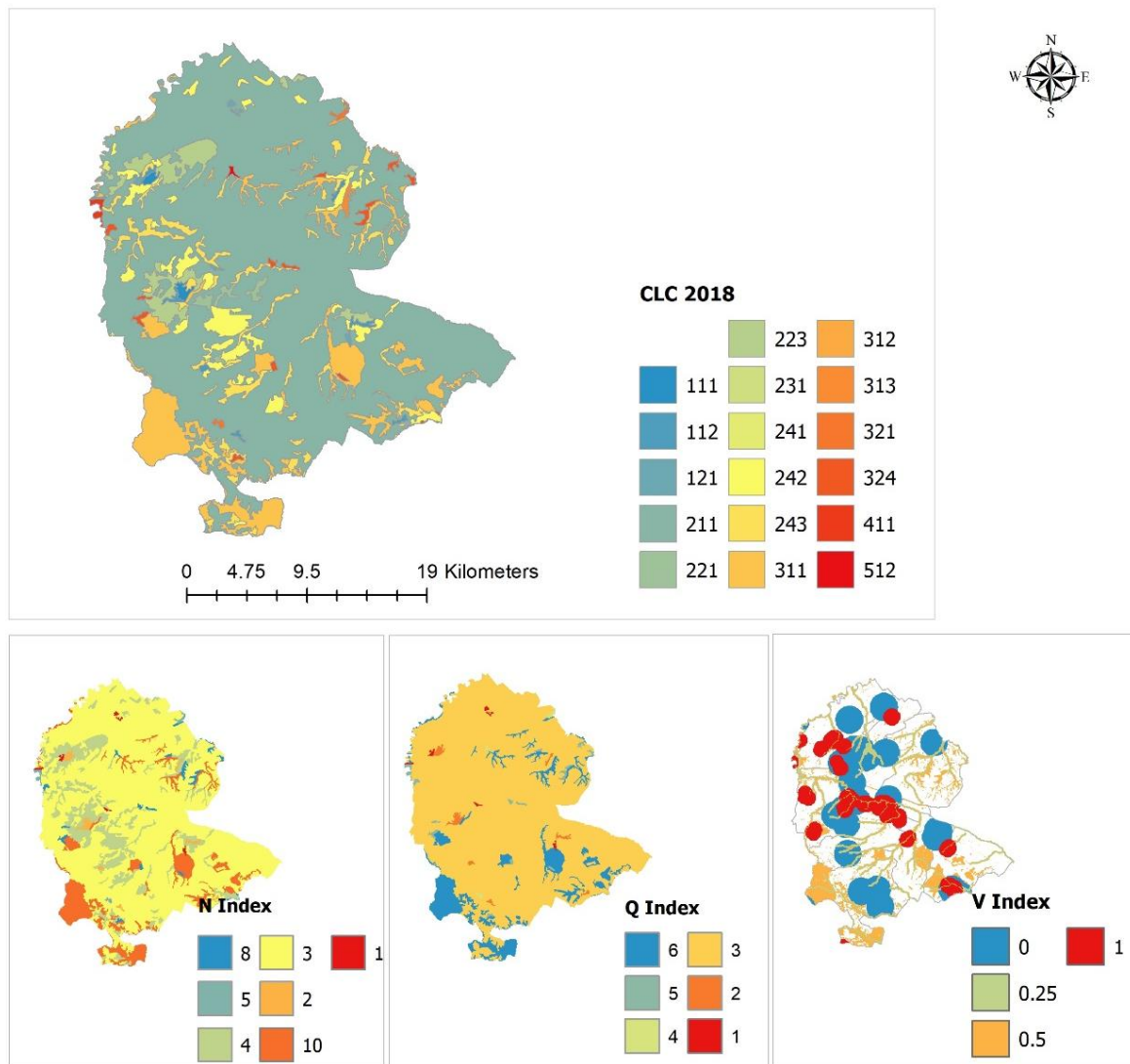


Fig.5. Transforming CLC codes to N, Q, and V indexes.

In the GIS environment, the values of the N, Q, and V indices were summed and resampled on a scale between 1 and 4 according to the methodology described above to derive the landscape value map of the territory. The map algebra operation allows the result to be obtained pixel by pixel. Figure 6 shows overlaid normalized indexes.

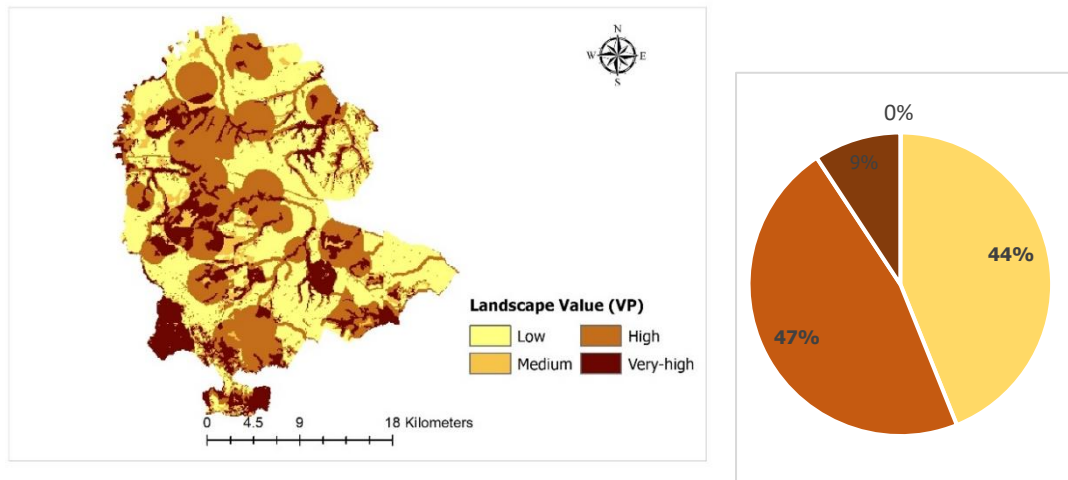


Fig.6. a) Landscape value map for the study area. b) landscape value percentage for each class.

The pie chart illustrates the proportional distribution across four categories based on absolute values. The High category constitutes the largest share at 47%, Medium at 44%, and Very High at 9%. Despite having a recorded value of 450,000, the Low category accounts for 0% of the total due to the relative magnitude of the other values.

VI calculation

The visual impact of wind turbines largely depends on their distance from the observer (Bishop and Miller, 2007). Visual impact assessments of wind turbines in Europe have been conducted since the early 1990s. The first reports published by the European Commission in 1995, focusing on the visual analysis of relatively small turbines with a height of approximately 45 meters, indicated that their maximum visibility range extends up to 20 kilometers. Thomas, based on a study conducted in Wales on wind turbines with heights ranging from 41 to 45 meters, demonstrated that the maximum range for visibility analysis should initially be limited to 15 km, later adjusting this threshold to 20 km (Wróżyński et al., 2016). At the turn of the century, increasingly taller wind turbines were constructed, and according to Bishop, their visibility could extend beyond 30 km. However, Bishop argues that beyond 20 km, the visibility of turbines becomes very limited, and their impact is minimal (Bishop, 2002).

In this study, we propose using the Scenic Quality model available within the InVEST software to assess the visual impacts of renewable energy installations. The InVEST Scenic Quality model computes the visual impact of features in the landscape in several steps, and for each structure site, calculates the visibility for each point feature viewshed algorithm. In addition to

identifying visible areas, the model also estimates the amenity or disamenity value of visibility by weighting the visibility results and applying the valuation function specified by the user in the interface. By summing the individual valuation rasters, the model generates a weighted aggregate that represents the overall visual impact across the area of interest. The weighted aggregate valuation raster is divided into quartiles to produce a final. The weighted aggregate valuation raster is divided into quartiles to produce a final raster that represents visual quality across the landscape. Additionally, the visibility rasters from all structure points are weighted and summed to generate a raster that reflects the total number of visible points, accounting for their relative importance. The valuation function is computed up to a maximum valuation radius that defaults to 8000 meters. The following section presents the model's required input data for running the analysis.

The first thing the model requires is defining the study area boundary, also known as the AOI, which is a polygon vector layer. In this study, we used the municipal boundaries downloaded from the official website of the Basilicata region, and the coordinate system was adjusted to WGS84 / UTM Zone 32N to ensure compatibility with the DEM. Furthermore, a point vector representing wind turbines that negatively impact the scenic quality of the study area. Optionally, there are possibilities to enhance the analysis through defining more attributes, such as maximum viewing distance, which limits the extent of the viewshed for each feature, viewshed importance coefficient, which weights the visual influence of each feature, and viewpoint height, which adjusts the elevation from which visibility is assessed. These parameters enable a more precise and context-specific representation of visual impacts. height here defines the maximum length of the line of sight originating from each viewpoint. If this field is not specified, the model will consider all pixels in the DEM during the visibility analysis. For this study, we used the actual height of each wind turbine as provided in the dataset. In cases where height data was missing, we assigned the average turbine height, which is 150 meters. Additionally, a radius value was included in the attribute table, with 30 km. This distance corresponds to the typical visibility range of a 100m high turbine. Fig6. shows generated rasters that represent the visual quality of each pixel across the study area for both the current situation and the authorized installation as a future scenario. The cells of the raster are classified based on percentile breaks, allowing for a relative assessment of visual impact.

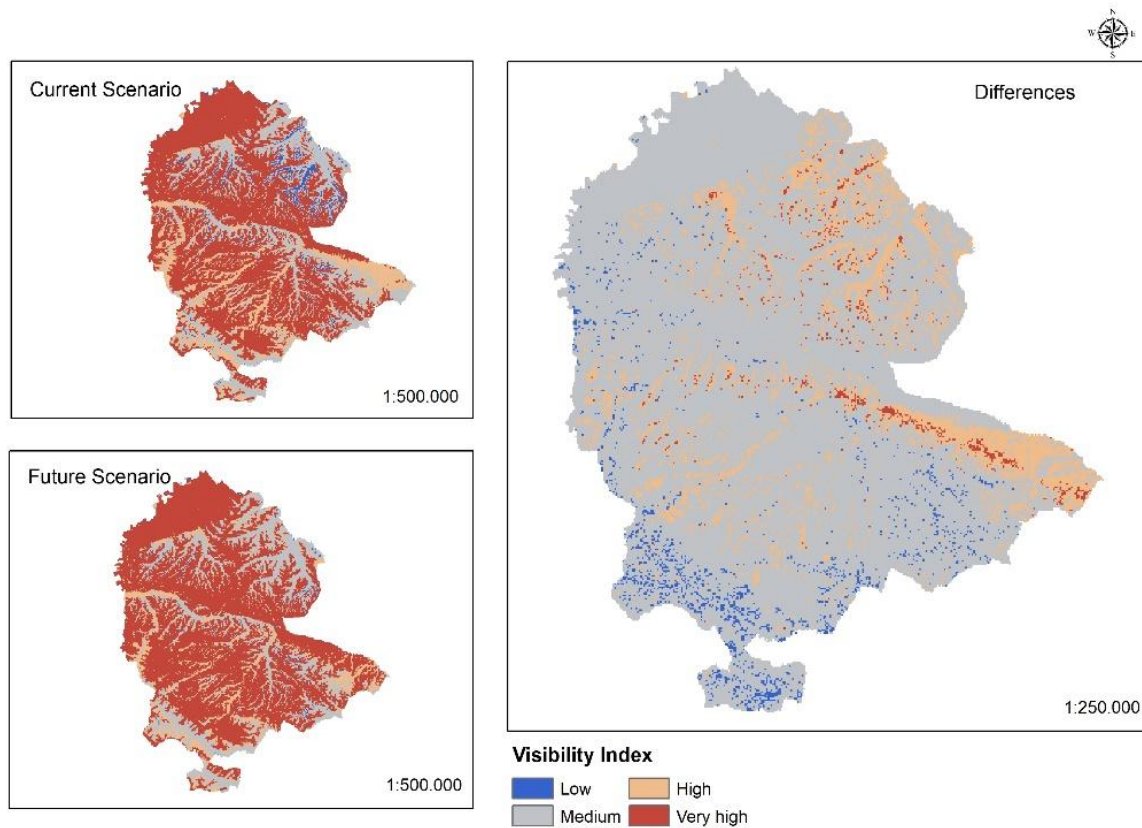


Fig.7. Comparison between current and future scenarios of the visibility index

Figure 7 shows that, for both the current situation and the predicted future scenario, the impact of these wind turbines on the environmental visual quality of the study area falls primarily into category four, meaning the impact is very high. Currently, this impact is about 60.35%, and with the addition of future wind turbines, this percentage increases by 5%, reaching around 65.10%. At the same time, the current category one impact, which is about 13.14%, will decrease in the future to approximately 11.08%, and this category will then shift into category four. Meanwhile, for category two, which indicates a medium-level impact, both the current and future scenarios remain relatively stable.

Overall Impact of Visual Disturbance on the Social Value of the Landscape

Finally, considering all the analyses carried out so far, in this section, we will present the results that address the main objective of this research: examining the impact of wind turbines on the visual value of the study area's landscape. Table 6 illustrates the IP index percentages, which are derived from the overlay of all the indicators we have discussed so far, along with their normalization and, ultimately, their reclassification into four classes: low, medium, high, and

very high. This figure includes both the current state, the future state, and the differences between these two timeframes.

Tab 6. Landscape value impacted by wind turbines

IP Value	IP Scale	Sup. ha	Sup. %	Sup. ha	Sup. %
		Current		Future	
Low	1	13,282	18.41	14,547	14.76
Medium	2	29,637	10.72	27,493	9.2
High	3	7,427	39.57	6,601	42.5
Very high	4	20,997	31.3	22,702	33.53

The results show that, for the two timeframes analyzed, both the current state and the future projections, the magnitude of changes in the high and very high categories is evident for both periods. Notably, the change in the first category representing low impact has decreased in the future scenario, meaning the difference is about 4% smaller in the future. On the other hand, the difference has increased for the fourth category, which has the greatest impact on the visual landscape of the area.

2.3. Result

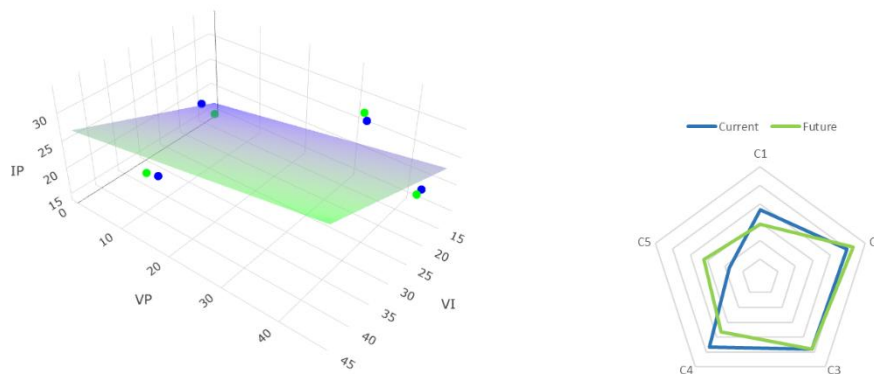


Figure 8. a) VI and VP relation with IP. b) Comparison of VI and VP impact on landscape value changes.

The figure 8b, Compare the impact of wind turbines on landscape value in the current scenario with the projected impact under future installation scenarios. The results indicate that, although the medium impact class (C3) remains constant across both scenarios, the

proportion of areas falling into the C5 category, representing very high impact, is projected to increase from 9% to 16%. On the other hand, a 3D regression plot (Fig. 8a) shows how two independent variables, VI and VP, together explain changes in IP. The colored surface in the 3D graph, displayed as a semi-transparent plane, represents the regression plane generated by a multiple linear regression model. This plane visualizes the fitted values of the IP as a function of the combined influence of the two explanatory variables. The green surface, corresponding to the future scenario, is positioned higher than the blue surface representing the current state. This change reflects a steeper gradient, implying a more pronounced increase in the landscape impact of wind turbine installations in the future. Although the overall landscape value remains constant between the two scenarios, the shift toward a more concentrated presence of high-impact classes suggests increasing visual dominance and changing perceptions of landscape disturbance.

2.4. Conclusion and discussion

One of the findings of the research highlights that, even with new approaches to decision-making processes, experts, especially local specialists who have been involved in environmental changes and driving factors over time, are essential and crucial. Environmental impact assessments sometimes require straightforward, practical steps rather than complex methods that can lead to confusion when many factors are not influential. Therefore, the role of these specialists should not be overlooked, and more opportunities for collaboration among stakeholders, such as academics, engineers, planners, economists, and policymakers, should be provided. It is important that, in the decision-making process, we always consider reliable plans at both the national and regional levels, and that the interests of all stakeholders take precedence over the benefits of any single group in planning and assessments. The results also show that it is possible to make a smart choice of assessment methods where needed, tailored to the type of impact. For instance, in the case of wind facilities, considering the nature of these structures and the residents' criticisms, especially regarding visual and landscape impacts, which have been a significant source of opposition, goes beyond just the economic benefits and the cleanliness of the energy. If the one-dimensional harm from these technologies increases, then, no matter how clean the energy is, it could ultimately become harmful to the environment. For this reason, we used the Scenic Quality Model through the InVEST software, which is the originality of this work, because until now, most of the research

conducted on the visual impact of wind facilities on the area and on the Basilicata region has typically relied on conventional methods, such as viewshed analysis available in GIS programs. However, this model, in addition to what viewshed analysis offers, also considers dimensions and scales, which are critical and decisive factors in how these facilities affect the landscape of the studied area. Furthermore, the assessment conducted in this research has issued warnings to future projects and facilities that are planned to enter the region. Given the current state and the significant impact on the landscape and aesthetic quality of the studied area, the assessment warns that adding these facilities will further increase these impacts. This poses a serious threat to the region, which, due to its relatively low population and moderate economic situation compared to other Italian regions, could see its role at both the national and international levels weakened.

CHAPTER 3

Spatial multi-criteria Analysis for identifying suitable locations for Green Hydrogen Infrastructure: a case study of an Energy-Intensive Industry

Abstract.

The global energy demand is shifting towards sustainability and local transfer options, and as a result, green hydrogen can serve as a viable and reliable solution. The use of the spatial multi-criteria analysis approach in this study evaluates the feasibility of deploying green hydrogen infrastructure in urban areas. A variety of factors, including technical, economic, environmental, and social aspects, are considered to identify areas that are suitable for establishing hydrogen production facilities, for their storage, and for hydrogen distribution. The analytic hierarchical process and GIS are combined to evaluate spatial data and to illustrate the relationships between indicators and spatial capabilities. The methodology is tested on a real-world case, which is an energy-intensive industry called *Siderpotenza S.p.A.*, located in the city of Potenza in the Basilicata region of southern Italy. This analysis considers the specific characteristics of each area, such as existing energy infrastructures, the potential for renewable energy, and the local demand for hydrogen. The results of this research provide a more comprehensive view of potential locations for green hydrogen infrastructure by considering factors such as proximity to renewable energy sources, transportation networks, and existing industrial synergies. This research also helps in understanding how green hydrogen can be utilized in urban contexts and guides policymakers and urban planners in moving toward a sustainable, fossil fuel-free future by incorporating multiple criteria and employing spatial analysis techniques.

Keywords: Green Hydrogen Infrastructure; Analytic Hierarchy Process; Geographic Information System; Energy-Intensive Industry.

3.1. Introduction

The energy sector is crucial to a country's economy (Resniova and Ponomarenko, 2021). Its efficiency and sustainability significantly impact economic, social, and environmental activities (Omer, 2008). Energy transition is one of today's major global topics, as nations often face numerous challenges stemming from economic, environmental, and social crises. Given the pressing concerns of climate change, it demands thoughtful and immediate actions. In this sense, the need to respond effectively to climate change caused by the massive use of fossil energy resources and pollutants has increasingly encouraged us to use Renewable Energy Sources (RES) (Ravestein et al., 2018). These energy sources are usually called "green energy" as they do not generate dangerous pollutants or Greenhouse Gases (GHG) in energy production. Transitioning to green energy is pivotal in the fight against climate change and the reduction of greenhouse gas emissions; however, it alone is not sufficient. It is equally crucial to realize that additional measures, such as energy efficiency, resource conservation, and behavioral and lifestyle adjustments, are needed to effectively limit the consequences of climate change. In the field of renewable energies, interest is emerging in the production and use of green hydrogen, which represents a sustainable and innovative solution to today's climate challenges (Dagdougui et al., 2011).

Green hydrogen has attracted considerable interest for two main reasons (Genovese et al., 2023). Firstly, no greenhouse gases are emitted during water electrolysis into oxygen and hydrogen gas. Secondly, using electricity from RES to power hydrogen production makes it environmentally sustainable. Consequently, green hydrogen can be considered a truly environmentally friendly energy vector when it is produced using electricity from renewable sources and adopting environmentally friendly production and transport methods (Inci, 2022; Raman et al., 2022).

Hydrogen is playing an increasingly important role, especially concerning refractory industries and transport (especially heavy and long-distance), as it can contribute to the decarbonization of sectors where electrification is not an efficient solution (hard to abate). However, two challenges still exist: high production costs and low demand (Abe et al., 2019). In recent times, however, competitiveness has matured thanks also to a policy of incentives activated both at the European level and by the Italian government through the National Plan for Remediation and Resilience (PNRR) ("Next Generation EU e il Piano Nazionale di Ripresa e Resilienza," 2023), which includes a financial allocation of EUR 3.2 billion for the "main action" called "Hydrogen." The main goal is to achieve by 2050 an increased use of hydrogen in the chemical and transport industries (up to 80% of long-haul trucks) and especially in the "hard-to-abate" sectors. To identify ideal ways to produce, transport, and store hydrogen, the legislation envisages the creation of "Hydrogen Valleys." These ecosystems include both the production and use of hydrogen. Therefore, in this scenario, rational environmental and urban planning (Casas et al., 2019; Scorza et al., 2020a), based on the principles of sustainable development, plays a crucial role (Murgante et al., 2011; Roseland, 2000).

The strategic setting of hydrogen facilities is crucial for minimizing costs, ensuring a reliable supply, and advancing the transition to a low-carbon energy system. Location analysis plays a key role in shaping infrastructure investment, operational efficiency, and the capacity to meet demand across the hydrogen supply chain. Proper seating of production, storage, and refueling facilities helps minimize transport distances, infrastructure demands, and overall supply chain costs. Studies consistently demonstrate that optimal facility placement can substantially reduce both the levelized cost of hydrogen (LCOH) and total investment needs (Riera et al., 2023; Ganter et al., 2024). Placing facilities close to high-demand areas such as urban centers, industrial hubs, and major transport corridors improves service coverage, increases utilization, and encourages the adoption of hydrogen technologies like fuel cell vehicles (Sun et al., 2017). Locating production facilities near renewable energy sources such as solar, wind, or biomass takes advantage of local resource availability, minimizes energy transmission losses, and advances decarbonization objectives (Mah et al., 2022).

The paper examines the criteria that contribute to identifying the most suitable sites for the location of plants, facilities, and networks needed to produce, store, and distribute green hydrogen. The methodology implemented is a multi-criteria spatial analysis integrating the AHP method in the GIS environment. All spatial analysis operations were performed using QGIS and ArcGIS software, allowing for the visualization of the relationships between the identification of sites and the analyzed criteria. The approach was tested on a real case study, namely an energy-intensive industry located in Basilicata (Italy): “Siderpotenza S.p.A.”. The first step concerns the identification of the three main criteria (technical, economic, and environmental) and their sub-criteria. Following the elaborations carried out, a land suitability map was produced. Subsequently, three alternative scenarios were analyzed, emphasizing the technical, economic, and environmental criteria. The result saw a comparison of three different land suitability maps to identify the best sites for plant locations.

Green hydrogen ecosystems in all sectors now seem to be geographically limited to the local or regional scale, with production and consumption occurring most of the time at relatively near distances, despite the rapid development in the number and capacity of installed electrolyzers. Currently, production, transportation, and consumption of green hydrogen inside entire countries or among neighboring countries are not integrated. This is the result of several factors, including the production sites' existing capacity limitations, the absence of an adequate transportation system, the overall slow demand for green hydrogen, and the regulatory obstacles. These factors keep green hydrogen far from benefiting from increased economies of scale and more effective and dependable supply management. Anyway, in the upcoming decades, especially in Europe, the European Hydrogen Backbone (EHB) effort intends to create a pan-European green hydrogen distribution network by quickly expanding the hydrogen transport infrastructure, by including more than 30 energy infrastructure operators

(Iamarino and D'Angola, 2025; “European Hydrogen Backbone,” 2024; “SNAM,” 2024; Finland, 2025). By repurposing existing natural gas infrastructures and constructing new pipelines where necessary, the EHB initiative, which is led by European gas transmission system operators, seeks to establish a network of dedicated hydrogen pipelines. By repurposing existing natural gas infrastructure and constructing new pipelines where necessary, the EHB initiative wants to establish a network of dedicated hydrogen pipelines.

Among these initiatives, the SouthH2 Hydrogen Corridor is a plan to use existing natural gas pipelines to transport green hydrogen from North Africa to Central Europe. It is based on the region's high potential for green hydrogen production as well as the anticipated rise in European demand for green hydrogen. Similarly, the Hy network project seeks to establish a national hydrogen transportation network in the Netherlands, while the BalticSeaH2 project aims to establish a cross-border green hydrogen ecosystem that links several nations in the Baltic Sea region. The announced 400 GW electrolysis capacity in Europe by 2030 will push green hydrogen penetration, reducing hydrogen production, storage, and transportation costs, which represent the most important barrier to the diffusion of green hydrogen.

In fact, as the green hydrogen market grows more integrated and gets closer to a global scale, it is expected that nations will position themselves differently based on their capacity to develop parts of the green hydrogen value chain. The availability of RES and the anticipated distribution of production costs, which presently tend to be lowest in the Middle East, Central and South America, and portions of South and East Asia, along with more industrialized regions like Australia and parts of the United States, will be the main factors influencing this positioning, as shown in a recent interactive map of the LCOH published by the International Energy Agency (“Levelised Cost of Hydrogen Maps – Data Tools,” 2024).

In response to persistent gaps in the literature, the present study advances existing research by applying a GIS-AHP-based spatial multi-criteria framework at the urban-industrial scale, explicitly grounded in a real, energy-intensive steel plant. Unlike previous studies, this work integrates technical, economic, environmental, and operational criteria; incorporates expert-based weighting supported by consistency checks; and evaluates alternative planning priorities through a multi-scenario approach. By anchoring the analysis in a concrete industrial context and embedding hydrogen infrastructure siting within an urban planning perspective, the study provides a more comprehensive and policy-relevant assessment framework. The novelty of this research lies in integrating a GIS-AHP-based spatial multi-criteria analysis for identifying optimal sites for green hydrogen infrastructure in urban contexts. Most studies on green hydrogen focus on regional or national scales, emphasizing technical feasibility or energy systems, but in this work, through the spatial multi-criteria analysis within an urban planning framework, showing how hydrogen infrastructure can be spatially integrated into urban

contexts. Furthermore, it lies in the adaptation of this integrated methodological framework specifically for the siting of green hydrogen infrastructure, a topic that remains relatively underexplored in the existing literature. This practical application provides policy-relevant and locally grounded insights into hydrogen adoption for decarbonizing heavy industries. Finally, this interdisciplinary bridge between energy transition and urban planning is a major conceptual innovation by linking hydrogen infrastructure to urban sustainability.

The main contributions of this study are summarized as follows:

- the development of a GIS-AHP-based spatial multi-criteria decision framework specifically designed for the siting of green hydrogen infrastructure in urban and industrial contexts;
- the integration of technical, economic, and environmental criteria within a unified spatial analysis workflow, enabling transparent and reproducible land suitability assessment;

The main practical implications of this study:

- the application of the proposed methodology to an energy-intensive steel industry, providing industry-validated insights into the spatial feasibility of local green hydrogen production;
- The evaluation of alternative planning scenarios by prioritizing different criteria sets supports decision-making for sustainable hydrogen infrastructure development at the local and regional scale.

The document is divided into three sections. The first concerns an in-depth study of methodology. The second section, multi-criteria spatial analysis, is applied to identify suitable sites for green hydrogen production to serve the industry and elaborates on three different scenarios. Finally, the third section discusses the results and collects observations on the work done.

3.1.1. Literature review

Green hydrogen is an emerging research field, and only a limited number of studies have explicitly addressed its spatial integration within urban planning frameworks. As shown in Table 7, the existing literature on green hydrogen infrastructure siting predominantly applies GIS-based spatial multi-criteria approaches at regional or national scales, with an emphasis on technical feasibility, renewable resource availability, and methodological development. While these studies provide valuable insights, they generally treat hydrogen infrastructure as a generic energy-system component, offering limited consideration of urban contexts, industrial operational requirements, and land-use compatibility. Moreover, the integration of economic and operational factors and the exploration of uncertainty through scenario analysis remain

underdeveloped. In contrast, this study advances the state of the art by applying a GIS–AHP-based spatial multi-criteria framework at a local, urban–industrial scale, explicitly tailored to the needs of an energy-intensive steel plant. By integrating technical, economic, and environmental criteria within an urban planning perspective and adopting a multi-scenario approach, this work directly addresses key research gaps identified in recent reviews and provides actionable, policy-relevant guidance for the sustainable deployment of green hydrogen infrastructure in urbanized industrial areas.

Tab. 7: Comparison of spatial multi-criteria approaches for green hydrogen siting

Study	Context & Scale	Methodology	Main Criteria Considered	Key Contributions	Limitations Identified	Difference / Advance of This Study
(Ali et al., 2022)	Regional scale (Southern Thailand)	GIS–MCDM	Technical, environmental, socio-economic	Identification of suitable sites for solar-based green hydrogen production	Limited integration of industrial demand and operational constraints	This study focuses on a specific energy-intensive industry and integrates operational proximity and industrial demand
(Hosseini Dehshiri and Zanjirchi, 2022)	Regional / supply-chain scale	GIS + mathematical optimization	Renewable availability, costs, infrastructure	Integrated spatial and techno-economic supply-chain analysis	Weak urban planning integration	This study explicitly embeds urban planning and land-use compatibility
(Amrani et al., 2023)	Regional scale (Eastern Morocco)	Multi-scenario GIS–MCDM	Environmental, technical, economic	Scenario-based assessment of PV–hydrogen units	Focused on large-scale energy planning	This study applies scenario analysis at an urban–industrial scale

(Flora, 2025)	National/regional scale (Cameroon)	GIS–MCDM + Monte Carlo	Mainly environmental and technical	Uncertainty treatment in site suitability analysis	Limited operational and industrial parameters	This study integrates industrial accessibility and infrastructure proximity rather than generic suitability
(Ransikarbum et al., 2024)	Multi-regional / generic hydrogen supply chain	Integrated MCDA	Technical and logistical criteria	Advanced MCDA framework for hydrogen sites	Limited local-scale validation	This study provides real-world validation through a concrete industrial case study

Green hydrogen technology

Natural gas, oil reforming, and coal gasification are the most widely applied processes for producing hydrogen. Among hydrogen production methods coupled with renewable energy sources, electrolysis is the most mature (Haase et al., 2014; Palm and Larsson, 2007). In electrolyzers, hydrogen is produced via the electrochemical conversion of water into oxygen and hydrogen by using electricity. There are three main categories of electrolyzers: alkaline (ALK), solid oxide (SOEC), and proton exchange membrane (PEM). Anion exchange membrane (AEM) electrolyzers represent an emergent technology, merging the advantages of PEM and ALK, but are still characterized by unstable behaviour and short lifetime of electrodes. PEM electrolyzers are characterized by a compact design and are suitable for operation even in partial load conditions and at higher pressures. Reducing the compression required to deliver hydrogen to the consumer. Moreover, PEM technology is characterized by lower energy consumption. Alkaline electrolyzers have the lowest capital cost of all types, but the electrolyte liquid nature results in leakage and high Ohmic losses, discouraging partial load operation. The solid oxide electrolyzer cell (SOEC) is the newest type of electrolyzer. Unlike PEM and alkaline electrolyzers, it has an extremely high operating temperature (up to 1000 C).

When the cell's operating temperature increases, the required electrical energy decreases due to a higher contribution of the required thermal energy. In this scenario, the cost of the hydrogen produced decreases even if the system's capital cost increases due to the high-quality materials required by the higher operating temperature. Combining renewable sources with the

electrolysis process has been extensively investigated and compared. Different studies show that integrating wind turbines and photovoltaic (PV) plants with electrolyzers is the most promising design.

In fact, nuclear energy, hydro, geothermal, and biomass are characterized by low efficiency and cost performance and typically lower performance in terms of social and environmental aspects. In more detail, solar energy is available everywhere and can be used to produce both electrical and thermal energy. PV modules can only generate electricity, so they can be coupled only with PEM and alkaline electrolyzers that don't require thermal energy. The coupling between PV and electrolyzers could be grid-independent or grid-connected. In the first case, PV plants are the only electric supply source, and the intermittent behavior of solar radiation is negatively reflected in hydrogen production. In grid-connected configurations, constant power is continuously supplied to electrolyzers. Still, the origin of the electric energy that the PV plant does not deliver is not certified as renewable energy, which is related to the power supply mix. In grid-connected configurations, a peak-shaving approach can be selected. In this case, if PV plants, which are originally and adequately designed to supply renewable energy to the grid, cannot deliver all the power produced by the PV cells, they provide excess energy to the electrolyzer. These systems can be designed only if the electricity demand fluctuations are very high.

Nowadays, by performing an economic analysis, one can see that none of the coupled renewable electrolysis systems are feasible ("Ecosystem Accounts for China: Report of the NCAVES project | System of Environmental Economic Accounting," 2021). Anyway, reducing the cost of RES and increasing the cost of fossil fuels will push green hydrogen production as an effective opportunity to counter climate change. Solar and wind energy sources are the most promising, particularly solar energy, almost available everywhere. A detailed analysis of the cost of hydrogen production by different RES has been presented in (Huguet Ferran et al., 2018). Hydrogen production cost depends on the availability of renewable sources on the specific site. Moreover, the cost of production is not the only factor to be considered due to other relevant aspects, such as remote areas and the availability of renewable sources.

3.2. Methodology

To identify the sites suitable for the location of Green Hydrogen production plants, the study utilizes Multi-Criteria Decision-Making Methods (MCDM). MCDM is recognized, in fact, as a relevant method for dealing with complex decision-making problems (Ali et al., 2022). More precisely, the site suitability analysis integrates the Analytic Hierarchy Process method into a GIS environment. The MCDM approach has been widely used for site selection and land evaluation, especially in urban planning and environmental assessments. By using the Bibliometrix package in RStudio, a comprehensive literature search was conducted for 430 papers. The 50 most relevant studies were selected for detailed review after a systematic

screening process. This analysis synthesizes recent advancements in the integration of MCDM with other analytical tools for land suitability assessment, emphasizing methodological innovations, application domains, and emerging research directions.

The results show that the most common integration occurs between MCDM and GIS, often complemented by remote sensing data. This combination enables spatially explicit, multi-criteria evaluations of land suitability for agriculture, urban development, renewable energy deployment, and industrial site selection (Salunkhe et al., 2023a). Integration of these methods enhances sustainable land management by promoting transparent, data-driven, and participatory decision-making processes that incorporate both quantitative and qualitative dimensions (Tuncel and Gunturk, 2024). GIS provides the spatial data management and visualization capabilities, while MCDM structures the decision process and criteria weighting. Another group of studies applies more hybrid approaches that combine MCDM with machine learning techniques such as *Random Forest* or *Artificial Neural Networks*, to improve classification accuracy and decision robustness (Tuncel and Gunturk, 2024). Furthermore, case study domain integration with MCDM is another approach to diverse geographic and socio-economic contexts (Liladhar Rane et al., 2024).

However, despite the benefits of this approach in environmental assessments and site selection, it's important to acknowledge that there are still gaps in the method, as observed in various case studies. For instance, many studies tend to focus primarily on environmental factors, while giving less attention to the integration of these factors with social, economic, and political dimensions, which are crucial for creating a more comprehensive and holistic site evaluation (Mozaffari et al., 2023). Moreover, assessments of uncertainty and sensitivity are often not sufficient, and this makes the evaluation process more challenging, affecting the stability and reliability of the model and the outputs it generates (Özkan et al., 2019). In this work, to address these gaps, we not only incorporated environmental factors but also included technical and economic dimensions into the framework. Furthermore, to enhance the reliability of the results, multiple scenarios were developed by adjusting conditions according to expert opinions. Considering the outcomes across these scenarios helps to partially address existing uncertainties and knowledge gaps.

The analysis is articulated in seven stages (see figure 9): i) Selection of the area of study; ii) identification of criteria and constraints; iii) construction of constraints maps; iv) identification of sub-criteria; v) application of the AHP method to determine the weights of the selected criteria; vi) assessment of the selected sub-criteria via spatial analysis techniques; vii) computation of site-suitability maps and identification of suitable areas.

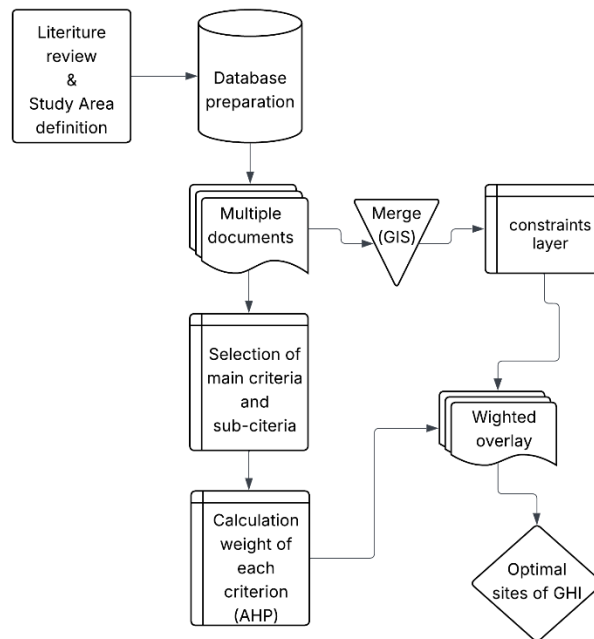


Fig. 9. Flowchart of the proposed methodology.

In this sense, applying MCDM is useful for dealing with complex decision-making problems involving qualitative and quantitative criteria (Al Garni and Awasthi, 2017; Genger et al., 2021; Hossain et al., 2007). Among the most common multi-criteria methods is the AHP (Messaoudi et al., 2019), which the literature also identifies as the most widespread technique for sustainable energy management (Ali et al., 2022). The decision to employ the AHP that incorporates the AHP approach within the GIS as a chosen methodology is justified by the existing scientific literature, which characterizes this tool as robust and well-established (Genger et al., 2021; Ghasempour et al., 2019; Hossain et al., 2007) for evaluating the appropriateness of different locations for implementing renewable energy plants (Al Garni and Awasthi, 2017). However, few studies have focused on applying this integrated methodology for the GHI location (Ali et al., 2022; Dagdougui et al., 2011; Esteves et al., 2015; Messaoudi et al., 2019; Taoufik and Fekri, 2023), primarily due to the complexity of identifying the criteria and assigning the appropriate weight to each criterion outlined by the AHP.

3.2.1. Analytic Hierarchy Process

AHP was developed by Thomas Saaty in the 1980s (Messaoudi et al., 2019) and later formalized as an axiomatic theory (R. W. Saaty, 1987). It takes the form of a measurement method based on scales of ratios that enable the evaluation and classification of different options according to specific criteria and sub-criteria (Saaty, 2008). Through the pairwise comparison technique,

the AHP can reduce the complexity of decision-making problems thanks to a tree structure. Having identified the general objective (goal), it is necessary to identify the criteria, their sub-criteria, and the possible alternatives useful for achieving the goal. In this phase, called decomposition, it becomes possible to clarify the problem using a multi-level hierarchical structure. In essence, the decomposition phase leads to the definition of a structure in which it is possible to order the information on the inter-relationships of the variables involved in the selection, breaking down the problem into its components. The entire problem can be examined through its parts, reassembled according to a hierarchical structure, assigned to a scale, and evaluated according to each part's impact on the overall system. In the hierarchical structure, the levels above “dominate” those below. Given two elements at the same level, it is always assumed that the decision-maker can make a comparison between the two concerning the element above through a scale of reciprocal relationships. In comparing each pair of elements, the decision-maker cannot judge one as infinitely superior. In essence, underlying the AHP hierarchical analysis is the assumption that the decision-maker can always express preference or indifference (uncertainty is not allowed) when comparing pairs of elements of the decision problem under consideration.

This comparison results from the dominance coefficient c_{ij} of element i concerning element j of the same level and element k of the higher level. Saaty states that if the dominance coefficient cannot be determined quantitatively, it is possible to provide a qualitative answer by using a semantic scale. This scale relates the first nine integers to a judgment of quality. The value scale proposed by Saaty (Saaty and Vargas, 1980) (Table 8) makes it possible to translate qualitative and comparative judgments into quantitative terms.

Tab.8 Saaty semantic scale.

Score	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance	Judgment slightly favors one activity over another
5	Strong importance	Judgment strongly favors one activity over another
7	Very strong importance	An activity is favored very strongly over another
9	Extreme importance	Favoring one activity over another is of the highest affirmation
2,4,6,8	Intermediate values	A compromise is needed

Equation 1 shows the structure of the comparison matrix C_x . The matrix is organized into a $n \times n$ matrix, where n represents the rank of the matrix, i.e., the number of elements compared. $C_x = [C_{ij} | \forall i, j = 1, 2, \dots, n]$ for n criteria that influence the ultimate objective of the study, where C_{ij} demonstrates the relative importance of the criterion C_i over C_j . The matrix is:

$$C_x = \begin{bmatrix} C_{11} & \cdots & C_{1n} \\ \vdots & \ddots & \vdots \\ C_{n1} & \cdots & C_{nn} \end{bmatrix} \quad (1)$$

- square: with size equal to the number n of sub-criteria compared;
- positive: ($C_{ij} > 0 \forall i, j$ and with $i, j = 1, 2, \dots, n$) with elements equal to 1 on the main diagonal ($C_{ii} = C_{jj} = 1 \forall i, j$ and with $i, j = 1, 2, \dots, n$);
- reciprocal: ($C_{ij} = 1/C_{ji}$).

Once the pairwise comparison matrix has been constructed for all levels of the hierarchy, it is necessary to calculate the weights of the elements of the higher levels on which the elements are being compared. Determining the weights is a fundamental step in determining the preferences of the decision-makers. Weights can be defined as values assigned to the elements of a hierarchy, indicating their relative importance compared to other elements: the higher the weight, the more important the element is in relation to the criteria or sub-criteria of a higher level. Weights are usually normalized so that the sum is equal to 1. Weighted elements can be calculated by considering the arithmetic mean of each row of the normalized comparison matrix. The normalization is computed as the ratio of each matrix element to the sum of all those in the same column (Fishburn, 1967).

Decision-makers' judgments may be tainted by unintended inconsistency. Experiments applying this method to real decision-making cases have shown that the level of this inconsistency increases with the matrix's increasing rank, i.e., as the number of required comparisons increases.

According to the AHP method, the level of consistency concerning the priorities expressed by the decision-maker can be determined by calculating the Consistency Ratio (CR) and setting its limit at 10%. If this threshold is exceeded, it may be necessary to conduct another pairwise comparison by creating a new matrix and adjusting the weights assigned in the comparisons.

CR is given by the ratio between the Consistency Index (CI) and the Random Consistency Index (RCI). CI is obtained with Equation 2:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (2)$$

$\lambda_{\max}$ represents the principal eigenvalue of the comparison matrix shown in Equation 1. Meanwhile, RCI depends on the number of variables, according to table 9.

Tab. 9 RCI values.

n	1	2	3	4	5	6	7	8	9
RCI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

To address the sensitivity of the composite suitability index to small variations in expert-assigned weights, a structured sensitivity analysis was performed using two complementary approaches: (i) Monte Carlo (MC) simulation and (ii) One-at-a-Time (OAT) perturbation analysis, also referred to as tornado analysis. These procedures were implemented to ensure that the spatial suitability rankings presented in the following section were not merely artefacts of a specific weighting configuration, but instead represented robust and reproducible patterns across a plausible range of parameter values.

In the MC simulation, all seven criterion weights were simultaneously perturbed by adding independent Gaussian noise ($\mu = 0$, $\sigma = 0.05$), yielding a perturbation range of approximately $\pm 10\%$ at the 95th percentile. Negative values were clipped to a minimum of 0.01, and all weight vectors were subsequently renormalised to sum to unity, preserving the fundamental AHP constraint. A total of 10,000 independent simulations were executed (seed = 42 for reproducibility), producing an empirical distribution of suitability scores for each candidate site from which 90% confidence intervals were derived.

In the OAT analysis, each criterion weight was varied individually across the range $[w_n - 0.20, w_n + 0.20]$ in increments of 0.05, while the remaining weights were proportionally rescaled to maintain the unity constraint. The resulting range of the composite suitability index for the highest-ranked site was recorded for each criterion, yielding a tornado diagram that ranks criteria by their influence on the final output. The sensitivity analysis was conducted in R (version 4.x) using base functions for numerical computation, while visualisations were generated with the ggplot2 package.

3.2.2. Spatial Multi-Criteria Analysis

In Spatial Multi-Criteria Analysis problems, the hierarchy concludes with the level of criteria and sub-criteria ("Landfill Siting Using Geographic Information Systems," 1996). The criteria

and sub-criteria can be represented using geographically referenced maps, and all the steps involved in the AHP technique can be integrated in a GIS environment: the weights assigned to the hierarchy elements and the geographical information can be processed within the same framework. The maps measure and display the spatial distribution of evaluation criteria values across the study area. Thus, the alternatives are portrayed geographically within the physical space of the study area, either as a digital raster covering the entire study area or as points, lines, or polygonal shapes if the GIS layer format is vector-based. The weights of the standardized cartographic levels for the criteria are combined using a map-algebra procedure to obtain an overall score for each alternative and objective. This approach is commonly known as the Spatial AHP method ("Landfill Siting Using Geographic Information Systems," 1996).

Definition of criteria and sub-criteria

The process of selecting the criteria and sub-criteria to be considered is a crucial step in the application of Multicriteria Spatial Analysis, as it determines the quality and accuracy of the results. The criteria identified fall into two main categories: constraining criteria, which define the areas excluded a priori due to their incompatibility with the project, and weighting criteria, which weight the characteristics of each area according to their suitability.

Constraining criteria

Constraint criteria define areas unsuitable for the location of a project, in this case, green hydrogen production. These criteria are generally derived from existing regulations and aim to automatically exclude certain areas from consideration for project implementation, regardless of other factors. The binding criteria identified are the following:

- Areas protected by law: This pertains to the regulatory framework for regional landscape planning as outlined in the European Landscape Convention (CEP) signed in Florence in 2000 and ratified by Italy with Law 14/2006. Additionally, the Cultural Heritage and Landscape Code established by Legislative Decree No. 42/2004 mandates an advanced landscape plan structure, which differs from the landscape plans approved under Law No. 431/85 in the 1990s. The Cultural Heritage and Landscape Code requires the preservation of cultural assets (Articles 10 and 45), landscape assets (Articles 136 and 142), and assets for the delimitation of further contexts (Article 143).
- The hazard areas of the PAI4, drawn up by the Basin Authorities, Regions, and Autonomous Provinces, represent a fundamental tool for correct territorial planning and consider both the areas already subject to events and those potentially susceptible to new landslide phenomena. Concerning landslide risk and flood risk, areas under hydrogeological restriction/protection are categorised as unsuitable; the different slopes falling within the Basilicata Region were considered.

- urbanized areas: areas categorized as urban centers or urban clusters, derived from ISTAT data, are considered unsuitable. These constraint criteria are processed through GIS tools, such as QGIS and ArcGIS, to generate maps that exclude unsuitable areas.

Weighted criteria

Weighted criteria, on the other hand, are factors that help to assess the suitability of a location for the implementation of a project, as in the case of green hydrogen plants. Each weighted criterion is associated with a weight calculated using the AHP method. This method allows the different criteria to be compared and weighed according to their relative importance. The definition of the AHP hierarchy and the weighting of criteria were carried out through a structured process of expert consultation involving academics with proven experience in spatial planning and industrial energy. The expert group included professors of urban and regional planning with expertise in multi-criteria analysis and applied GIS, as well as energy professors with extensive experience in research and technical consulting in heavy industry and hydrogen-based decarbonization projects. In addition, the industrial partner (Siderpotenza S.p.A.) provided technical, energy, and environmental data on the plant and supported the validation of the analysis methodology, enabling the calibration of industrial and territorial criteria based on actual production needs.

The AHP-derived weights were integrated into the GIS-based analysis through a weighted overlay procedure. Each spatial layer corresponding to a sub-criterion was first standardized to a common suitability scale (S_i) and then multiplied by its associated AHP-derived weight (W_i). The overall suitability index (S) was computed as the linear combination of the weighted standardized layers, according to:

(3)

$$S = \sum (W_i \times S_i)$$

where W_i represents the weight of the i -th sub-criterion derived from the AHP process, and S_i denotes the standardized suitability score of the corresponding spatial layer. The resulting suitability index was used to generate the composite suitability map.

In this case, the weighted criteria fall into two categories: (main) criteria and sub-criteria.

The main criteria include:

1) Technical criteria concern the area's physical and operational characteristics. The relevant sub-criteria are slope and solar radiation.

2) Economic criteria: indicate the costs associated with the project's special features and the realization of the necessary infrastructure. The sub-criteria belonging to this section are accessibility to roads, accessibility to industry, distance to RES, and distance to the pipeline.

3) Environmental criteria allow the assessment of the environmental impact resulting from the project's realization. The relevant sub-criterion is land use.

Table 10 shows the division between the main criteria and their sub-criteria, the data type and layer, and the data source.

Table 10: Descriptions and sources of the layers used in the spatial analysis.

Main Criteria	Sub-Criteria	Data	Type of layer	Source
Technical	Slope	Digital Terrain Model (DTM)	Raster	Regional Spatial Data Infrastructure of Basilicata (RSDI)
	Solar radiation	Digital Terrain Model (DTM)	Raster	RSDI
Economic	Road Accessibility	Road Network	Vector	RSDI
	Industry Accessibility	Industrial lots	Vector	RSDI
	Distance of RES	Industrial lots	Vector	RSDI
	Distance of GAS pipelines	GAS distribution network	Vector	RSDI
Environmental	Land Use	Corine Land Cover	Vector	European Union, Copernicus Land Monitoring Service 2018, European Environ

The selection of criteria and sub-criteria was based on a comprehensive review of the literature on hydrogen infrastructure siting, renewable energy facility location, and GIS–MCDM applications. Several studies consistently identify technical feasibility, economic accessibility, and environmental compatibility as key dimensions influencing site suitability. Accordingly, the criteria adopted in this study reflect these dimensions and are aligned with approaches commonly used in spatial decision-support analyses. Table 11 summarizes the rationale for the selected criteria, the evaluation approaches adopted in other GIS–MCDM studies, and the specific methods applied in this work.

Tab.11 Selection and assessment of criteria and sub-criteria based on relevant literature.

Main criterion	Sub-criterion	Rationale for criterion selection	Evaluation approaches in other studies	Evaluation adopted in this study
Technical	Slope	Slope is widely recognized as a primary technical constraint in the siting of energy and industrial infrastructures, as it directly affects construction feasibility, installation costs, and operational safety.	In GIS–MCDM studies, slope is commonly evaluated using percentage or angular classes, often excluding areas above threshold values typically ranging from 10% to 20%, followed by ordinal reclassification. (Liladhar Rane et al., 2024; Ghasempour et al., 2019; Al Garni and Awasthi, 2017; Messaoudi et al., 2019).	Raster reclassification of slope: >15% excluded; 13–15% = 1; 9–13% = 2; 3–9% = 3; 1–3% = 4; 0–1% = 5.

	Solar radiation	Solar radiation is extensively used in green hydrogen and renewable energy studies to assess local energy availability and the feasibility of integrating photovoltaic generation.	Previous studies derive solar radiation from DTM or meteorological datasets and classify results into kWh/m ² /year intervals, assigning increasing suitability scores to higher irradiation levels.(Ali et al., 2022; Ghasempour et al., 2019; Al Garni and Awasthi, 2017; Messaoudi et al., 2019; Dagdougui et al., 2011; Esteves et al., 2015)	Solar radiation modeling and reclassification: <900 kWh/m ² /year excluded; 900–1000 = 1; 1000–1200 = 2; 1200–1400 = 3; 1400–1600 = 4; >1600 = 5.
Economic	Road accessibility	Access to the road network affects construction logistics, operation, and maintenance costs, and hydrogen transport efficiency.	In many GIS–MCDM studies, accessibility is approximated using Euclidean distances or buffer-based proximity to roads; more recent works and industrial applications adopt network-based analyses using travel times or traffic flows. (Ganter et al., 2024; Riera et al., 2023; Sun et al., 2017; Genger et al., 2021).	Network-based accessibility analysis using travel-time isochrones (5–25 minutes), to realistically represent transport conditions in an urban–industrial context.
	Industry accessibility	Proximity to industrial hydrogen consumers is essential to reduce transport costs and losses and to ensure supply reliability in energy-intensive sectors.	Previous studies typically assess proximity to demand centers using Euclidean distances or buffers; hydrogen supply-chain and infrastructure studies increasingly apply network-based or cost-oriented accessibility measures (Ganter et al., 2024; Riera et al., 2023; Sun et al., 2017; Mah et al., 2022).	Network-based accessibility analysis using travel-time isochrones from the industrial site (Siderpotenza), explicitly accounting for logistical accessibility.

	Distance of RES	Access to renewable electricity is a prerequisite for green hydrogen production and is commonly included in spatial suitability analyses.	Typically evaluated through proximity analyses (Euclidean distance or buffers) to existing RES installations, often combined with local renewable potential indicators. (Ali et al., 2022; Mah et al., 2022; Messaoudi et al., 2019; Dagdougui et al., 2011; Esteves et al., 2015)	Proximity analysis to RES installations with reclassification into distance classes and increasing suitability for shorter distances.
	Distance of gas pipelines	Proximity to gas pipeline infrastructure facilitates integration with existing energy networks and supports future hydrogen transport or blending strategies.	Previous studies generally evaluate distance to pipelines using Euclidean distance classes as a proxy for connection feasibility and cost. ("European Hydrogen Backbone," 2024; "SNAM," 2024; Finland, 2025; Iamarino and D'Angola, 2025; Messaoudi et al., 2019)	Proximity analysis to the gas pipeline network with reclassification into distance classes and increasing suitability for shorter distances.
Environmental	Land use	Land use is a key environmental criterion to minimize land-use conflicts, comply with regulatory constraints, and protect ecologically sensitive areas.	GIS-MCDM literature generally assigns low suitability scores to natural or protected areas and higher scores to industrial, degraded, or already anthropized land uses. ("Ecosystem Accounts for China: Report of the NCAVES project System of Environmental-Economic Accounting," 2021; Haase et al., 2014; Huguet Ferran et al., 2018; Özkan et al., 2019; Salunkhe et al., 2023b)	Reclassification of land-use classes, penalizing natural and protected areas and favoring industrial or brownfield areas.

While several studies approximate accessibility using Euclidean distance-based proximity measures, the present study adopts a network-based accessibility approach using travel-time isochrones for criteria related to logistical accessibility (i.e., road and industrial accessibility). For energy and infrastructure-related criteria, such as proximity to renewable energy sources and gas pipelines, Euclidean distance-based analyses are employed, in line with common practice in the literature. This methodological distinction ensures internal consistency and enhances the realism and reproducibility of the spatial analysis. These criteria are described in the following sections, specifying their relevance to developing the GHI.

Slope

Among the technical criteria used in Multi-Criteria Spatial Analysis, the slope of the terrain plays a crucial role, as it directly influences the technical feasibility and construction costs of facilities. Terrain with a high slope may present more significant logistical difficulties for constructing infrastructure, requiring more complex engineering interventions, such as levelling or consolidation works, which increase the overall project costs. In the case of the location of GHI plants, all areas with slopes exceeding 15% were preventively excluded. These areas are deemed unsuitable due to structural stability concerns and difficulties related to accessibility and maintenance of the facilities. The slope can also directly influence the position, orientation, and stability of solar panels used to generate renewable energy. Steep slopes can pose challenges in terms of installation and maintenance in the study area. Therefore, areas with moderate slopes are generally more favourable for installing solar panels, as they allow for greater flexibility in their design and positioning, as well as maximum exposure to sunlight during the day. This 15% threshold represents a limit beyond which the terrain is considered unsuitable, ensuring that the selected areas offer optimal conditions for the installation and operation of the system.

Solar radiation

At local scales, topography plays a crucial role in determining the distribution of solar radiation across the surface. Variations in elevation, surface orientation, and shading caused by surrounding terrain generate significant local differences in insolation and, consequently, in related variables such as ground temperature (Batlles et al., 2008). Solar radiation is a key criterion for determining the suitability of a particular area for the implementation of green hydrogen if, as in the case analysed, it is assumed that the renewable energy source is exclusively solar. The amount and intensity of solar radiation in each area directly influence the efficiency and feasibility of the system. Consequently, assessing solar radiation levels at a prospective plant site offers relevant information on the correspondence between potential energy generation and the energy demand associated with green hydrogen production. To assess solar radiation accurately, Digital Terrain Models (DTM) are used to simulate the impact

of the sun on a specific geographical area during the day and throughout the year. This cartographic assessment, combined with other factors such as topography, land use, and the presence of existing infrastructure, provides a complete representation of the feasibility of the installation. Integrating this information helps optimize plant siting to maximize solar exposure and, thus, the efficiency of renewable energy production required for green hydrogen production.

Road accessibility

Road accessibility is a key economic criterion for optimizing logistics operations and minimizing transport costs associated with the production and distribution of green hydrogen. Accessibility was evaluated through an isochrone-based approach, which measures travel time along the road network rather than Euclidean distance. Isochrones were generated using the OpenRouteService (ORS) plugin within the QGIS environment. Routing calculations rely on the OpenStreetMap (OSM) road network as implemented in the ORS backend. Travel times were computed using the ORS heavy-vehicle routing profile, which incorporates default speed limits, road hierarchy, and traffic restrictions suitable for freight transport. These default impedance settings were adopted to ensure transparency and reproducibility of the analysis. The analysis was conducted using a single and consistent set of travel-time thresholds (5, 10, 15, 20, and 25 minutes), selected to represent functionally relevant accessibility levels for daily industrial logistics. Isochrones were computed from the main road junctions within the study area, allowing the spatial distribution of areas with different degrees of road accessibility to be identified. Isochrones are lines that connect points reachable within the same time interval, allowing for a graphical visualization of an area's accessibility in relation to the road network.

This approach enables the accurate identification of areas with better access to the road network, considering the specific characteristics of the road network and each intersection node. Although the study area extends over approximately 728 km², the selected travel-time thresholds are appropriate for the intended accessibility assessment, as isochrone analysis evaluates relative accessibility rather than uniform spatial coverage. The 5–25 minute range was selected to capture functionally relevant travel times for daily industrial logistics, with particular consideration given to heavy-vehicle transport conditions. In logistics studies, the critical time threshold for access to the motorway network is typically reported to range between 30 minutes and one hour (Aksoy, 2024). However, the decision to adopt a lower upper limit of 25 minutes is justified by the orographic characteristics of the study area and the resulting geometry and quality of the regional secondary road network. Areas located beyond the maximum isochrone threshold were not excluded from the analysis; rather, they were assigned lower suitability scores during the reclassification process, thereby ensuring that the entire study area was retained within the multi-criteria evaluation framework.

Accessibility to industry

Accessibility to the industrial site was assessed by applying the same isochrone-based approach described in Section 3.3.2.3, using the Siderpotenza S.p.A. plant as the reference destination. Travel-time isochrones were computed for the same set of thresholds (5, 10, 15, 20, and 25 minutes) to evaluate the spatial distribution of areas that can efficiently serve the industrial hydrogen demand. The resulting isochrones were post-processed using GIS tools (clip and dissolve) to obtain a final accessibility map representing relative proximity to the industrial facility.

Distance of RES

Distance of RES, such as PV plants, is a key criterion for the location of plants that require a constant supply of sustainable energy. Renewable energy sources can experience fluctuations in electricity availability, affecting the production process's overall reliability. For this reason, the green hydrogen production plant must be strategically located close to renewable energy facilities that can provide a continuous and stable flow of energy.

To calculate the distance to RES, spatial analyses use tools such as the NEAR function in ArcGIS, which allows the identification of energy production sites closest to the vacant areas for the plant location. This approach makes it possible to select geographical areas that guarantee an efficient supply of renewable energy, reducing the risk of interruptions in the production process and optimizing the system's overall effectiveness. Proximity to RES, together with energy storage solutions, can thus significantly improve the sustainability and operational continuity of a plant.

Distance of GAS Pipelines

Distance to the gas pipeline is another relevant economic criterion when choosing plant locations, especially when the transport and distribution of gas, such as hydrogen, plays a central role. Proximity to the gas transmission network minimizes logistical and transport costs by reducing the distances required to connect the plant to the existing network. In addition, a well-developed gas transport infrastructure can ensure faster and more reliable distribution of the product to markets or other areas of use.

Again, the distance to gas networks is calculated using GIS tools such as the NEAR function of ArcGIS, which allows the proximity of vacant areas to existing pipelines to be measured. Proximity analysis makes it possible to identify the most suitable areas based on their proximity to the gas transmission network to reduce the costs associated with connecting infrastructure and improve the efficiency of the distribution process. The selection of sites close to the pipeline is, therefore, a strategic factor in ensuring a sustainable and rapid supply, maximizing the economic competitiveness of the plant.

Land use

Land use represents a fundamental criterion in analysing the location of plants for green hydrogen production since it is closely linked to environmental sustainability. The choice of an area for the plant must consider the land use, avoiding restricted areas or areas of special environmental value. The objective is to reduce the environmental impact, favouring the use of disused or already industrialized areas, which are less critical in terms of soil consumption and preservation of ecosystems.

Depending on the land use classification, different areas can be evaluated according to their suitability to host the plant. Green areas, for example, are generally less suitable as they are intended for preserving or managing natural heritage and natural services, including carbon sequestration and storage, crop production, water regulation, and habitat quality. In contrast, areas already compromised or under-utilized, such as industrial areas, are more suitable for minimizing environmental impact and optimizing the use of existing resources.

3.2.3. Case studies

This study aims to identify suitable sites for locating GHIs to serve energy-intensive industries in the Basilicata region. To this end, the methodology applied, Multi-Criteria Spatial Analysis, follows the steps shown in figure 9.

Application of the methodology for the “Siderpotenza” steel plant

“Siderpotenza S.p.A.” is part of the Pittini Group, an important Italian steel company. The Group is a leader in producing long steels for construction and mechanical engineering, with a 12.6% share of the national output. Siderpotenza, founded in 2002, is in the industrial area of the city of Potenza and produces reinforcing steel using an electric arc furnace, a more sustainable technology than the blast furnace. The company is classified as “energy-intensive” due to its high electricity and natural gas consumption. The production cycle also requires large quantities of water, mainly used for plant cooling. This quantity (approximately 218,000 m³) is discharged into the industrial drain at the end of the process. Water consumption was considered under the assumption that the water discharged into the sewage system at the end of the production process is treated, demineralized, and reused in the electrolysis process for producing green hydrogen.

The quantity of green hydrogen produced inside the plant is strictly related to internal demand and requires only a fraction of water availability. In the steel industry, green hydrogen is used as a reducing agent instead of coal or grey hydrogen and can also be used to partially replace (20% blending in natural gas) other fuels in combustion in order to reduce CO₂ emissions. For the Siderpotenza case study, considering the conversion factor from not demineralized water into hydrogen of 20 l of water for 1 kg of hydrogen (almost 50 kWh of renewable electric energy), production is much higher than the demand. The study area (Figure 10) covers approximately 728 km². It includes the municipality of Potenza, where Siderpotenza S.p.A. is located, and the municipalities of the first belt: Vaglio Basilicata, Picerno, Pietragalla, Ruoti, Tito, Brindisi

Montagna, Pignola, Avigliano, and Cancellara. The area surrounding the plant also includes other industrial, commercial, craft, and office settlements, other areas with totally or partially built-up urban parts, and the road and urban transport system. The first step in the analysis was to identify all the unsuitable areas (described in paragraph 3.3.1) in order to obtain a map (Figure 2) representing the available areas and the constrained areas where the GHI cannot be located.

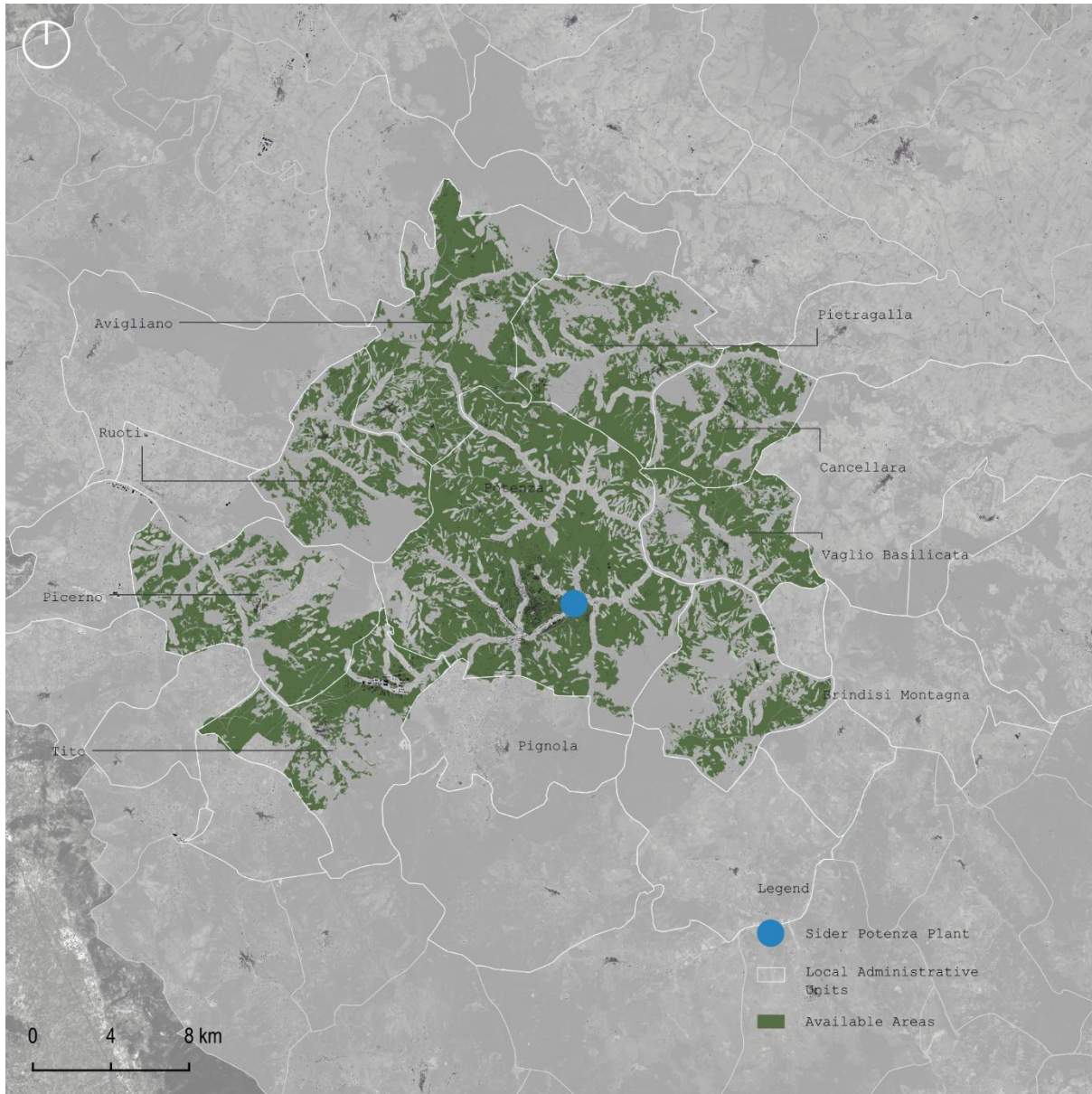


Fig. 10. Selection of the study area and identification of Available areas.

For each identified criterion, weights were calculated using the AHP method using a pairwise comparison matrix (Table 12). The vector represents the weights w_i of the matrix; the criterion

with the most relevance is C_7 or land use. The results' consistency level was then checked (Table 13).

The hierarchy of weights obtained from the AHP analysis shows that the optimal location for green hydrogen infrastructure is guided by criteria of proximity and integration with industry. The criterion of 'accessibility to industry' (28%) is the most influential, followed by 'land use' (20%) and 'distance from photovoltaic panels' (18%), reflecting the need to combine logistical efficiency, territorial sustainability, and the availability of renewable energy. Criteria related to solar radiation (14%) and road accessibility (10%) are of intermediate importance, while slope (4%) and distance from the gas pipeline (6%) are marginal. The Consistency Ratio (CR = 8.59%) falls within acceptable limits (<10%) but indicates moderate inconsistency due to the difficulty of differentiating between criteria of similar importance, particularly between energy and environmental factors (C2–C5–C7). However, the weighting structure is consistent with the aims of the study, and the sensitivity analysis confirms the stability of the ranking of alternatives with respect to weight variations of up to $\pm 5\%$.

Tab.12 pairwise comparison matrix and weights of sub-criteria.

	C1	C2	C3	C4	C5	C6	C7	Wi (%)
C1	1,00	0,25	0,25	0,20	0,20	0,50	0,33	4
C2	4,00	1,00	3,00	0,50	0,33	3,00	0,50	14
C3	4,00	0,33	1,00	0,33	0,50	3,00	0,33	10
C4	5,00	2,00	3,00	1,00	3,00	3,00	2,00	28
C5	5,00	3,00	2,00	0,33	1,00	3,00	0,50	18
C6	2,00	0,33	0,33	0,33	0,33	1,00	0,33	6
C7	3,00	2,00	3,00	0,50	2,00	3,00	1,00	20

Tab.13 consistency check.

$\lambda_{\max}$	n	CI	RCI	CR	CR (%)
7,68	7	0,11	1,32	0,09	8,59

Stability of Criterion Rankings

Table 13 presents the frequency with which each criterion maintained its baseline ranking across the 10,000 MC simulations. The results indicate a high degree of ranking stability for the most influential criteria. Industry Accessibility (C4; baseline weight = 28%) retained the first rank in 81.3% of simulations and the second rank in an additional 14.1%, demonstrating that its dominant contribution to the suitability model is robust to uncertainty. Land Use (C7; 20%) emerged as the second most stable criterion, occupying the first rank in 11.3% of simulations and the second rank in 43.9%. Distance to Renewable Energy Sources (C5; 18%) consistently ranked second or third, accounting for 28.5% and 35.5% of simulations, respectively. In contrast, criteria associated with lower baseline weights, namely Slope (C1; 4%) and Distance to Pipeline (C6; 6%), showed an almost negligible probability of attaining a leading rank,

confirming that their limited influence within the weighting scheme is not merely an artefact of the initially assigned values.

Table 13: Rank stability of AHP criteria across 10,000 Monte Carlo simulations.

Criterion	Baseline Weight (%)	Rank 1 Freq. (%)	Rank 2 Freq. (%)	Rank 3 Freq. (%)
Slope	4.0	0.0	0.1	0.7
Solar Radiation	14.0	1.4	10.1	21.8
Road Accessibility	10.0	0.2	2.7	8.4
Industry Accessibility	28.0	81.3	14.1	3.7
Distance to RES	18.0	5.7	28.5	35.5
Distance to Pipeline	6.0	0.0	0.4	2.3
Land Use	20.0	11.3	43.9	27.5

One-at-a-Time Sensitivity and Tornado Analysis

Figure 11 presents the tornado diagram derived from the OAT perturbation analysis. Industry Accessibility (C4) is confirmed as the most influential criterion, exhibiting a suitability range of 0.242 when its weight is varied by $\pm 20\%$, a value approximately 40% higher than that of the second-ranked criterion, Land Use (C7; range = 0.174). This outcome is consistent with the functional and spatial logic of the study area, as the Siderpotenza steel plant provides unique co-location advantages for green hydrogen infrastructure, including existing grid connectivity, hydrogen offtake demand, and logistical accessibility, which cannot be adequately substituted by other spatial determinants when its weight is reduced.

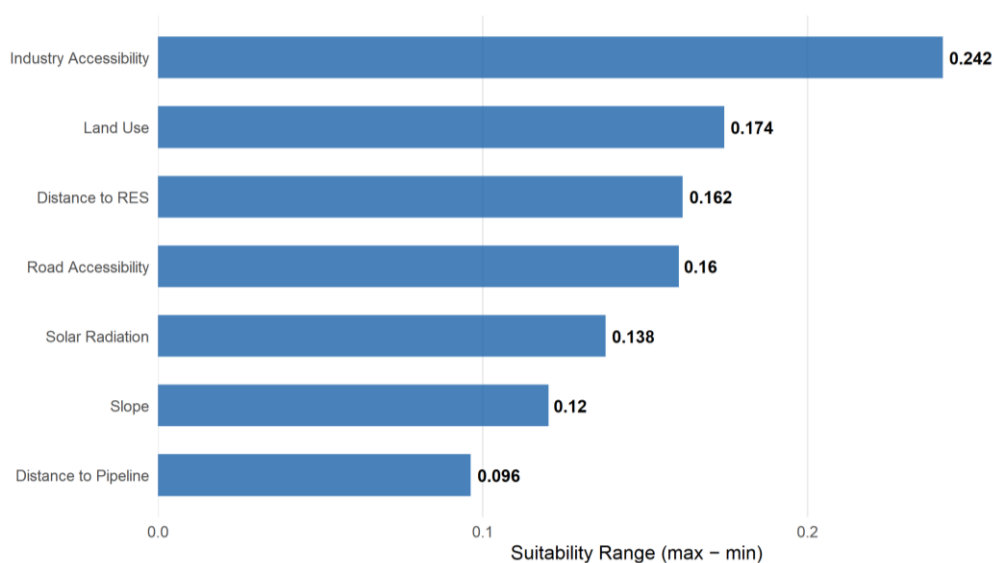


Fig. 11. OAT Sensitivity

Distance to Renewable Energy Sources (C5; range = 0.162) and Road Accessibility (C3; range = 0.160) display comparable intermediate levels of influence, whereas Solar Radiation (C2; range = 0.138), Slope (C1; range = 0.120), and Distance to Pipeline (C6; range = 0.096) exert comparatively lower leverage on the model outcomes. Overall, the predominance of proximity-to-industry and land-use suitability over purely biophysical variables (e.g., slope and solar irradiance) in shaping the final ranking reflects the industrial–urban character of the study area and differentiates the proposed framework from conventional rural or greenfield renewable energy siting approaches commonly reported in the literature.

3.2.4. Elaboration of criteria maps

Determining the criteria's weights enables the development of accurate spatial analyses of the variables relevant to the overall assessment. The spatial analysis of the criteria and their sub-criteria led to maps representing the specific aspects considered, as shown below (Figs. 12–18). Each map is described through a legend whose values follow a suitability scale, where 1 indicates low suitability and 5 indicates optimal suitability conditions. Table A in the appendix summarizes the standardization and scoring scheme for weighted criteria.

Figure 12 represents the first of the sub-criteria analysed, namely slope. Areas with a slope of more than 15% are considered unsuitable. Areas with very low suitability, indicated by a value of 1 of the corresponding indicators, present slope values ranging from 13 to 15%. Areas with low suitability (identified by a value of 2 of the slope indicator) present slope values in the 9–13% interval. Moderate suitability (slope indicator equal to 3) is estimated for areas with a slope ranging between 3% and 9%. High and very high suitability levels are estimated for areas with slopes included in the 1–3% and 0–1% intervals, respectively. Considering the morphology, many areas fall in the range with slopes above 15%.

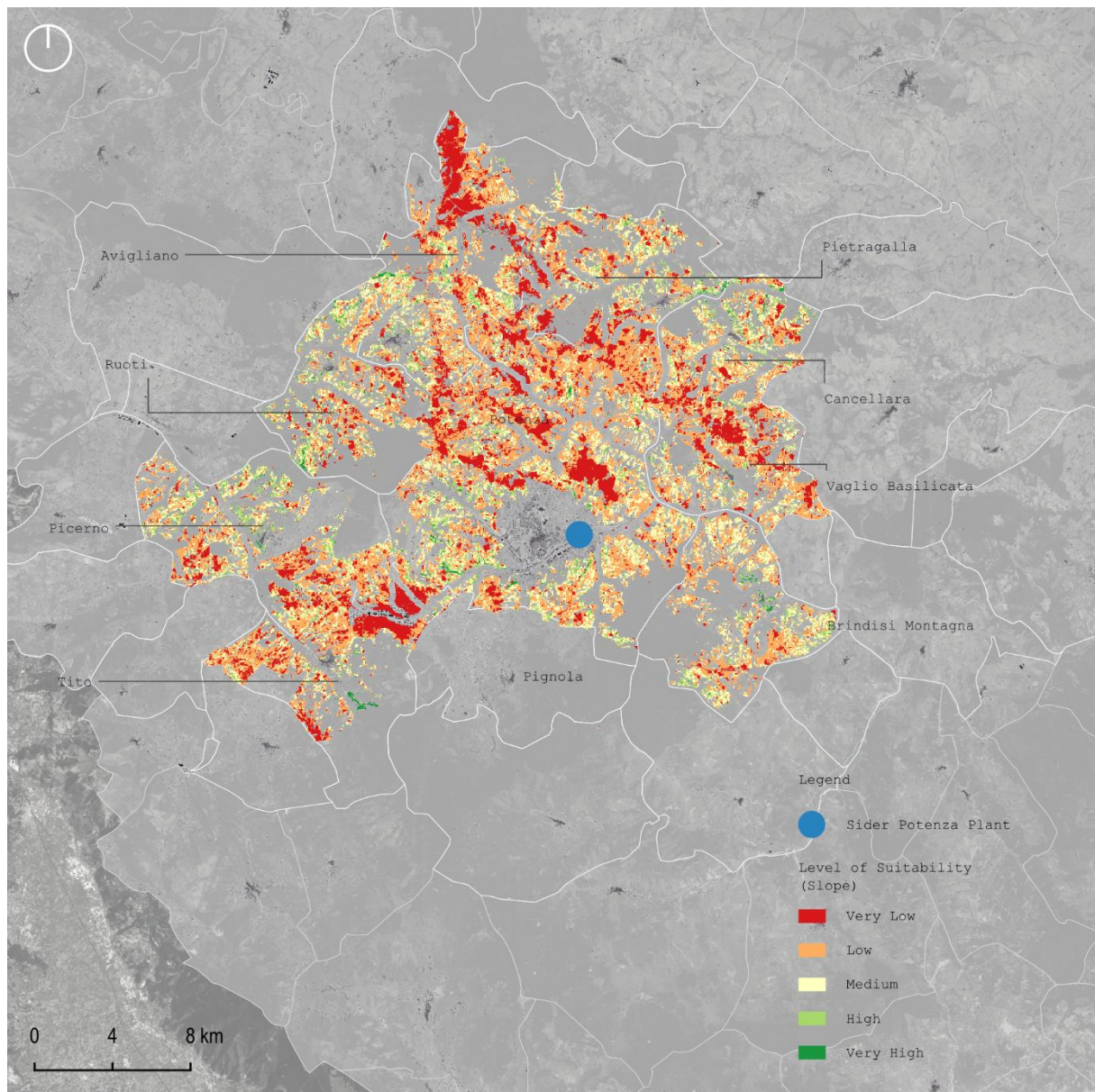


Fig. 12. Level of suitability based on the Slope sub-criterion.

Figure 13 shows the solar radiation map. This shows a high degree of suitability for the entire area. In this case, suitability is evaluated in terms of global horizontal irradiance per year ($\text{kWh/m}^2/\text{year}$), the representative value of the amount of solar radiation incident on the PV panel. Areas with values below $900 \text{ kWh/m}^2/\text{year}$ were excluded (unsuitable areas). The areas with a very low degree of suitability present levels of global horizontal irradiance per year comprised in the range $900\text{-}1000 \text{ kWh/m}^2/\text{year}$, the low degree refers to values between 1000-

1200 kWh/m²/year, the moderate degree to the range 1200-1400 kWh/m²/year, the high and very high degree to values between 1400-1600 and above 1600 kWh/m² /year.

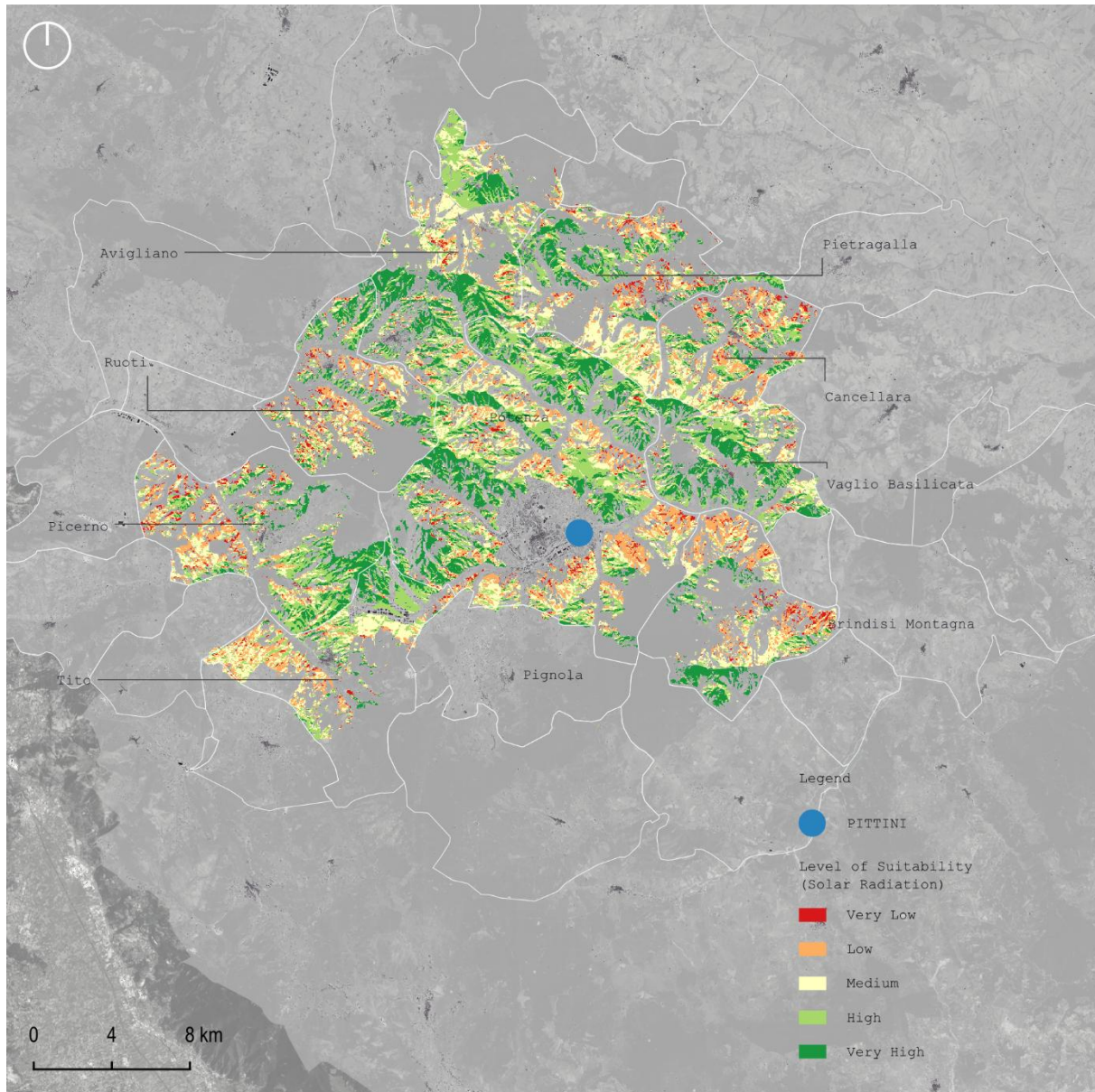


Fig. 13. Level of Suitability of available areas based on solar radiation sub-criterion.

Two distinct approaches are utilized to create proximity maps. Isochrones are computed to determine the distance from roadways (Figure 14) and industrial locations. In this case, proximity is evaluated in terms of time travel along the shortest paths from a predefined set of origin points. On the other hand, the NEAR tool is utilized to evaluate proximity, in terms of linear distance, from available RES plants and existing gas pipelines. The assumption is that

closeness to roads, RES plants, gas pipelines, and industrial areas affects the production of green hydrogen as well as hydrogen transportation from the place of production to the point of consumption. This, in turn, influences the process's cost and efficiency. Specifically, situating a green hydrogen generation facility near a major road or highway can significantly reduce transportation costs and enhance process efficiency. In this case, the ORS tool in GIS is utilized to compute the isochrone distance, a time-dependent approach for calculating closeness to junctions of major highways in the study area. The isochrones are computed based on the commercial speed of heavy vehicles and travel times ranging from 5 minutes to 25 minutes. Figure 5 indicates that a heavy vehicle can reach at least one highway junction within 30 minutes from each point of the study area. The SiderPotenza steel plant is selected as the end consumer of green hydrogen. Therefore, a similar approach has been adopted for the assessment of the proximity to the industrial area, thus estimating the percentage of the land units located at time intervals included in the 5 - 25 minutes range from the industrial site. According to the results (see Figure 14), only a limited portion of the study area is located at a distance from the Siderpotenza plant, which is equal to a travel time of 5 or 10 minutes.

The results show that, when considering the combined isochrones generated from multiple road intersections, the adopted time thresholds ensure adequate spatial coverage of the study area, while still allowing accessibility differences to be meaningfully distinguished.

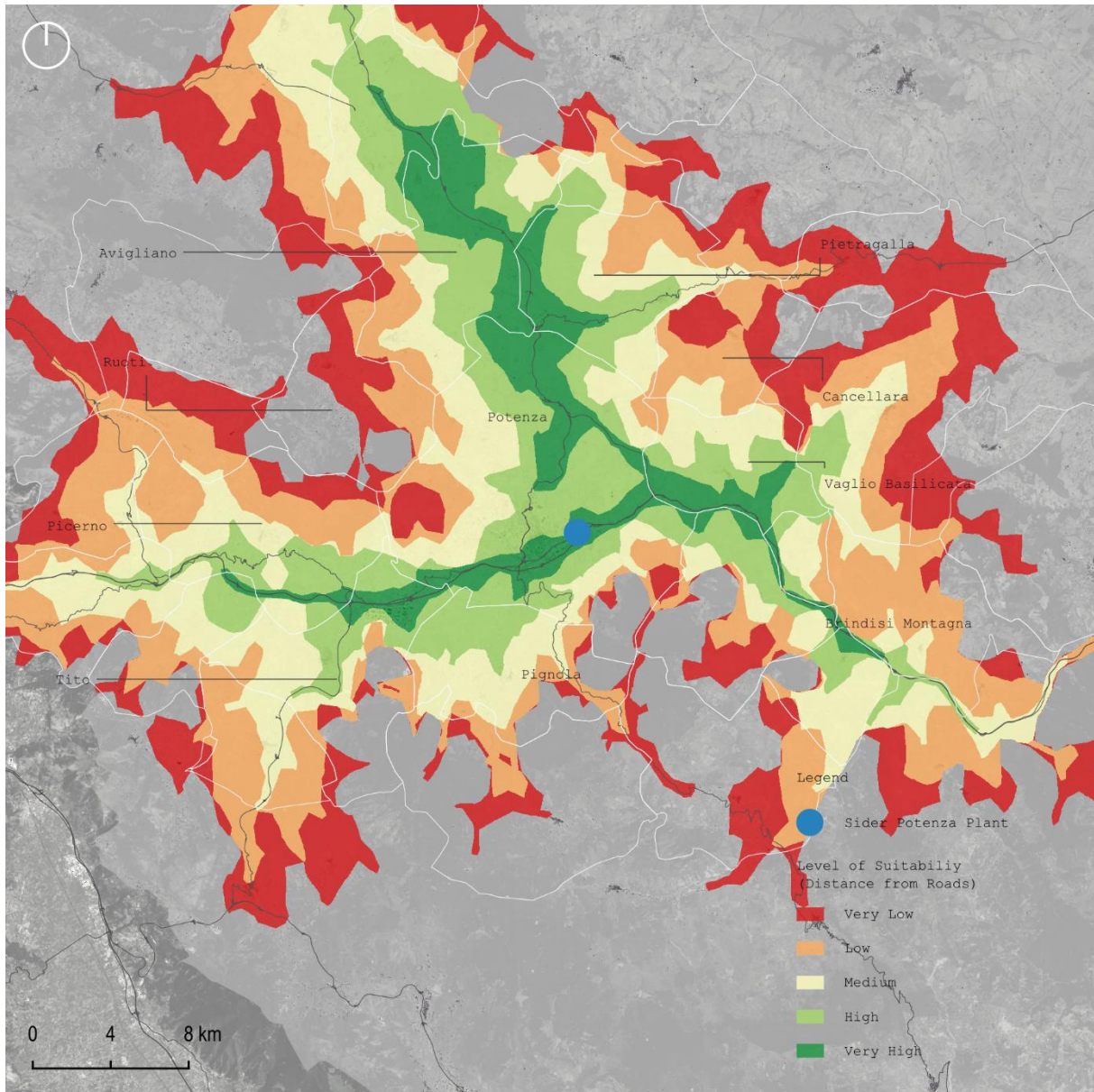


Fig. 14. Road Accessibility map.

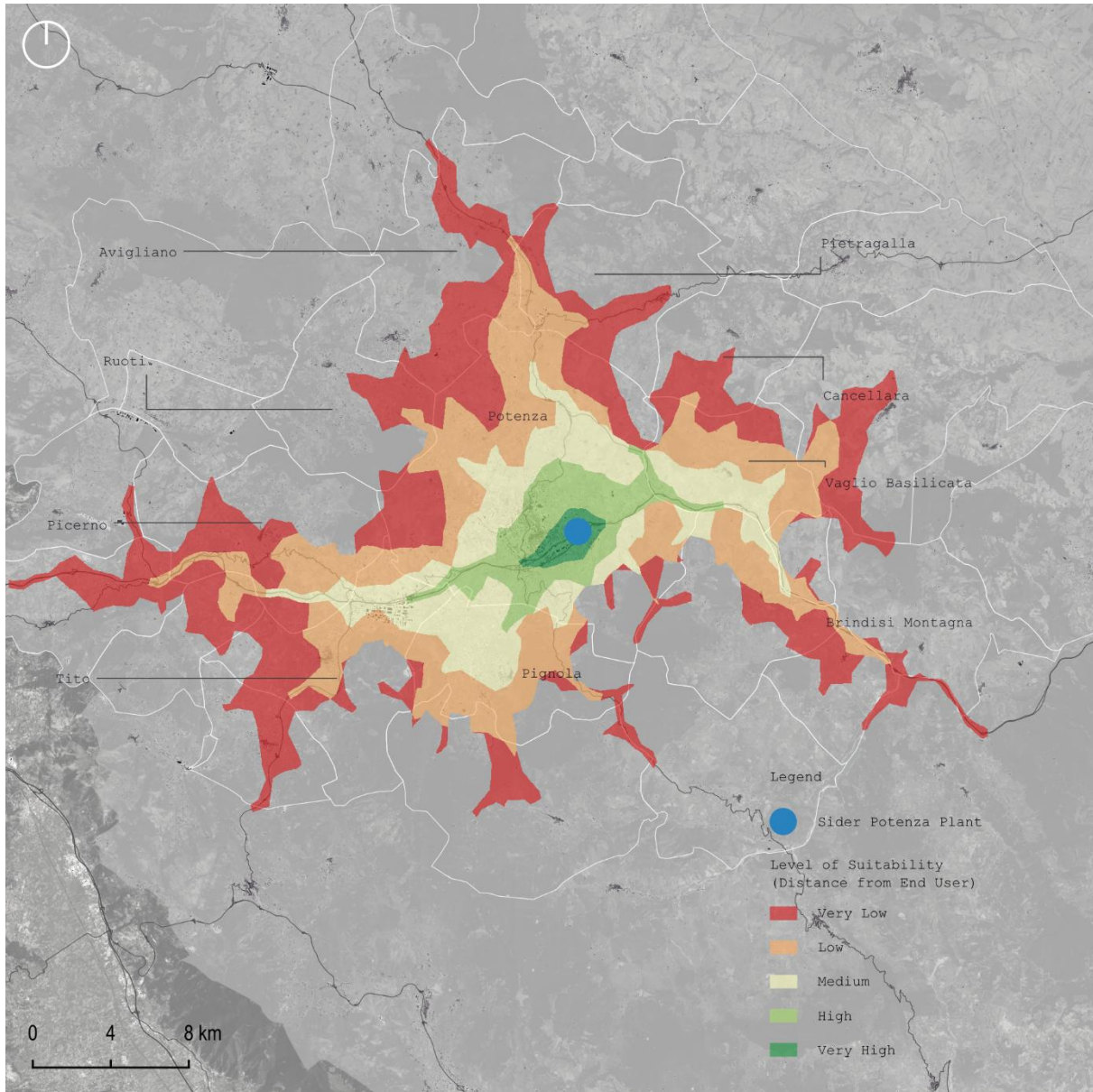


Fig. 15. Siderpotenza industry accessibility map.

To analyse the impact of the availability and reliability of RES on the production process, the distance of available areas from PV plants and gas pipelines was examined using GIS tools. Specifically, in Figure 16, the NEAR function of ArcGIS was applied to identify the sites closest to PV plants, highlighting areas where interventions can ensure a steady energy supply. The same approach was used for Figure 17, where proximity to gas pipelines was analysed: the most suitable areas, shown in green on the map, are those near the gas transmission

network. This allows for identifying strategic zones for plant development, ensuring an efficient connection to existing energy infrastructures.

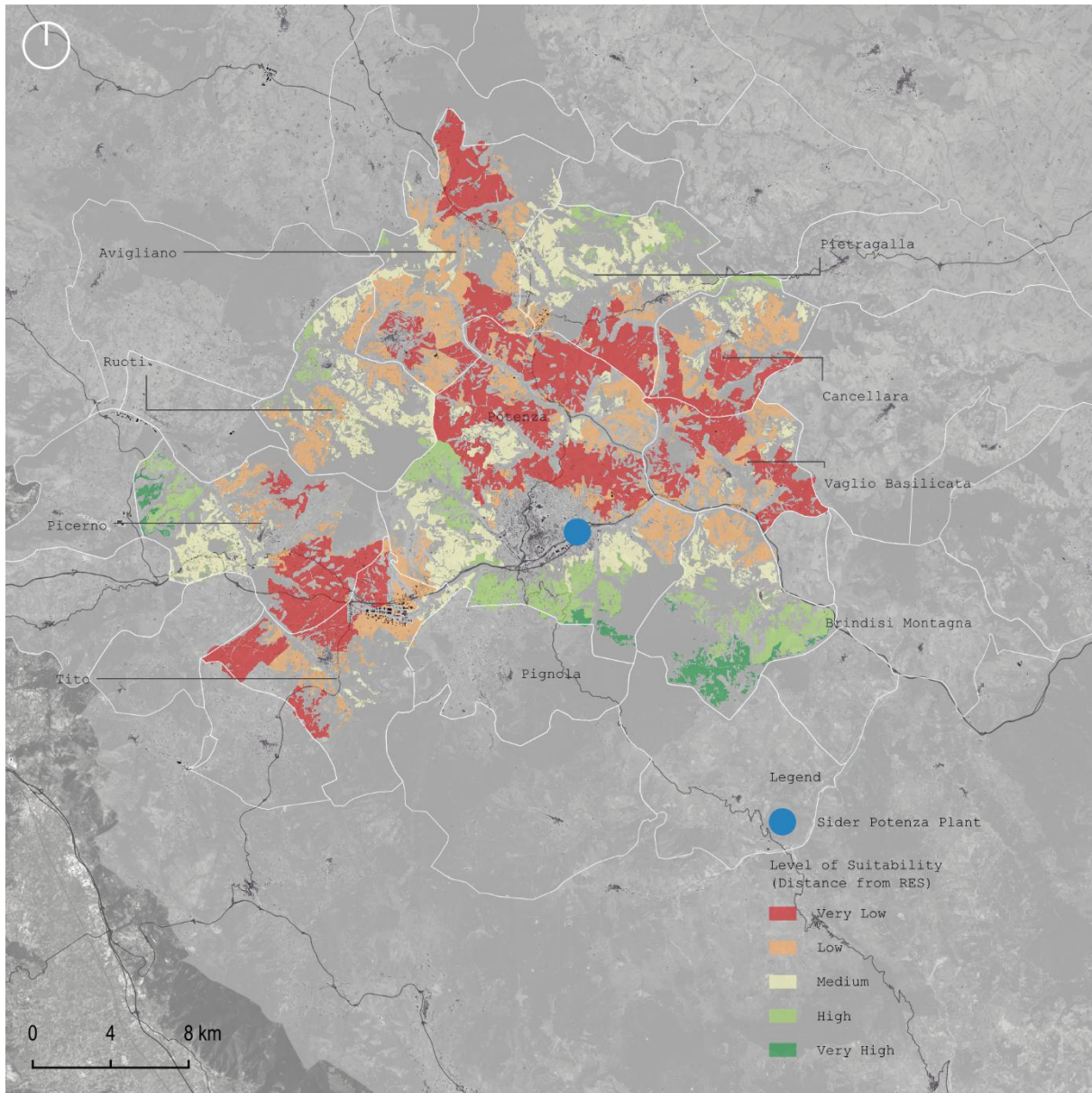


Fig. 16. Level of Suitability of available areas based on Distance from RES.

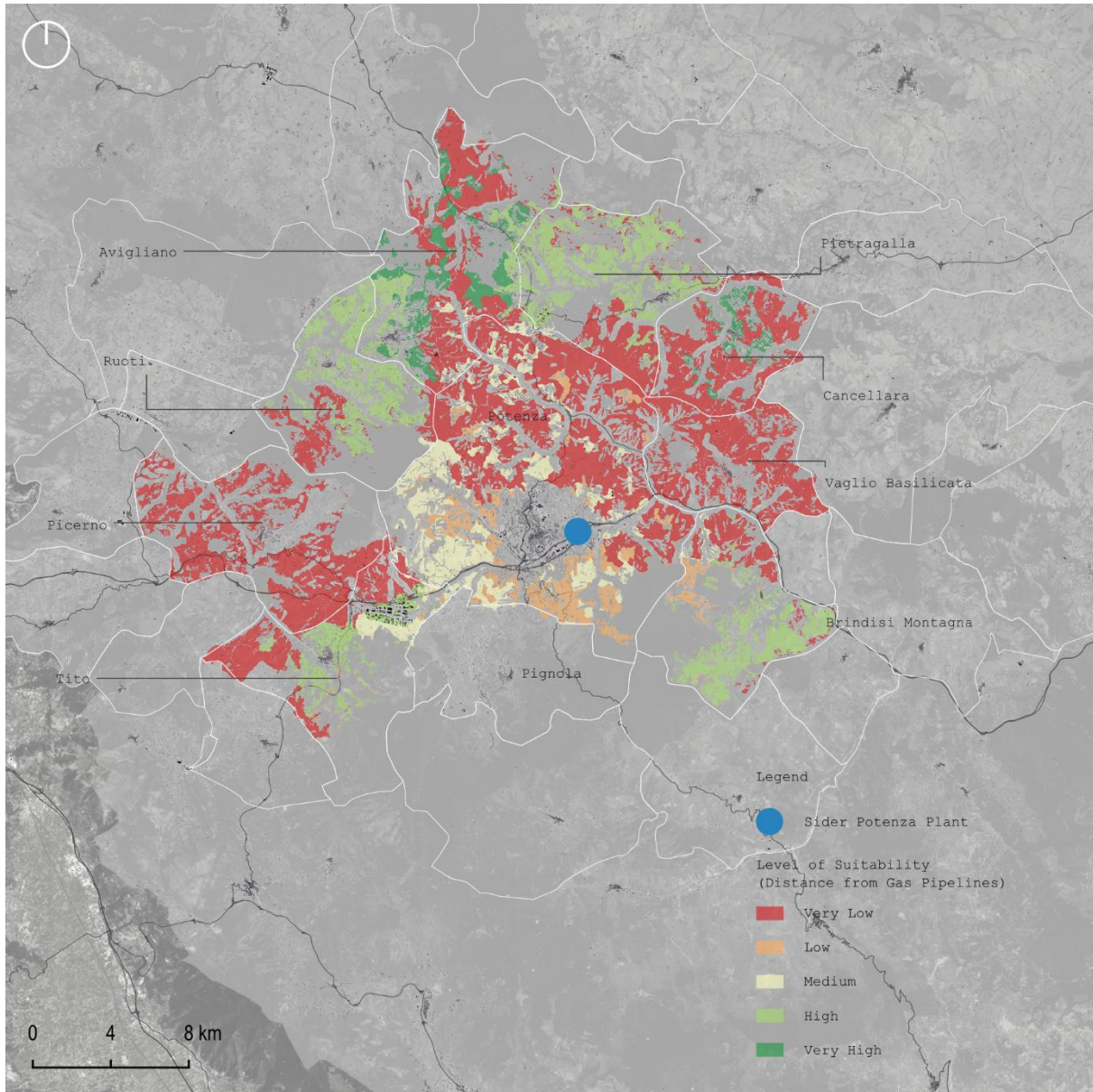


Fig.17. Level of Suitability of available areas based on Distance from the gas pipeline.

Land use plays a crucial role in the decision-making process for locating green hydrogen plants and is closely linked to environmental sustainability. Site selection must avoid protected areas or regions with high ecological value, favouring abandoned or industrialized spaces to minimize environmental impact and reduce land consumption. This approach mitigates issues related to ecosystem conservation. In the case study analysed, land use was also classified into five distinct categories, as shown in Figure 18, to identify the most suitable areas for green hydrogen plants. Abandoned and industrial areas are identified as the most suitable. In contrast, natural and semi-natural areas designated for conservation

were considered less suitable, receiving a score of 1 (shown in red on the map). This classification identifies areas with the lowest environmental impact, optimizing site selection to ensure sustainable production.

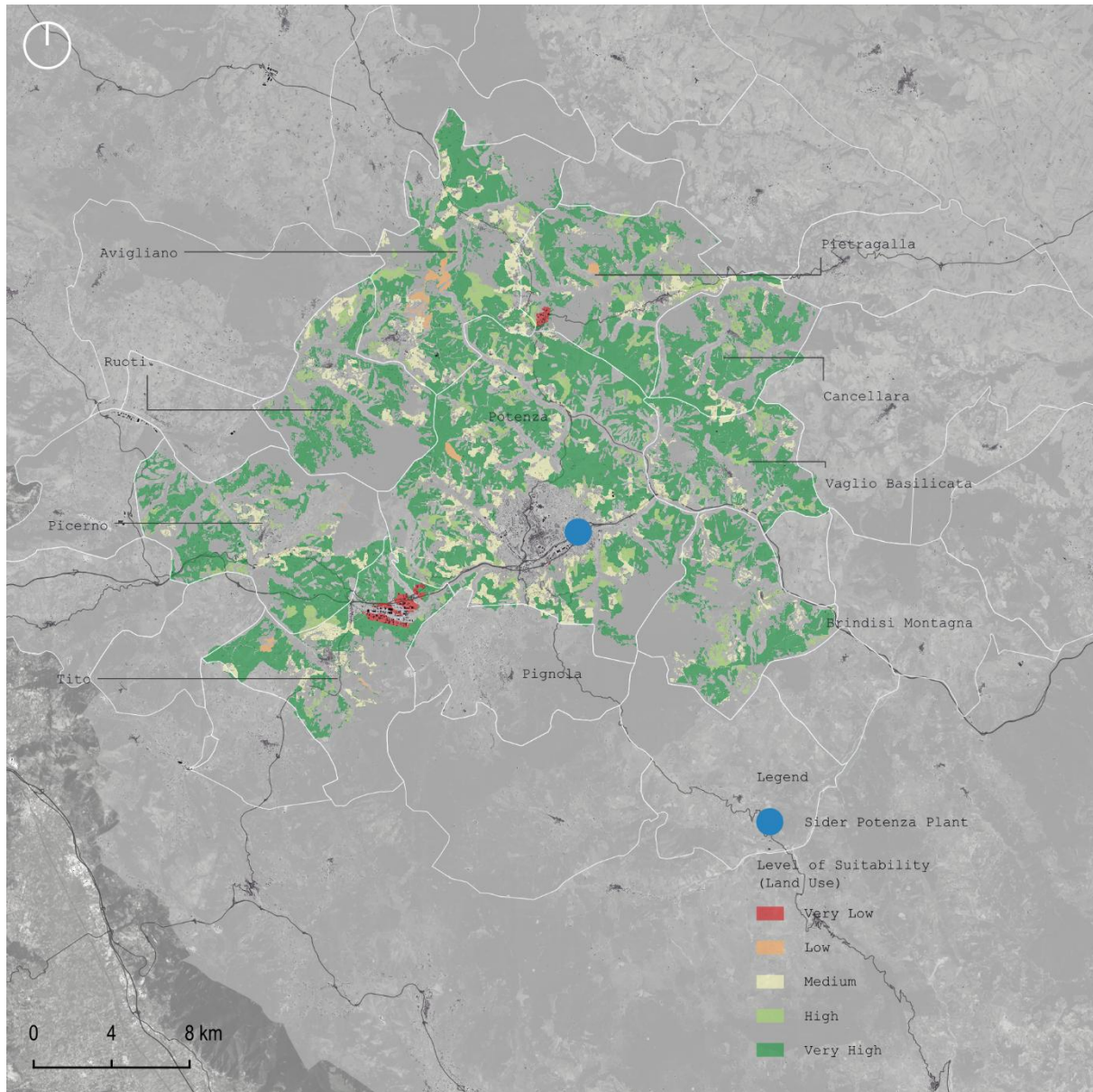


Fig. 18. Level of Suitability of available areas resulting from impact on Land use.

3.2.5. Land suitability map

The result of the Multi-Criteria Spatial Analysis, shown in Figure 19, provides a comprehensive overview of the most suitable areas for locating an infrastructure dedicated to green hydrogen production to serve Siderpotenza S.p.A. To achieve this, the overlay tool in

GIS was used, allowing the combination of various analysed criteria to identify the optimal site. The map produced by the analysis highlights a rather limited presence of high-medium suitability areas (9%), suggesting that ideal conditions for plant installation exist only in small portions of the considered territory. Most of the land falls under a medium suitability level (70%), with the most favourable location found near the Siderpotenza facility, thus ensuring easy access to existing infrastructure and a direct connection to the industrial plant. The analysis indicates that the most significant percentage of available areas is classified as medium or medium-low suitability (21%). This result reflects the complexity of the territory and the need to balance various factors, including environmental sustainability, access to RES, and integration with transportation and distribution networks. The spatial distribution of suitable areas shows that the availability of renewable energy, the presence of adequate infrastructure, proximity to transport systems, and population density are crucial elements in assessing site suitability. Therefore, the analysis suggests that, while there are some favorable areas, the location choice must carefully consider all these factors to ensure maximum efficiency and sustainability for the green hydrogen plant.

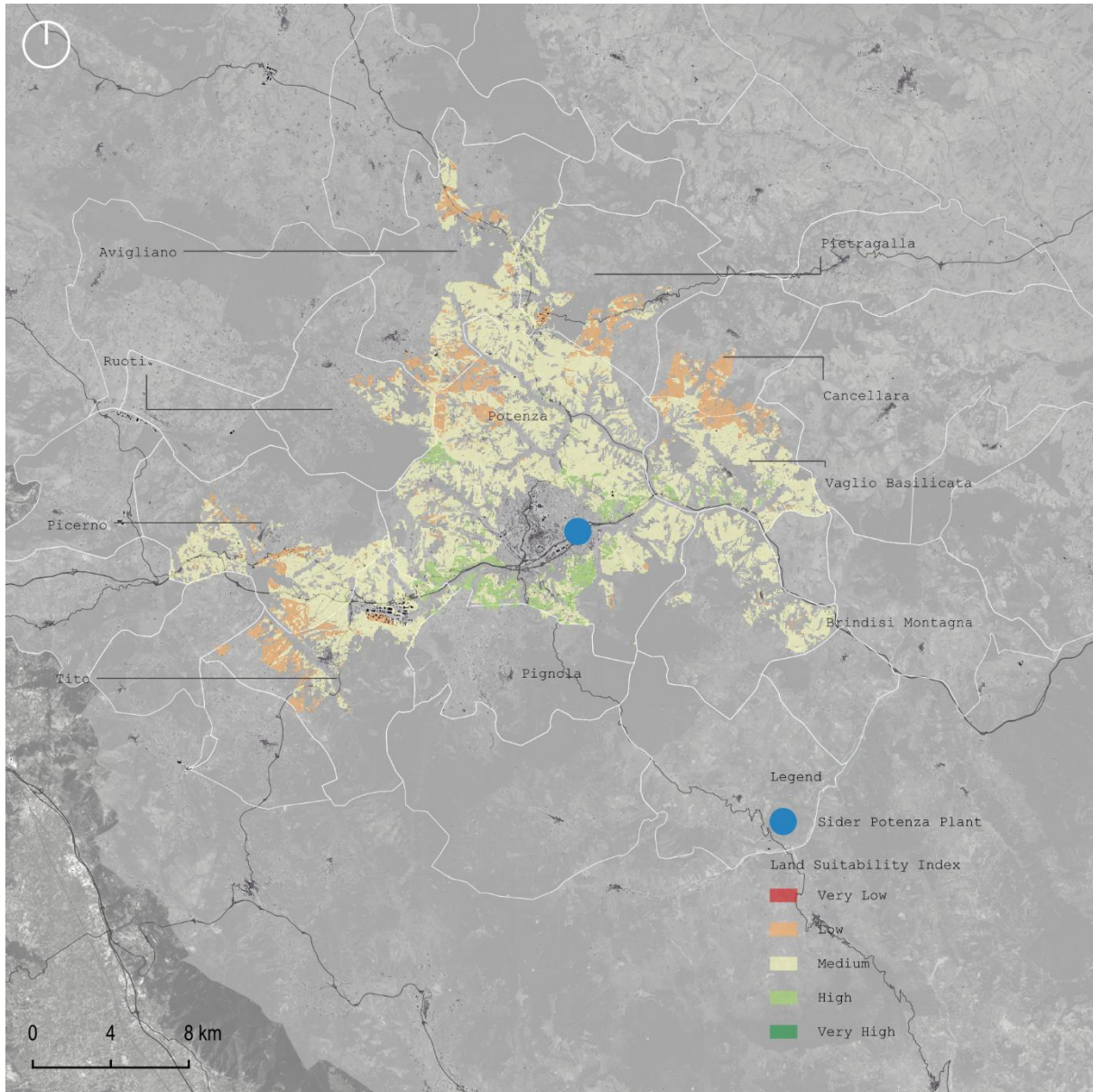


Fig.19. Land Suitability map.

3.2.6. Elaboration of three alternative scenarios

Further elaborations were developed to propose three different alternative scenarios to the result previously obtained. The three different scenarios derive from emphasizing the three main criteria already identified, namely: a) technical criteria (Scenario 1), economic criteria (Scenario 2), and environmental criteria (Scenario 3). Table 14 shows the weights of the sub-criteria for the three scenarios.

Tab.14 The weights of sub-criteria for different scenarios.

a.		b.		c.	
w_i (%)		w_i (%)		w_i (%)	
C₁	6	C₁	3	C₁	3
C₂	44	C₂	22	C₂	22
C₃	2	C₃	4	C₃	2
C₄	15	C₄	30	C₄	15
C₅	5	C₅	9	C₅	5
C₆	3	C₆	6	C₆	3
C₇	25	C₇	25	C₇	50

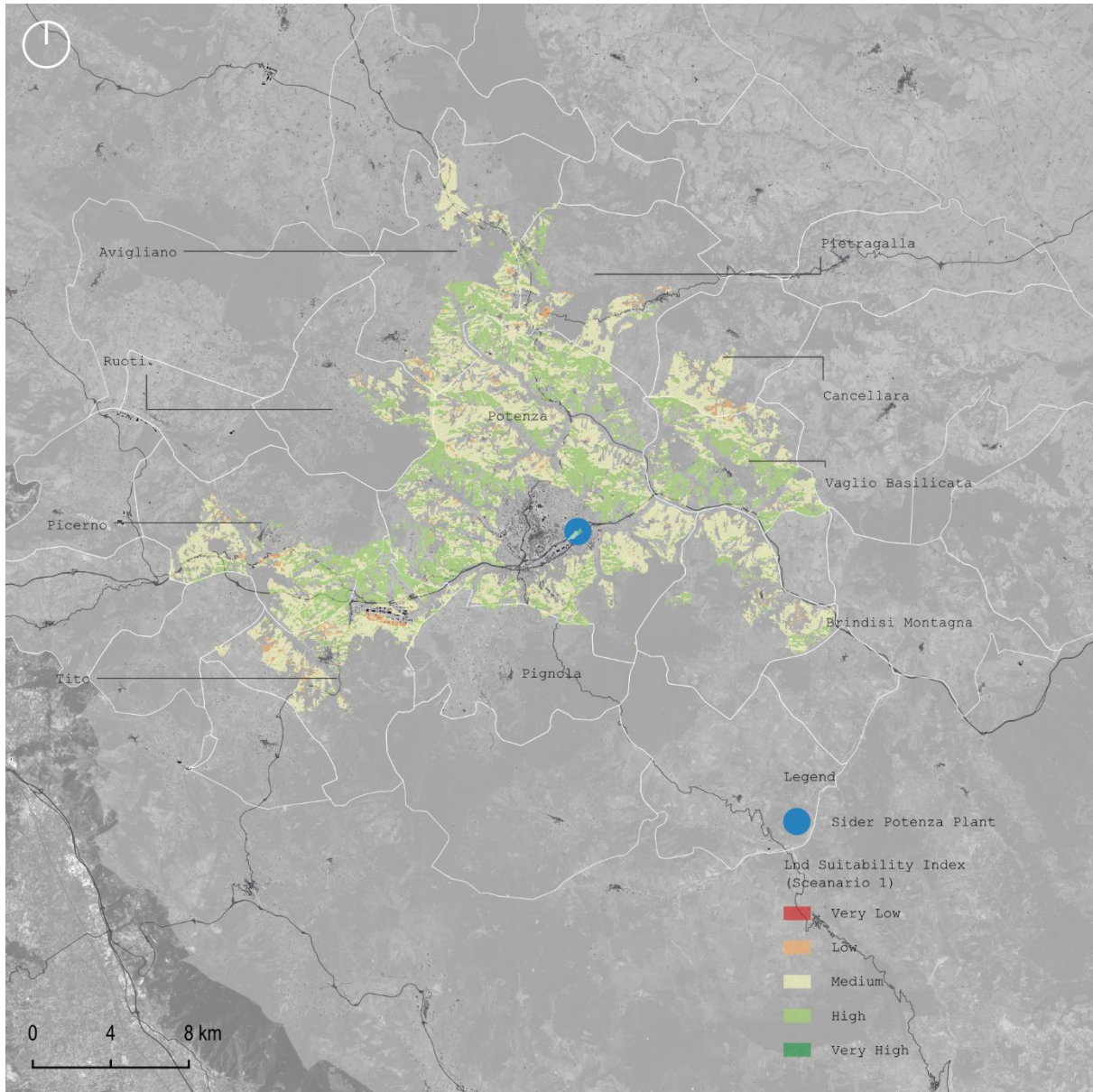


Fig. 20: Land Suitability under Scenario 1.

The three scenarios developed within the framework of the project indicate possible alternative future contexts in which new structures and related stakeholder discussions could take shape. For each scenario, the sub-criteria weights were adjusted to prioritize technical, economic, or environmental criteria. The following steps are the same as those previously followed in the GIS environment. The results show the land suitability depicted in Figures 20, 21, and 22 for scenarios 1, 2, and 3, respectively. The first scenario prioritized technical criteria, favouring areas with low slopes and high solar radiation availability. The results show that the areas have a high percentage of medium and medium-low suitability. Emphasizing technical criteria makes it possible to identify sites suitable for installation with

less effort in adapting the territory for the location of the infrastructure. The areas with the highest suitability level fall in proximity to the Siderpotenza, i.e., in the industrial area of the city of Potenza. The result shows a higher percentage of eligibility for the middle and lower middle levels when emphasizing economic criteria. Also, in this scenario, areas that are located close to the industry are favored in terms of suitability, such as areas with lower costs for locating the planned infrastructure for the production and distribution of Green Hydrogen.

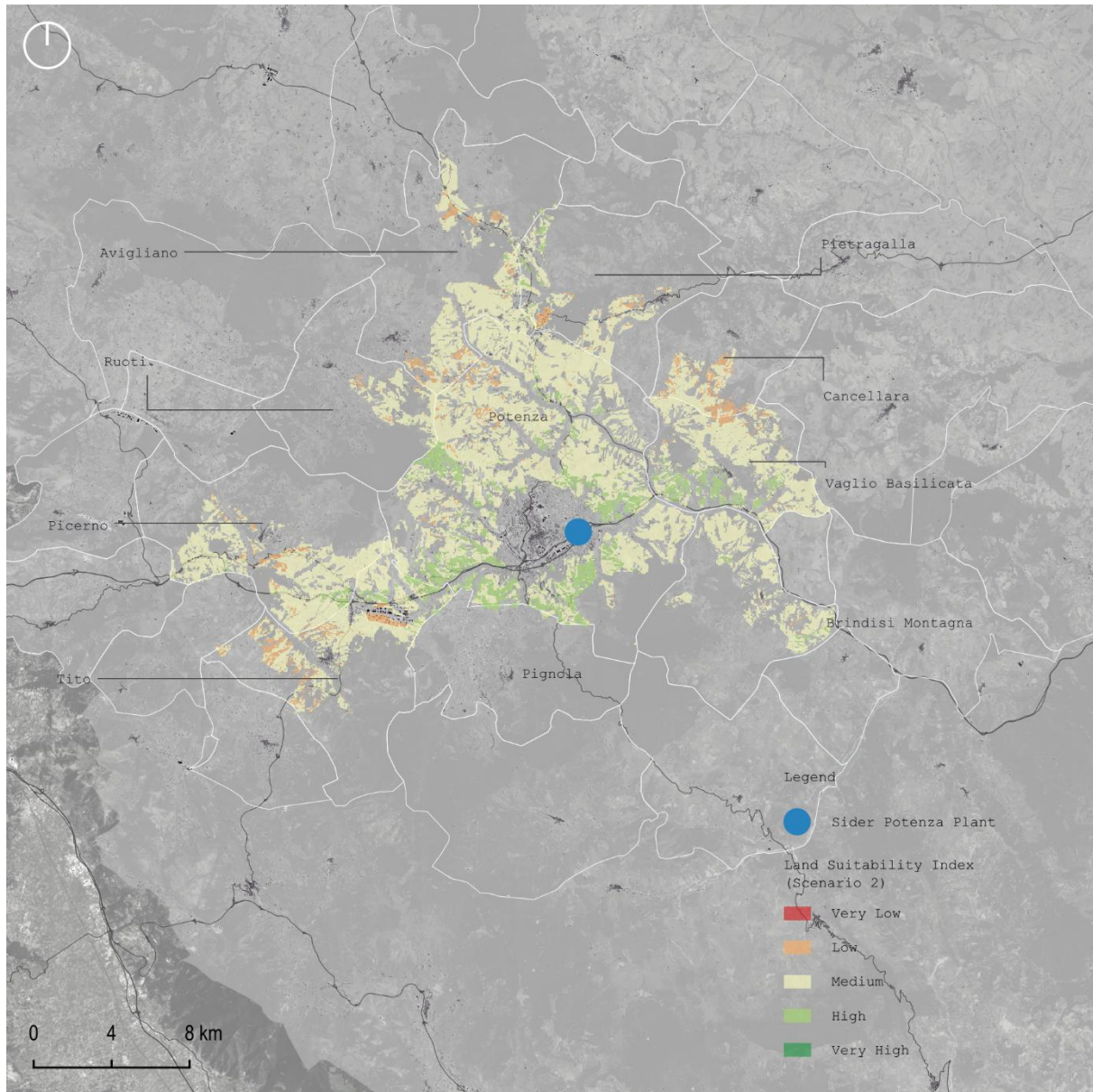


Fig. 21. Land Suitability under Scenario 2.

Among the economic criteria, accessibility to the industry plays a key role since the steel industry is the main end user of the hydrogen produced. Scenario 3 is the only one that highlighted the presence of an area of about one hectare with high suitability, located near an industrial site. These areas are mainly located within non-irrigated arable land, which is compatible with the development of hydrogen production infrastructure. They are also situated within a 10-minute proximity to the main road network, improving accessibility and reducing infrastructure costs compared to more remote locations. The attribution of greater importance to the environmental criterion, in particular land use, determined greater suitability in the overlay and, consequently, in the final assessment of the suitability of the land. This approach highlighted the preference for areas already characterized by the presence of industrial sites. The orientation towards the choice of these areas also draws attention to the environmental aspect, emphasizing sustainability and minimizing the impact on new territories.

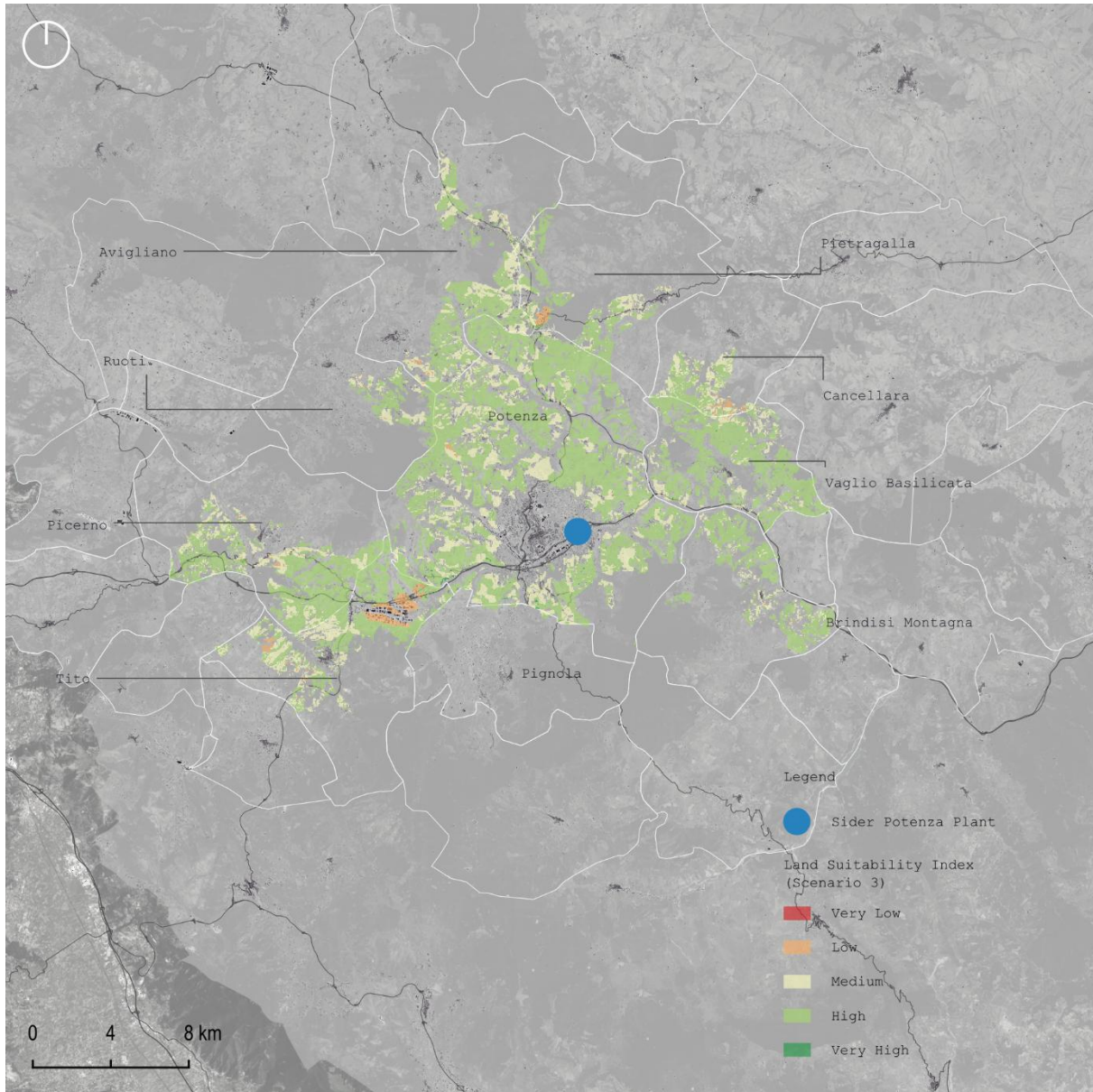


Fig. 22. Land Suitability under Scenario 3.

In conclusion, the three alternative scenarios developed offer different points of view for the future, depending on the criteria considered as priorities. Each scenario highlights different aspects of the suitability of the territory, highlighting the trade-offs between the feasibility of the infrastructure, costs, and environmental impact. Scenario 1 highlights the technical advantages of areas with low slopes and good availability of solar radiation. In contrast, Scenario 2 focuses on the economic benefits of accessibility and reduced costs in proximity to existing industrial sites. Scenario 3, which gives greater importance to environmental criteria, highlights areas with high suitability thanks to the already consolidated presence of industrial sites, which are in line with sustainability objectives. In this way, the scenarios offer

a useful framework for making more informed decisions, allowing stakeholders to choose the most suitable option for the future development of green hydrogen infrastructure.

3.3. Discussion

The implemented methodology, based on the integration of the AHP technique in the GIS environment, i.e., Spatial Multi-Criteria Analysis, allows a broad assessment of site suitability considering multiple criteria and sub-criteria. The case study conducted on the energy-intensive industry Siderpotenza, located in the Basilicata region, highlighted the peculiarities of the methodology. While AHP allows the complex decision-making process to be broken down into several sub-problems considering both quantitative and qualitative criteria, its integration with GIS provides a spatial, economic, environmental, and technical dimension to sustainability. The main difficulties can be found in the attribution of weights, as the formulation of expert judgments can be affected by inconsistency, since the green hydrogen sector is still an experimental field. Transforming individual criteria and sub-criteria into digital maps and determining the appropriate unit of analysis for processing is a very complex task.

Overall, the spatial analysis and the AHP application provided valuable information on potential green hydrogen production and distribution sites in the analyzed regions. More precisely, the land suitability indicators computed for the “Siderpotenza” case study showed that only a few areas are highly suitable for hydrogen production and distribution facilities. Most sites were classified as being of medium to high suitability, especially in the vicinity of industry. In addition, three alternative scenarios were developed, emphasizing technical, economic, and environmental criteria, respectively. Each scenario resulted in distinct land suitability maps, highlighting the importance of considering different perspectives when planning a green hydrogen infrastructure. The results emphasized the importance of considering multiple criteria and alternative scenarios to make informed decisions and ensure sustainable development in the context of green hydrogen infrastructure.

In addition to the Spatial Multi-Criteria Analysis approach mentioned above, a customized Model Builder in a GIS environment was implemented to comprehensively assess the suitability of green hydrogen infrastructure for energy-intensive industries. The Model Builder in GIS, whose architecture is shown in Figure 23, enabled the seamless integration of various data layers, criteria, and spatial analysis tools, simplifying the entire decision-making process.

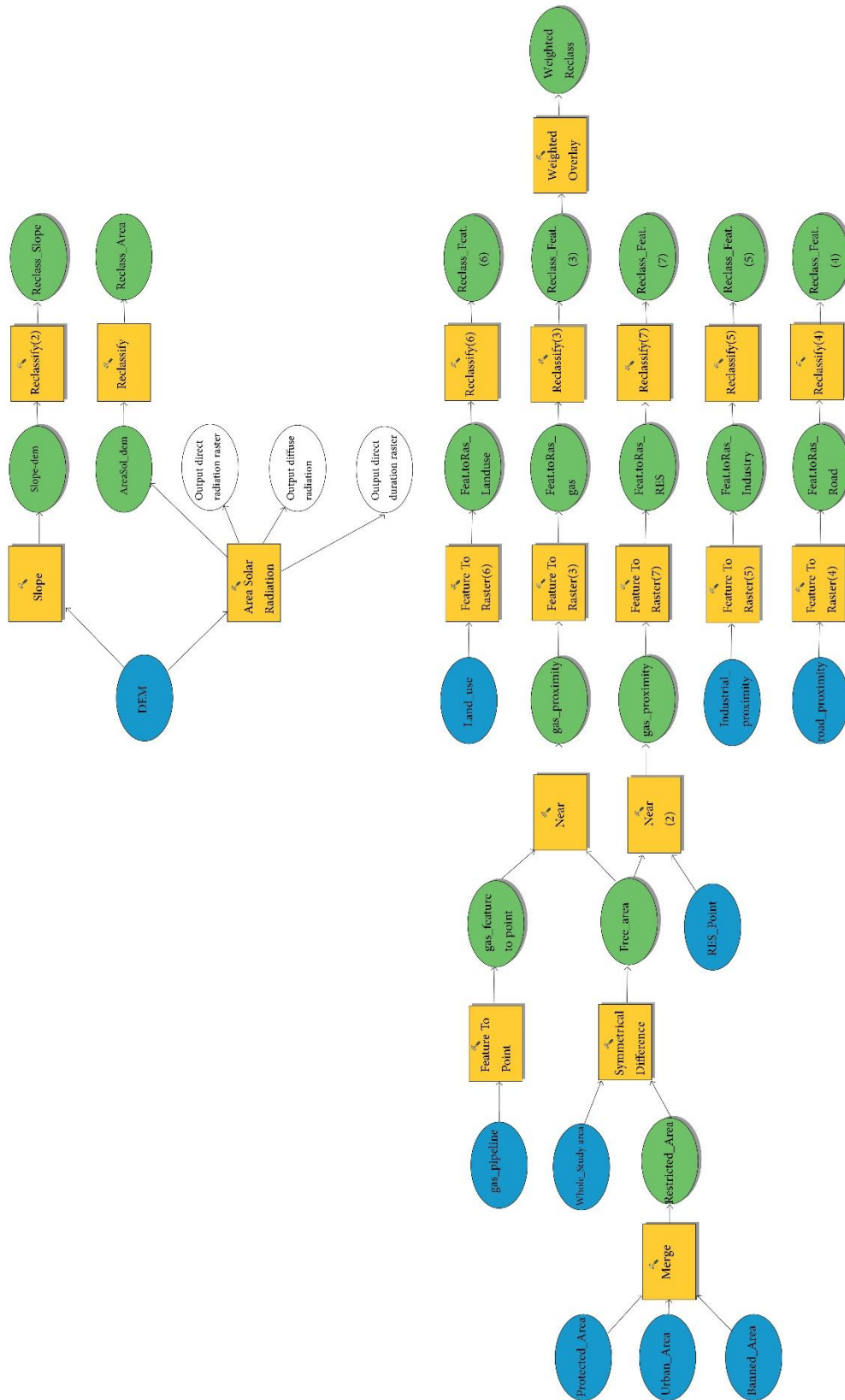


Fig. 23. Model Builder architecture.

The model was specifically designed to address the complexities of green hydrogen infrastructure planning by incorporating the following key components:

- Data integration: the Model Builder efficiently brought together different data sets, including geographical, topographical, and environmental data, and information on existing infrastructure, such as pipelines and RES. This integration ensured that all relevant factors were considered during the analysis.

Criteria weighting: The model Builder incorporated the AHP methodology to determine the relative importance of each criterion and sub-criterion. The model enabled the transparent and systematic assessment of the importance of technical, economic, and environmental factors in the decision-making process by involving stakeholders and domain experts.

Spatial analysis: Using GIS capabilities, the model conducted a series of spatial analyses, such as overlap and proximity assessments, to identify suitable areas for installing green hydrogen infrastructure. These analyses provided valuable information on the suitability and accessibility of the land, considering geographical and logistical constraints.

- Scenario development: The Model Builder was instrumental in generating alternative scenarios by recalculating the criteria weights according to different priorities. Through creating these scenarios, decision-makers could explore various perspectives and imagine potential future frameworks for developing green hydrogen infrastructure.

- Land suitability mapping: the final output of the model was a set of land suitability maps depicting areas classified according to their suitability levels for green hydrogen production and distribution facilities. These maps helped visualize the spatial distribution of suitable areas, enabling informed decision-making and effective resource allocation.

Using the customized Model Builder in the GIS environment, decision-makers and stakeholders will be equipped with a powerful tool to make well-informed choices regarding optimal locations for green hydrogen infrastructure. The model's flexibility in accommodating different criteria, data sources, and scenarios provides a solid basis for sustainable planning and development in renewable energy integration for energy-intensive industries.

3.4. Conclusion

Finally, the paper aims to identify suitable sites for designing and implementing Green Hydrogen Infrastructure. The aim is also to promote the energy transition based on sustainable low-carbon energy systems such as green hydrogen. The relevant contribution of the study results from the development of a replicable and flexible procedure of multi-

criteria spatial analysis for solving the problem of individuating suitable locations for GHI to optimize economic, social, and environmental co-benefits and minimize the alteration of natural and agricultural land cover. More precisely, the proposed procedure addresses specific aspects central to the development of strategies of climate alteration mitigation focused on the decarbonization of the industrial sector: i) the formalization and measurement of factors relevant to the location and sizing of energy infrastructure; and ii) the formalization and evaluation of synergies and trade-offs among environmental, economic, and infrastructural factors, in the definition of alternative localization options for energy infrastructures.

The developed method is a valuable support tool for planners, evaluators, entrepreneurs, and decision-makers involved in critical decision-making processes. One of its key strengths is its adaptability, allowing it to be tailored to different sites and sectors engaged in the energy transition. This flexibility makes it a powerful tool for assessing the feasibility and effectiveness of green hydrogen as a viable alternative to traditional hydrocarbon-based energy sources.

To enhance its applicability, the Model Builder has been designed to formalize and streamline the proposed procedure, facilitating its implementation across various contexts. However, it is important to acknowledge that the results of this study require further validation, as ongoing research and technological advancements may influence the feasibility of green hydrogen projects. The Model Builder supports this iterative process by enabling the continuous refinement and updating of multi-criteria spatial analysis, integrating new data and evaluation criteria as technology and knowledge evolve.

As a result, this model can serve as a valuable resource for future projects, both within the same regions and for similar assessments in different areas. Providing a structured and adaptable framework lays the foundation for informed decision-making in pursuing sustainable and renewable energy solutions for energy-intensive industries.

A key methodological contribution of this work is the integration of a dual-method sensitivity analysis, combining Monte Carlo simulation ($n = 10,000$) and One-at-a-Time perturbation into the AHP-GIS siting framework. This addition directly addresses the well-known limitation of AHP regarding weight subjectivity and provides quantitative evidence that the spatial suitability rankings reported in this study are robust across the plausible range of expert weight configurations. To our knowledge, this level of sensitivity validation has not been applied in previous AHP-GIS studies focused on green hydrogen infrastructure siting in post-industrial urban contexts, and it substantially strengthens the methodological rigour and reproducibility of the proposed framework.

CHAPTER 4

Renewable Energy Sustainability Assessment in Basilicata: From Expert-Based to Data-Driven Approach

Abstract

The transition to renewable energy sources is a critical component of global climate mitigation, yet the rapid deployment of solar and wind infrastructure often leads to unforeseen landscape transformations and environmental trade-offs. This study investigates these impacts in the Basilicata region of Southern Italy, a Mediterranean area characterized by high environmental sensitivity and increasing pressure from RES expansion. To overcome the limitations of traditional expert-based evaluations, such as subjective bias and the inability to capture complex nonlinear interactions, this research integrates a traditional Analytic Hierarchy Process with a data-driven Self-Organizing Map unsupervised machine learning approach. Utilizing the InVEST modeling suite, the study assesses four key ecosystem services - habitat quality, carbon storage, crop pollination, and crop production- alongside geospatial metrics like land fragmentation and visual impact across three temporal intervals, including a 2030 prospective scenario. The originality of this work lies in its explicit consideration of the future trajectory of renewable energy systems and their projected landscape-scale effects, rather than limiting the assessment to static or historical conditions. The analysis identifies three distinct landscape clusters within the RES footprint: (1) productive agricultural landscapes with high visual sensitivity, (2) intensive agricultural zones facing environmental risks, and (3) high-value ecosystem priority zones. Findings reveal a significant expansion of low-quality habitat (rising from 3.92% to 18.72%) and a gradual erosion of carbon-rich natural areas within the projected timeframe. By cross-validating expert judgment with unsupervised clustering through a transitional matrix, the study demonstrates that ecologically valuable areas are consistently identified as high-sensitivity zones by both methods. This hybrid framework provides a transparent, evidence-based tool for regional planners to balance energy production goals with the preservation of ecosystem integrity.

Keywords: SOM, Unsupervised learning, Ecosystem services, Sustainability, Spatial decision-support system.

4.1. Introduction

In recent years, urban expansion, agricultural overexploitation, and deforestation driven by rising resource demand have accelerated land-use change across Europe (Cogato et al., 2023b; Rabelo et al., 2023; Shaw et al., 2020). The transition to Renewable Energy Sources (RES) has added a new driver of land-use change through expanding energy infrastructure, raising environmental and social concerns (Cogato et al., 2023b; Delafield et al., 2024). Understanding how RES-driven land-use changes affect ecosystem services (ES) is essential for sustainable regional planning (Wehbi, 2024).

Investigating the relationship between Renewable Energy Sources (RES) development and ecosystem services (ES) is essential for leading sustainable energy transitions that adapt climate mitigation goals with the preservation of ecological integrity and societal well-being (Picchi et al., 2019a; Virah-Sawmy and Sturmberg, 2025; Zardo et al., 2023a). As RES infrastructure increasingly reshapes terrestrial and aquatic systems, it exerts both beneficial and adverse effects on the capacity of landscapes to deliver provisioning, regulating, cultural, and supporting services (Gayen et al., 2024). Understanding these interactions is therefore critical for anticipating trade-offs, identifying synergies, and informing spatial planning and policy design. However, despite growing scholarly attention, recent systematic reviews consistently highlight substantial conceptual and methodological gaps, including fragmented indicators, inconsistent analytical frameworks, and limited cross-study comparability, which collectively hinder robust assessments of RES–ES relationships.

One of the most frequently identified issues concerns the absence of standardized metrics. For example, (Jager et al., 2021) report that studies rely on widely varying indicators and analytical frameworks, leading to poor comparability across investigations and a paucity of long-term and cumulative assessments at the landscape scale. These inconsistencies limit the capacity to detect broader spatial and temporal trends in ecological responses to renewable energy development. Related concerns are highlighted by (Galparsoro et al., 2022), who note the limited availability of long-term before–after–control–impact (BACI) datasets. The infrequent use of BACI designs, combined with inconsistent indicators and measurement methods, reduces the reliability of impact attribution. Because BACI frameworks enable the distinction between anthropogenic effects and natural environmental variability, their absence substantially weakens the evidence base supporting conclusions about biodiversity and ecosystem changes associated with RES. Methodological heterogeneity is also emphasized by (Bøe et al., 2023), who argue that the lack of harmonized protocols prevents the calculation of single, comparable indicators across studies. They advocate for the development and adoption of standardized metrics and coordinated assessment procedures to improve comparability and facilitate meta-

analytical approaches. Moreover, there is a pronounced imbalance in research coverage across both RES technologies and ecosystem service categories. (Esp cie et al., 2019a), Based on a screening of 151 publications, the literature is heavily dominated by hydropower research (approximately 90%), with substantially fewer studies addressing wind energy (7%) and only marginal attention to solar, biomass, biogas, or geothermal sources. Also, provisioning services, particularly freshwater and food provision, receive disproportionate emphasis, whereas regulating, cultural, and supporting services remain comparatively underexamined. Finally, this review evidences that research activity is geographically concentrated, primarily in China, the United States, and Brazil.

4.1.1. Expert Knowledge and Data-Driven Methods in Landscape-Scale Renewable Energy Impact Assessment

Landscape impact assessment provides a particularly relevant integrative framework for evaluating the effects of RES deployment on ecosystem services. RES projects, such as wind farms, solar parks, hydropower facilities, and bioenergy systems, often generate impacts that extend beyond project boundaries, influencing landscape structure, connectivity, and multifunctionality over long temporal horizons (Li and Carter, 2025; Salak et al., 2024; Siksnelyte-Butkiene et al., 2023). Landscape-scale assessments enable the cumulative and spatially explicit evaluation of these effects, capturing interactions among multiple RES installations and their combined influence on ES provision (Picchi et al., 2019b). By embedding RES–ES analyses within a landscape impact assessment perspective, it becomes possible to move beyond site-specific evaluations toward a more holistic understanding of how renewable energy development transforms landscapes and their capacity to support ecological processes and human benefits.

Landscape impact assessment broadly integrates ecological, cultural, and perceptual values through a combination of quantitative and qualitative indicators. The most advanced frameworks adopt a multidimensional approach, encompassing ecological, land-use, socioeconomic, historical-cultural, environmental, and perceptual factors, to fully capture the complexity and interconnections underlying landscape change and its multiple values (Cassatella, 2011; Medeiros et al., 2021b). Ecological and land-use indicators are the most used, emphasizing biodiversity, habitat quality, land cover, and landscape fragmentation (De Montis et al., 2020; St rck and Verburg, 2017). Although less often integrated, socioeconomic, cultural, and perceptual indicators are equally important, as they capture stakeholder values, cultural heritage, and visual or aesthetic qualities (Fagerholm et al., 2012). To support cross-regional comparisons, composite approaches that combine patch density, infrastructure, and settlement data are often used, along with reference values such as protected areas serving as benchmarks (Sch pbach et al., 2020b). Furthermore,

participatory and stakeholder-based methods, including mapping and surveys, ensure that intangible and non-utilitarian values are incorporated, thereby improving both the relevance and acceptance of assessments (Dale et al., 2019).

Although comprehensive frameworks and participatory approaches can improve the accuracy and inclusiveness of landscape assessments, when data are limited or uncertainty is high, expert judgment is often used to inform the initial phases of decision-making. Expert-based approaches rely on the knowledge and judgment of individuals with specialized expertise to guide the assessment and management of ecosystems and their environmental impacts (Hemming et al., 2018; Kuhnert et al., 2010). Expert-based decision processes have been widely applied across diverse environmental planning contexts, including the selection of water treatment technologies, flood risk management, urban development, green infrastructure, and sustainable energy planning (Vrana et al., 2012).

Expert judgment supports the identification of sustainability variables that most influence project success and informs procurement decisions, enabling the selection of consultants and technologies that optimize economic, environmental, and social sustainability outcomes and facilitate the effective integration of sustainability into project management (Lam, 2019; Martens and Carvalho, 2016). Furthermore, expert systems, particularly when integrated into a Geographic Information System (GIS), facilitate the rapid identification and assessment of environmental impacts, thereby supporting more informed and timely design decisions (Herrero-Jiménez, 2012; Van Eldik et al., 2020). On the other hand, expert-based approaches exhibit several inherent limitations, including susceptibility to bias, inconsistency, and overconfidence among experts. These factors can compromise the reliability of decisions, particularly in contexts where the available evidence is limited or uncertain (Abels et al., 2023; Pomerol, 2022). Moreover, expert judgments often inadequately capture uncertainty, as conventional approaches tend to produce a single deterministic solution that overlooks the spectrum of possible outcomes and the inherent limitations of expert knowledge. Although expert input remains valuable, it should serve to complement rather than substitute systematic research and analytical approaches in the decision-making process (Morgan, 2014; Pomerol, 2022).

Data-driven analytical approaches are increasingly regarded as an important complement to expert-based assessments in a variety of fields. Studies in environmental and sustainability assessment have shown that integrating expert-based assessments with data-driven analytical approaches, especially unsupervised machine learning, is increasingly recognized to improve both feature selection and decision-making in environmental and sustainability contexts. The combination of unsupervised ML and expert input leads to more objective, transparent, and actionable assessments (Mrabet and Sliti, 2024; Paulvannan Kanmani et al., 2020; Wang and Ren, 2025). Unsupervised learning techniques, particularly self-organizing maps (SOMs), have become widely used for analyzing complex, high-

dimensional spatial and socio-economic data due to their ability to cluster and visualize patterns without prior labeling. In urban studies, these methods have been employed to segment urban areas, classify urban–rural gradients, and identify multifunctional landscapes by integrating variables such as land use, night-time light intensity, and socio-economic indicators, providing planners with tools to interpret urban dynamics and sustainability challenges (Gao et al., 2014; Wang and Biljecki, 2022). Similarly, these approaches enabled the identification of distinct urban–rural typologies and varying levels of integration, uncovering regional disparities in human capital, including differences in education, skills, and workforce composition (Murgante et al., 2025; Wosiek, 2020; Zeng and Chen, 2023). In agricultural research, SOMs have been applied to cluster municipalities or regions based on land use, management intensity, and crop diversity, revealing both spatial and temporal changes in agricultural systems and uncovering hidden structures in census and production data to support data-driven policy and planning. (Abrantes et al., 2023; Rabelo et al., 2023; Santos et al., 2021)

In the field of renewable energy research, the application of SOM-based approaches remains relatively limited, despite the growing need to balance energy development with ecosystem conservation and landscape planning objectives. To date, most studies have predominantly employed suitability assessments, optimization techniques, or multi-criteria decision-making frameworks, frequently relying on expert-based weighting schemes. (Bedle et al., 2023)

4.1.2. The main objective of the present study

In response to the growing adoption of data-driven methodologies, particularly unsupervised learning techniques, in environmental and urban research, this study aims to bridge such approaches with traditional expert-based assessment frameworks. While data-driven models offer strong exploratory and predictive capabilities, their outputs often lack interpretability and contextual grounding when applied in isolation. Conversely, expert-based frameworks provide conceptual rigor but may struggle to capture complex, nonlinear interactions at the landscape scale. This study addresses this methodological gap by integrating expert knowledge with unsupervised machine learning to achieve a more comprehensive and robust understanding of the interactions between RES development and ES. Specifically, SOM is employed alongside the Analytic Hierarchy Process (AHP) to identify spatial patterns and latent relationships that may be overlooked by conventional methods, while reducing reliance on subjective judgments. The study evaluates renewable energy impacts through a multi-dimensional framework that extends beyond habitat quality, carbon storage, and pollination to include additional spatial and landscape-related indicators, such

as land-use dynamics, fragmentation patterns, visual exposure, and clustering of socio-ecological typologies.

The empirical analysis focuses on the Basilicata region in southern Italy. The multiplication of renewable energy installations in the Basilicata region, especially wind farms, has caused notable territorial fragmentation, landscape transformation, and loss of habitat quality. These impacts are intensified by the lack of a robust regional planning framework, resulting in scattered installations that disrupt ecosystem services and biodiversity. The spatial pattern and density of these plants, along with associated infrastructure, are key drivers of negative ecological effects, including diminished aesthetic values and ecosystem functionality (Muzzillo et al., 2020; Pilogallo and Saganeiti, 2023; Saganeiti et al., 2020; Scorza et al., 2020c). Although the geographic scope is intentionally limited, it serves as a representative case study for Mediterranean landscapes characterized by high environmental sensitivity, increasing pressure for renewable energy expansion, and heterogeneous land-use patterns (Martínez-Sastre et al., 2017; Ramondetti, 2025). Previous studies conducted in Basilicata have primarily investigated renewable energy development through site suitability assessments, visual impact analyses, and land-use change evaluations, with particular emphasis on the expansion of photovoltaic and wind energy systems. These studies have provided important insights into infrastructure distribution, landscape transformation processes, and environmental constraints. Nevertheless, most existing approaches remain sector-specific and methodologically fragmented, often focusing on isolated indicators or relying on expert-driven suitability frameworks without adequately incorporating ecosystem service dynamics, long-term spatial interactions, or data-driven landscape classification techniques. As a result, significant gaps persist in understanding how renewable energy expansion simultaneously affects ecosystem functionality, landscape structure, and broader regional sustainability objectives.

In contrast to much of the existing literature, which has predominantly addressed hydropower-related impacts on ecosystem services, this study explicitly examines solar photovoltaic installations and wind turbines. These technologies are rapidly expanding across Mediterranean and European landscapes, yet their cumulative and spatially differentiated effects on ES remain insufficiently understood. Importantly, the methodological contribution of this research extends beyond the case study itself.

4.2. Material and Method

4.2.1. Study Area

The Basilicata Region, located in Southern Italy, occupies an area of approximately 10,000 km² between the Tyrrhenian and Ionian seas. Administratively, it is composed of two

provinces, Potenza and Matera, with Potenza serving as the regional capital (see figure 24). The region is characterized by a predominantly mountainous and hilly terrain: the Apennine chain dominates the western and central sectors, while the eastern portion gradually transitions into the coastal plains of Metaponto. With reference to land covers, agricultural areas represent the dominant land use in Basilicata, accounting for 56.96% of the territory; as a result, slightly less than half of the regional land is occupied by woodland and semi-natural environments. Basilicata has a relatively small population of approximately 550,000 inhabitants, resulting in one of the lowest population densities in Italy. Many inhabitants reside in the main urban centers, including Potenza (~67,000 inhabitants) and Matera (~61,000 inhabitants), while rural and mountainous areas are sparsely populated (“Territorio e cartografia,” 2024). Many smaller towns and villages experience declining populations due to migration toward urban areas or other regions of Italy. The region’s climate varies from Mediterranean along the Ionian coast, with mild winters and hot summers, to a more continental temperate climate in the higher inland areas. This environmental diversity, combined with the scattered and heterogeneous population distribution, creates distinct patterns of land use and human-environment interaction (Santarsiero et al., 2022). Such characteristics make the Basilicata region a compelling study area for evaluating the impacts of renewable energy development on both ecosystems and local communities.

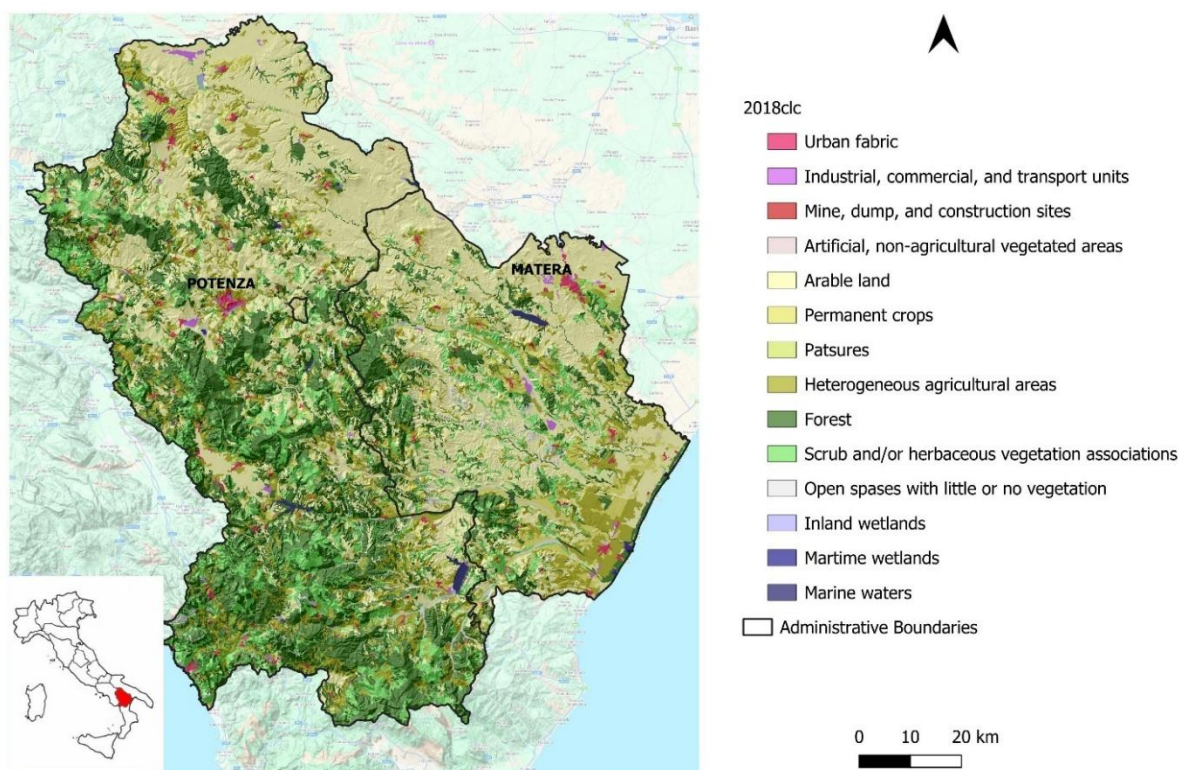


Fig.24. Basilicata location in southern Italy

Renewable energy sources have played a significant role in electricity production in Basilicata. In 1990, approximately 37% of the electricity was generated from renewable sources, primarily hydroelectric power. This share declined over the following years, reaching 23% in 1998, but increased again to 30% by 2005, largely due to the development of wind energy and the use of solid urban waste for electricity generation. The wind energy sector began to emerge in Basilicata in 2001, marked by the commissioning of the region's first wind power plants. According to 2005 data, seven wind farms were installed in Basilicata, with a total capacity of 76 MW and an annual production of approximately 148 GWh. These installations were subsequently expanded, bringing the total installed capacity to 198 MW by 2008 (Angeloni et al., 2007). Despite the recognition of photovoltaic electricity generation as a key strategy for sustainable development, its adoption has remained limited due to high production costs, making it the most expensive among other RES. Consequently, in the absence of adequate incentive policies, the diffusion of this technology has been slow. To address this issue, Italy introduced the 'Conto Energia' (Energy Account) in July 2005 through the approval of a ministerial decree aimed at promoting the deployment of photovoltaic systems (Di Leo et al., 2021). In 2018, the Basilicata Regional Authority approved the regional law on "Decarbonisation and Regional Policies on Climate Change (Basilicata Carbon Free)," marking a strategic step toward reducing greenhouse gas emissions and advancing sustainable energy transitions.

Basilicata has pursued a multifaceted strategy for renewable energy, balancing the expansion of RES with the careful management of environmental and territorial impacts. Regional policies have strongly promoted the development of wind and solar power, resulting in electricity generation from renewables that surpasses initial projections and aligns with European decarbonization goals, including substantial reductions in CO₂ emissions and improvements in energy efficiency (Di Leo et al., 2021).

4.2.2. Methodological framework

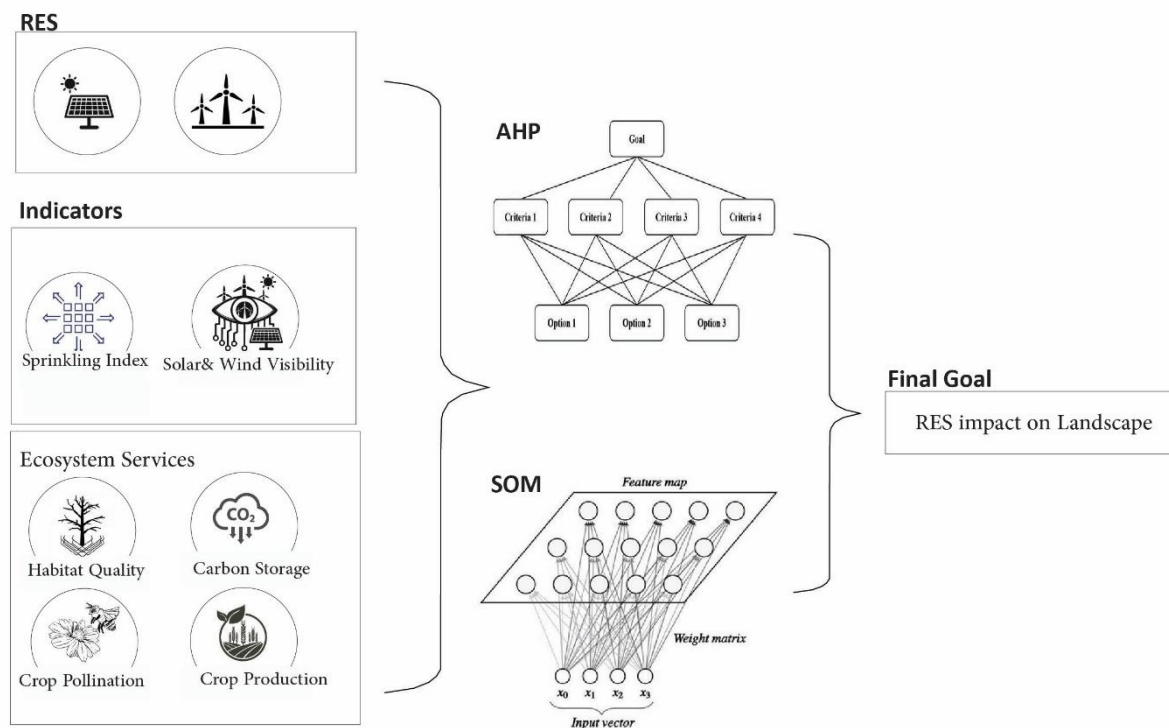


Fig. 25. Flowchart of the methodology framework

The overall RES assessment was based on multiple indicators that can be grouped into two complementary sets. The first one, representing the geo-spatial dimension, reflects the spatial characteristics of RES deployments and includes two indices: sprinkling index and visual index. The second set, representing the ecosystem services dimension, provides an ecological perspective on RES interactions with environmental functions and includes four indicators: habitat quality, carbon storage, crop pollination, and crop production.

All the indicators were calculated for three distinct time intervals to capture both the spatial and temporal dynamics of RES effects: (1) the first one (2006–2008) represents the initial phase of the analysis, corresponding to the arrival of the earliest installations in

the area; (ii) the second interval (2008–2024) reflects the period of continued development; (iii) the last interval (extending from 2024 into the prospective scenario) represents a prospective scenario. To operationalize these indicators, diverse input raster layers and tabular data were integrated. Raster layers included land use/land cover maps (LULC), digital elevation models (DEM), and climate bin maps. Tabular data encompassed carbon pools, FAO statistics, and biophysical and guild tables.

To assess RES impacts, we implemented two parallel analytical approaches, allowing us to identify clusters and latent spatial patterns in RES–ES interactions (Figure 25): an expert-based approach grounded in AHP and a data-driven SOM process. By drawing on expert

knowledge, the input indicators were systematically weighted using AHP and subsequently aggregated into three final expert-based scenarios. Second, the unsupervised classification based on SOM is a machine learning technique that groups spatial units into clusters based on the similarity of the geo-spatial and ES indicators, thereby revealing emergent patterns without relying on prior assumptions or expert judgment. Finally, the outputs from the expert-based (AHP) and data-driven (SOM) classification were compared and integrated through the construction of a transitional matrix. This step last facilitated cross-validation between expert judgment and data-driven results, while also highlighting areas of convergence and divergence between the two approaches.

Input Geodata

Geographical information on wind turbines and solar panel installations was obtained from regional and national sources. The primary dataset derives from the Technical Regional Cartography (TRC), produced by the Basilicata Region and distributed through the Open Geospatial Consortium (OGC) (“Catalogo Dati,” 2013) Compliant services within the Regional Spatial Data Infrastructure (“Catalogo RSDI,” 2018). Additional information was integrated from the National Energy Services Manager (GSE) (“Atlaimpianti portale: Mappa degli impianti energetici GSE,” 2021), which provides authoritative data on renewable energy installations across Italy. Due to missing or outdated records, we developed a new map of RES installations by digitizing updated features from multi-temporal aerial photogrammetric surveys, integrating high-resolution orthophotos to ensure accurate spatial representation.

Land use maps are a commonly required input for all ES assessments. For the initial year, the mid and the recent period of our analyses, we used the CORINE land cover (CLC) 2006, 2012, and 2018, respectively, at level 2 (“Copernicus Land Monitoring Service,” 2018). Another requirement is the Digital Elevation Model (DEM). The national DEM used in this study represents the elevation of the bare ground and was created by merging individual DEMs from the administrative regions of Italy (Tarquini et al., 2023) with a spatial resolution of 10 meters, upscaled to 100 meters for the aim of our analyses.

4.2.3. Geo-spatial indicators

RES footprints

To spatially define the impact zone of each renewable energy installation, we defined a concept called the RES footprint, the area considered to be functionally affected by a given installation, including both its physical surface and its immediate surroundings. The entire study area was divided into a 1 km² grid, and RES footprints were delineated individually for each installation type using a buffer-based approach.

For photovoltaic (PV) fields, a uniform 25-meter buffer was applied around each installation's perimeter. Given the continuous and clearly bounded nature of PV panels, this

single buffer is sufficient to capture the area where land use has been directly altered or excluded from prior uses.

For wind turbines, a two-step procedure was applied to reflect the more complex spatial influence of these installations:

1. Individual buffers were first drawn around each turbine according to its power class: 15 meters for mini turbines, 25 meters for medium turbines, and 35 meters for large turbines. These distances approximate the area directly occupied by each turbine's base, access infrastructure, and immediate exclusion zone.
2. Cluster aggregation was then applied: turbines whose buffer zones fell within 250 meters of one another were merged into a single composite polygon, referred to as a functional cluster. This step reflects the fact that the land lying between closely spaced turbines, even if not physically occupied by infrastructure, is typically rendered unsuitable for its prior land use (e.g., agriculture, natural habitat). The resulting cluster footprint therefore accounts not only for the surfaces directly occupied, but also for the interstitial land effectively diverted from its natural function.

The areas between turbines are assumed to partially lose their suitability for prior land uses, reflecting the installation's broader spatial influence. Accordingly, the aggregated area accounts not only for directly occupied surfaces (e.g., grassland, access roads, and technical facilities) but also for the extent of land effectively and irreversibly diverted from its natural function. An aggregate is defined as a composite polygon formed by merging two or more polygons whose mutual distance, either between RES buffer zones or between individual building polygons, does not exceed a predefined threshold (Saganeiti et al., 2020).

All the geo-spatial indicators were subsequently calculated exclusively within these RES footprints, thereby restricting the analysis to areas potentially affected by renewable energy developments and ensuring consistency between impact assessment and ecosystem service evaluation.

Sprinkling Index

The RES contribute to land fragmentation primarily through direct land occupation, the construction of access roads, and the spatial dispersion of infrastructures. For instance, wind farms necessitate extensive road networks and turbine platforms that disrupt habitats and diminish large contiguous, undeveloped areas (Diffendorfer et al., 2019). Solar farms transform extensive areas of agricultural or natural land, which causes habitat loss, landscape alteration, and changes to local ecological dynamics (J. Wang et al., 2025). The sprinkling index (SPX) is a spatial metric used to quantify the degree to which elements such as renewable energy installations are scattered or dispersed across the landscape. Higher SPX values indicate a more fragmented and widely distributed spatial pattern, whereas lower

values reflect a more clustered or concentrated arrangement. The concept of “sprinkling,” defined as the distribution of small quantities in the form of scattered particles or droplets, has previously been shown to be effective in describing settlement fragmentation (Saganeiti et al., 2018). SPX assumes that the most compact configuration of settlement growth consists of a single, circular agglomeration in which all built-up areas are concentrated around one central point. To quantify the deviation of an observed settlement pattern from this idealized compact form, the index calculates the Euclidean distances between the centroids of all built-up aggregates and the centroid of the dominant nucleus within each reference cell. Larger distances correspond to a more dispersed spatial configuration.

Visual index

In urban planning, visual impact is a key factor, so integrating RES in a way that preserves the landscape can help balance energy generation with social acceptability and avoid local opposition (Florio et al., 2021). For solar panels, the spatial extent and surface coverage play a more critical role in shaping their visual impact on the landscape, whereas for wind turbines, the height of the installations is the main factor driving visual disturbance. To assess the visual impact of RES installations, we used an open-source GIS tool developed by Minelli et al. (Minelli et al., 2014). The method combines visibility analysis, human visual perception, and basic geometric principles to estimate how much of an observer’s field of view is occupied by an installation. For low-profile solar panels, a cylindrical field of view is used, while wind turbines, due to their height, are assessed with a spherical field of view. The tool calculates a non-dimensional visual impact index (NDVI) by comparing the perceived size of the installation within the observer’s view to the total field of view, providing a quantitative measure of visual disturbance.

4.2.4. Ecosystem-services indicators

Traditionally, RES assessments focus on their direct environmental impacts and may overlook broader effects on ecosystem services and human well-being (Esp cie et al., 2019b). Additionally, the expansion of renewable energy can involve trade-offs, including habitat loss and impacts on historical or cultural values, despite the climate benefits it provides (Mart nez-Mart nez et al., 2022). Thus, including the ES in landscape analysis can be highly beneficial. In our case, mapping ES alongside identifying suitable locations for these RES can help minimize negative impacts and social conflicts, and consequently improve public acceptance and reduce opposition (Zardo et al., 2023b). Moreover, accounting for ES in environmental assessments not only helps us analyze costs and benefits more accurately but also enables clearer communication with policymakers and project stakeholders (Esp cie et al., 2019b).

Considering the diversity of the indicators that define the relationship between humans and the environment, our focus in this study is on four main ES components: habitat quality, carbon storage, crop pollination, and crop production. Ecosystem service assessments were

conducted using the InVEST modelling suite, with Land Use/Land Cover (LULC) maps as the primary spatial input. For each model, LULC classes were associated with service-specific biophysical parameters derived from the literature, empirical datasets, or expert knowledge, representing the capacity of each land cover type to supply the service under consideration. Carbon storage was estimated by assigning carbon stock values to LULC classes, while pollination, crop production, and habitat quality relied on suitability and sensitivity coefficients that act as proxies for ecological processes.

Model outputs are spatially explicit and deterministic; however, uncertainties primarily stem from parameterization rather than model structure. Consequently, results were interpreted in a comparative and scenario-based framework rather than as absolute estimates, consistent with the intended use of InVEST for relative ecosystem service assessment. We examined the evolutionary trends for these indicators over time, during the years before the RES were introduced to the Basilicata region, a mid and recent period, plus predictions for the prospective scenario, analyzing changes across that temporal span.

The individual InVEST models used for pollination, crop production, habitat quality, and carbon storage assessments are described in greater detail in the following sections. The parameters adopted to assess each ES are reported in tabular form in the Appendix (tables B.1 to D.2).

InVEST models also enable the simulation of prospective ecosystem service conditions through the use of scenario-specific land cover maps. To support this analysis, a LULC map representing a prospective scenario was developed and applied in this study, constituting a key methodological contribution of the present work.

Land Cover Future Predictions

Prospective land cover scenarios were generated using the Land Change Modeler (LCM) in TerrSet (D'Onofrio, 2024), which requires three temporal land cover maps: T1 and T2 to quantify class transitions (i.e., changes in land cover classes over time), and T3 for model validation. The Transition Potential Model produces transition probability maps, capturing nonlinear relationships between explanatory variables and observed transitions, while the Markov component estimates the expected quantity of change, enabling validation of simulated T3 against observed data. Using transition probabilities from T2 and T3, LCM combines the spatial likelihood of change with the expected quantity of change to simulate the distribution of land-use classes for T4 (prospective scenario). To assess the transition probabilities, we selected a Multi-Layer Perceptron (MLP) neural network. MLP consists of layers of interconnected nodes that process information through weighted connections and is particularly suitable for modeling land-use dynamics because it can capture complex, nonlinear relationships among multiple interacting factors.

In this study, T1, T2, and T3 correspond to CLC level-2 maps for 2006, 2012, and 2018, prepared as 100 m raster datasets to ensure consistency in background, legend, and spatial

characteristics. The prospective scenario (T4) was estimated for 2030. To focus on significant dynamics, transitions affecting areas smaller than 20 km² were excluded. Spatial explanatory variables included DEM, slope, aspect, population density, urban centers, proximity to roads, and carbon storage. Observed transitions between 2006 and 2012 highlight both losses and gains across major land-use classes (Appendix, Figures B.1–B.2). The inter-rater reliability is examined using the Kappa Index of Agreement (KIA), which indicates very high reliability (0.9234).

Habitat quality

Habitat quality refers to the ecosystem's ability to provide suitable conditions for the survival of species and populations in an area. InVEST Habitat Quality model evaluates the capacity of each land-cover type to support biodiversity after accounting for anthropogenic threats. For each land-cover class, we defined habitat suitability scores (H) and assigned sensitivity values (Table A2) (a key component of the degradation term, D) to each threat. The H score ranges between 0 (fully degraded) and 1 (optimal habitat), enabling comparison of biodiversity conditions across the landscape. Spatial threat layers (e.g., land-use conversion, infrastructure, human presence) were parameterized using user-defined decay distances and relative weights (Table A2). The model calculates habitat degradation (D) for each pixel as the distance-weighted cumulative influence of all threats. This formulation produces a habitat quality score between 0 (fully degraded) and 1 (optimal habitat), enabling comparison of biodiversity conditions across the landscape. Habitat quality (Q) is then computed as a nonlinear function of habitat suitability, degradation, the half-saturation constant (k, set to 0.05), and scaling parameter (z).

$$Q_{\{xj\}} = H_j * \left(1 - \left(\frac{D_{\{xj\}}^z}{D_{\{xj\}}^z + k^z} \right) \right)$$

In this study, we assigned habitat quality values to each land cover class based on Natura 2000 data (European Environment Agency and European Commission, 2025). This dataset specifically identifies areas that contribute to habitat quality, areas that can support species populations, and areas that do not provide suitable habitat. The model also requires data on habitat threat density and their effects on habitat quality. In this study, these include agricultural lands, urban areas, industrial sites, mining areas, and roads. For the mid-period and prospective scenarios, wind turbines and solar panels were also added to the list of threats. The impact of threats on habitat is mediated by four factors: (1) the relative weight of each threat, reflecting differences in their potential to degrade habitat; (2) the distance between the threat source and the habitat pixel; (3) the maximum effective distance over which each threat acts; and (4) the sensitivity of each habitat type to each threat.

Carbon Storage

InVEST is a robust and flexible modeling framework for assessing carbon storage and sequestration in both natural and urban ecosystems. By integrating scenario analysis with optional economic valuation, the model supports evidence-based land-use planning and climate policy development. Carbon storage is estimated by quantifying four primary carbon pools: aboveground biomass, belowground biomass, soil organic carbon, and dead organic matter. The model relies on land-use/land-cover maps in combination with biophysical tables to assign carbon density values to each land-cover class (Table B). For each class, carbon content estimates, typically expressed in megagrams per hectare (Mg ha^{-1}), must be provided for at least one of the four carbon pools.

Crop pollination

Crop pollination plays a key role in both agricultural productivity and ecosystem health. Pollinators such as bees, butterflies, and other insects are essential for crop reproduction, helping to increase yields and improve crop quality (Khalifa et al., 2021). Focuses on the resource needs and flight behaviors of pollinators. The biophysical parameters required by the model were compiled following the Joint Research Centre (JRC) technical report of the European Commission (“Science for policy - The Joint Research Centre,” 2025).

Crop production

Crop production was assessed using the InVEST Percentile Model, which estimates yields for 175 crops based on observed production data and percentile summaries derived from FAO and sub-national datasets (Monfreda et al., 2008). According to ISTAT statistics, wheat, rye, barley, oats, maize, sorghum, beans, lentils, peas, potatoes, and olives represent the dominant crop types in the Basilicata region (“Censimento Agricoltura,” 2020). These crops were then listed in the biophysical table using the corresponding InVEST-compatible crop names, enabling the model to link each LULC code to its specific crop type. By integrating ISTAT-derived crop information into both the LULC map and the biophysical table, the model produces region-specific estimates of crop yields and production for Basilicata.

Expert-based vs data-driven approach

Although the entire Basilicata region was discretized into a 1 km^2 grid, the analytical domain of the AHP and SOM models was restricted to grid cells intersecting the RES footprint, defined as the area potentially affected by renewable energy installations. This footprint includes direct land take as well as indirect influence zones related to visual exposure and landscape fragmentation. Cells outside the RES footprint were excluded from the multi-criteria and clustering analyses, as they are not currently subject to renewable energy-related pressures. Consequently, all AHP scores and SOM-derived clusters refer exclusively to areas potentially impacted by existing or planned RES installations.

Analytic Hierarchy Process

The AHP simplifies complex decision problems by structuring them into a hierarchical framework and deriving priorities through pairwise comparisons. Once the overall objective is defined, the method requires the identification of relevant criteria and sub-criteria that contribute to its achievement (Kuo and Chen, 2023). The model was developed by Saaty in the 1980s and later formalized within an axiomatic structure (R.W. Saaty, 1987). The AHP is particularly useful when input data are qualitative or cannot be precisely quantified. In such cases, expert judgments are expressed using Saaty's nine-point scale, which ranges from one (equal importance) to nine (extreme importance). Because the method does not explicitly account for uncertainty, the involvement of domain experts is essential.

Weight determination represents a key step in capturing decision-makers' preferences. However, pairwise comparisons may introduce inconsistency, especially as the number of comparisons increases. To assess the reliability of the comparison matrix, the AHP employs the Consistency Ratio (CR), with a threshold of 0.10 indicating acceptable consistency. When this threshold is exceeded, a revised comparison matrix must be constructed, and the associated weights adjusted accordingly (Moussaoui et al., 2018). To integrate the AHP within a spatial framework, we implemented the method using GIS-based map algebra. This procedure produces an overall score for each alternative and decision objective, an approach commonly referred to as Spatial AHP.

4.2.5. Self-Organizing Maps

In parallel to AHP, this study applies a data-driven approach based on the Self-Organizing Map (SOM) (Kohonen, 2013), to perform the final stage of the analysis, aggregating the fragmented information within each spatial unit into coherent clusters. Unlike AHP, the SOM does not require predefined weights or expert-driven assumptions, which is particularly advantageous when exploring complex, multidimensional datasets. The data-driven structure allows the SOM to autonomously reveal latent relationships and uncover novel, meaningful patterns that may not emerge through traditional, assumption-based methods. The SOM is known for its clustering, visualization, and classification capabilities (Miljkovic, 2017). Furthermore, SOM offers useful supplementary outputs, such as feature-distribution heatmaps, which greatly support visual exploration of the relationships among input variables (Tonini et al., 2025).

Computationally, SOM is a type of competitive learning neural network that projects high-dimensional input data onto a two-dimensional grid of interconnected units. Each unit contains a codebook vector, which has the same dimensionality as the input data and represents the characteristics of that unit. During training, input vectors are presented sequentially, and the unit whose codebook vector is closest to the input vector, called the

best-matching unit (BMU), is identified. The BMU and its neighboring units are then updated iteratively, with the neighborhood radius gradually decreasing. This process preserves the topological relationships of the input data, ensuring that similar observations are mapped to nearby units on the SOM grid. The choice of grid size is important: too few units can obscure meaningful differences, while too many units may create only minor distinctions. The model performance can be assessed using the quantization error (QE), defined as the mean distance between each input vector and its codebook vector, with lower values indicating better representation. After optimizing the grid and other parameters through trial-and-error, the final configuration consisted of a 50×50 grid matching the study area, 1000 training iterations, a learning rate decreasing from 0.05 to 0.01, and an initial neighborhood radius covering two-thirds of the unit-to-unit distances. This setup produced a very low QE (1.8×10^{-3}) and a high explained variance (~99%).

Finally, the SOM grid was further simplified by aggregating units into a smaller number of main clusters. Hierarchical clustering was applied to this end, merging units iteratively based on the Euclidean distance between their codebook vectors, which reflect the similarity of the original input variables. In the present study, SOM was evaluated using the ‘Kohonen’ package (Wehrens and Buydens, 2007; Wehrens and Kruisselbrink, 2018) implemented in the R open-source computational environment (version 4.3.2; R Core Team, 2023).

4.3. Results

4.3.1. Relative impact of the indicators

The multitude of indicators computed to assess the impact of RES on the spatial environment and ES were mapped within a geographical framework, and their relative impact was evaluated using a four-interval classification scheme. Temporal development trends were analysed across three time intervals: (a) the initial phase (2006–2008), (b) the mid-period (2008–2024), and (c) a prospective scenario (2004–2030). This integrated spatial-temporal approach supports the decision-making process by enabling a systematic comparison of RES impacts across both space and time. Overall, these maps reveal a notable increase in the territorial impact of RES in the Basilicata region. This critical issue aligns with the concerns raised by Murgante and Scorza (Scorza et al., 2016), who emphasized the importance of integrating energy planning with landscape planning, particularly in environmentally vulnerable regions such as Basilicata.

Sprinkling index

Namely, for the sprinkling index (Figure 26), these findings underscore that the energy transition can lead to increasingly pronounced dynamics of landscape fragmentation without proper governance through spatial planning instruments. During the initial phase, both the SPX values are relatively low, indicating an early stage of development characterized by concentrated installations and minimal spatial dispersion. During this period, the impact on the landscape was limited, as installations were primarily located near existing

infrastructure or in areas already modified by human activity. The mid-period marks a noticeable transitional phase and indicates a significant shift in installation dynamics. Three key trends emerge at this stage: (i) a progressive saturation of the most suitable sites for renewable energy development; (ii) the beginning of a shift toward more dispersed spatial distribution of installations; (iii) and a noticeable escalation in SPX values, reflecting an emerging fragmentation. The future scenario reveals a significantly altered situation, with a sharp increase in SPX values confirming the establishment of an increasingly dispersed settlement model. The future scenario allows us to evaluate how the aesthetic value of the landscape is expected to change with increased solar panel deployment.

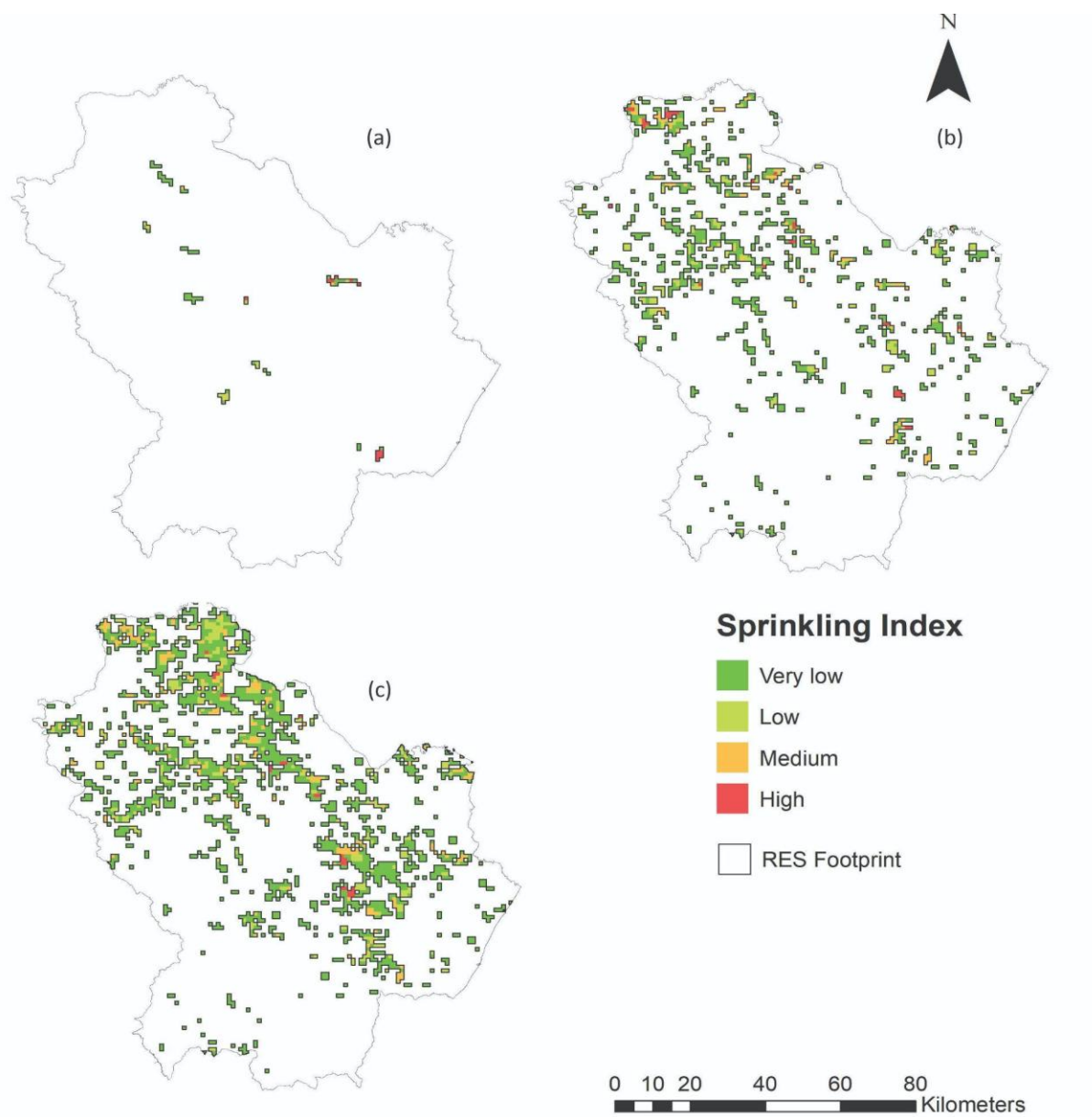


Fig.26. Sprinkling index trends evaluated for RES in Basilicata during three-time intervals: a) initial phase (2006-2008); b) mid-period (2008-2024); c) prospective scenario (2024-2030)

Visibility index

Output maps for the solar visibility index (Figure 27) indicate a clear and continuous expansion in areas affected by solar installations. Although the number of solar panels is increasing in the three investigated periods, the visual impacts of solar panels remain moderate. Also, for the future scenario, the impact is mainly very low, with only 6% of visually affected areas in the range of high.

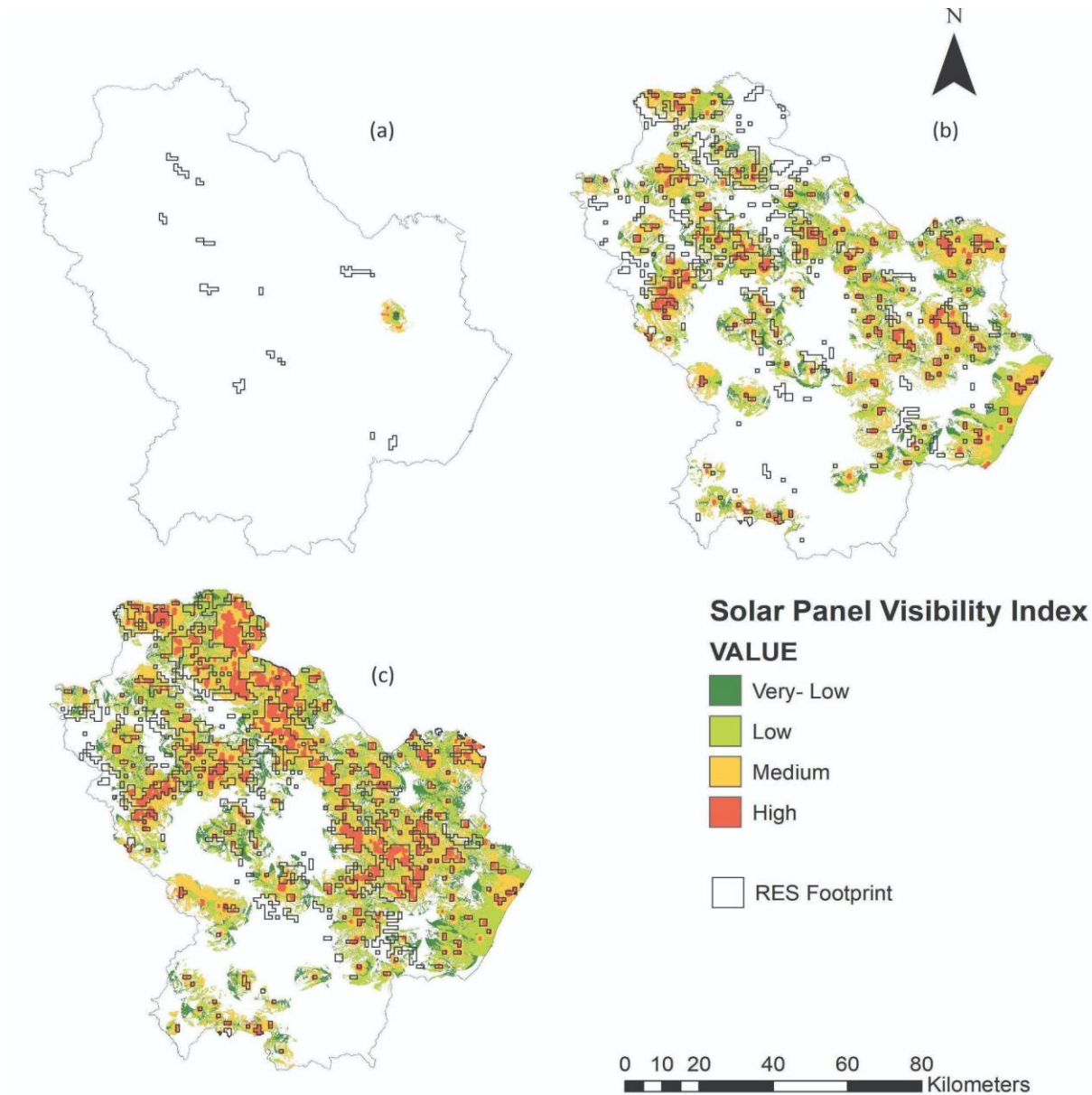


Fig.27. The visibility index evaluation for solar panels in Basilicata during three time intervals. a) initial phase (2006-2008); b) mid-period (2008-2024); c) prospective scenario (2024-2030).

For the wind visibility index (Figure 28), during the initial phase, the majority of the area (53%) was classified as “Unaffected or Low,” indicating limited visual disturbance. However, over time, there is a clear shift toward greater visual impact: the share of low-impact areas drops to just 12% in the future scenario. Simultaneously, the proportions of “Medium” and “High” impact categories increase, rising from 12% in 2008 to 22% in both 2024 and the future. This trend suggests a progressive decline in wind visibility, largely influenced by the growing presence of wind turbines in the landscape.

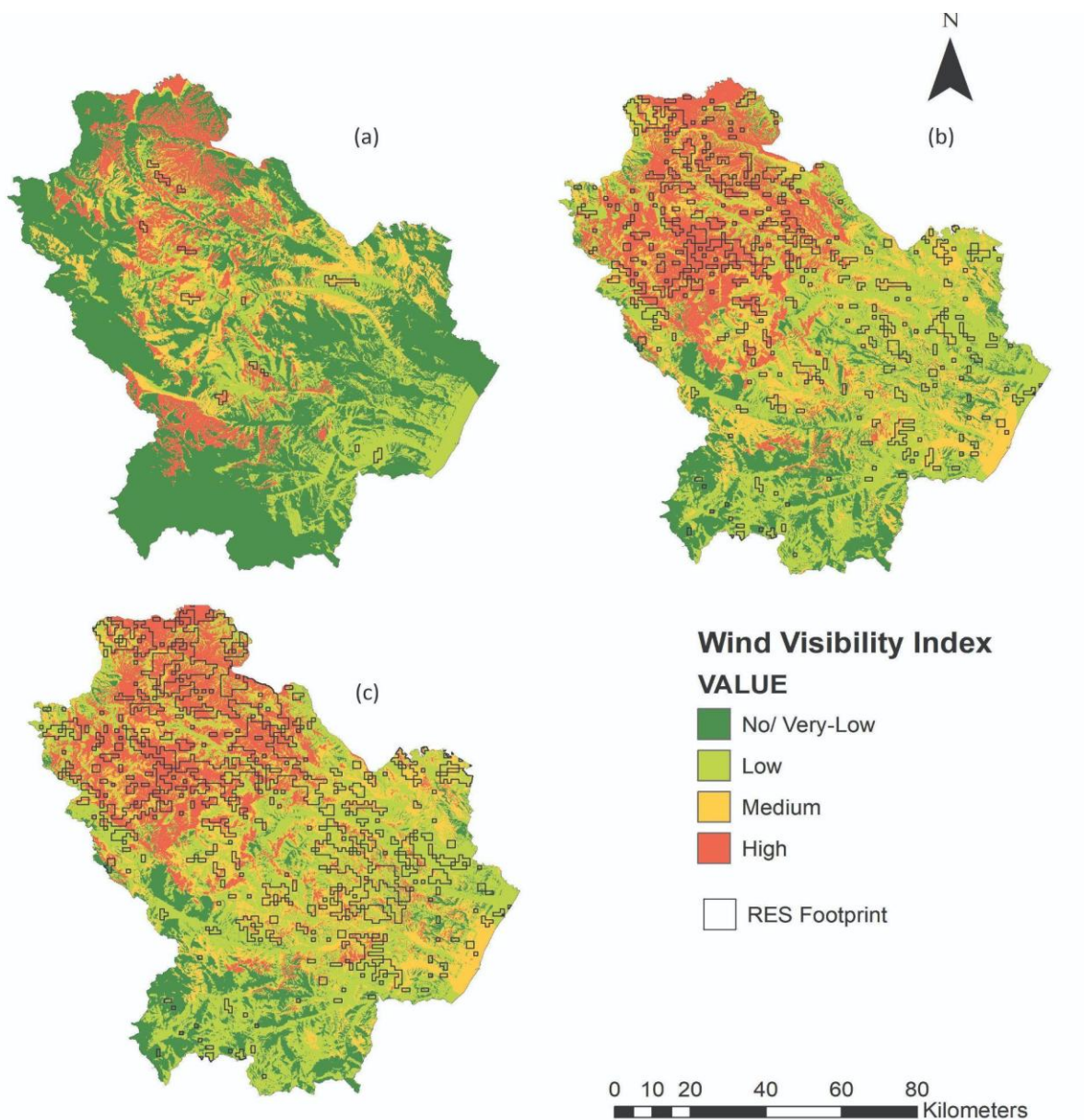


Fig.28. The visibility index evaluation for wind turbines in Basilicata during three time intervals. a) initial phase (2006-2008); b) mid-period (2008-2024); c) prospective scenario (2024-2030)

Habitat quality

The habitat quality maps depict the relative contribution of land-cover classes to the overall habitat quality score within the RES footprint (Figure 29). This score is dimensionless and does not correspond to a specific biodiversity metric. When aggregated by land-use type, forested areas provide the largest contribution to overall habitat quality (20.83%), reflecting both their spatial extent and their relative insulation from anthropogenic pressures. Scrub and herbaceous vegetation (16.67%) and arable land (12.5%) also contribute to habitat quality within the footprint, although to a lesser extent. In contrast, urban, industrial, and other artificial surfaces contribute negligibly, as heavily modified landscapes offer limited support for ecological functions. Wetlands and marine areas show moderate contributions (approximately 4–6%), indicating some ecological value, though their overall contribution remains lower than that of forest ecosystems.

Within the RES footprint in the study area, there is a major increase in low-quality habitat, rising from 3.92% in the initial period to 18.72% under the prospective scenario. This substantial change indicates a marked expansion of degraded or low-quality areas over time. Medium-quality habitat remains the dominant class across both periods; however, its proportion declines notably from 57.19% to 43.46%. This reduction suggests that a considerable portion of medium-quality habitat is being converted primarily into lower-quality classes, with only limited transition to higher-quality conditions. High-quality habitat exhibits a slight but discernible decrease, from 38.89% to 37.82%. Although the magnitude of change is relatively small, it nonetheless reflects a gradual erosion of the highest-quality habitat within the RES footprint.

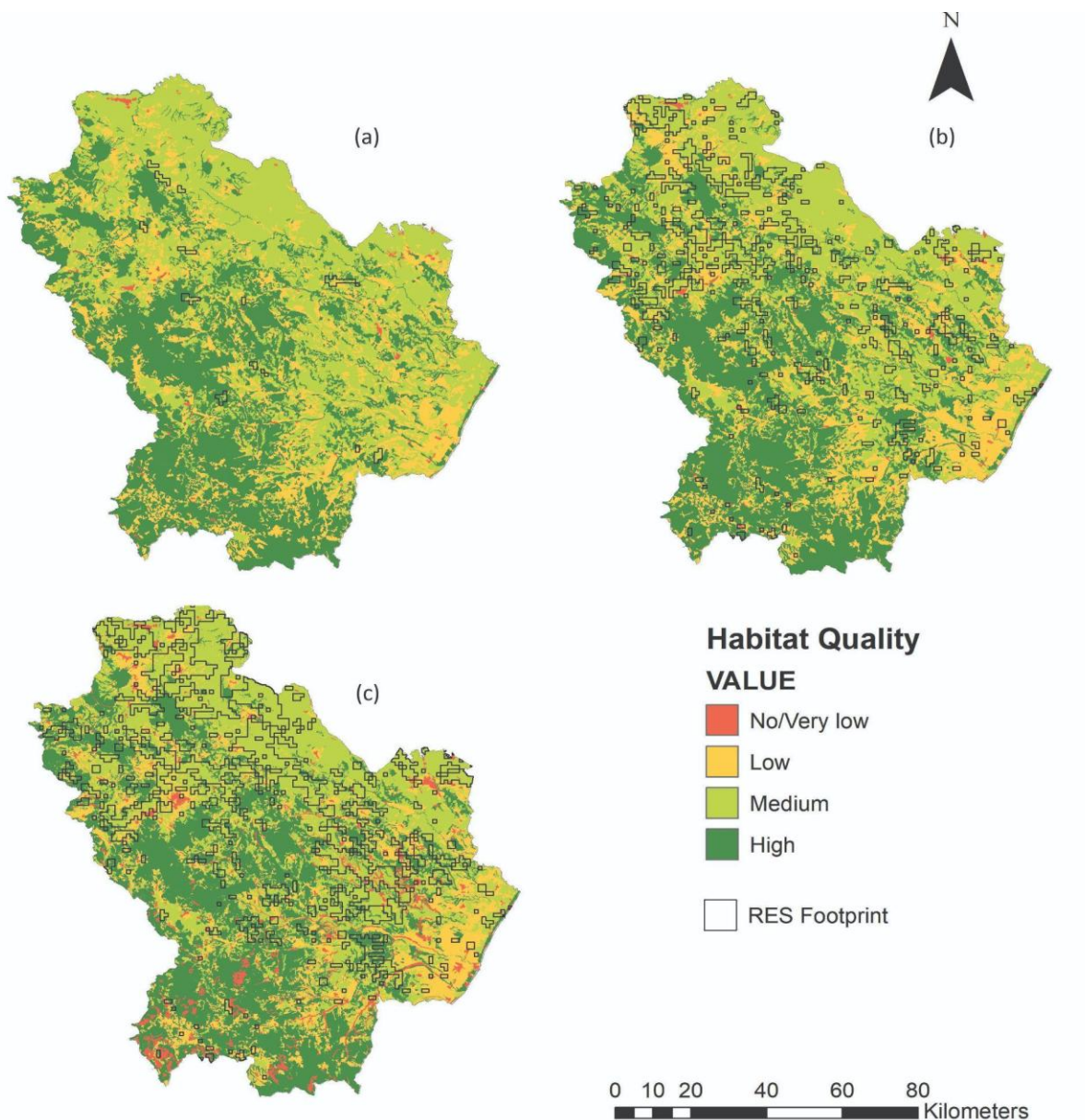


Fig.29. Habitat quality evaluation in Basilicata during three time intervals. a) initial phase (2006-2008); b) mid-period (2008-2024); c) prospective scenario (2024-2030)

Carbon storage

The carbon storage maps depict the relative contribution of land-cover classes to total carbon storage within the RES footprint (Figure 30). When aggregated by land-use type, forested areas account for the largest share of total carbon storage (35.96%), reflecting their spatial extent and high biomass density within the study area. Scrub and herbaceous vegetation (17.05%) and heterogeneous agricultural areas (16.91%) also make substantial contributions to overall carbon storage. Open spaces with little or no vegetation (13.64%) and inland wetlands (5.93%) provide moderate contributions. In contrast, artificial non-agricultural vegetated areas (2.86%), permanent crops (2.20%), arable land (1.98%),

pastures (1.61%), urban fabric (0.77%), industrial areas (0.22%), and mine or dump sites (0.44%) contribute relatively little to total carbon storage within the footprint. Maritime wetlands (0.44%) contribute marginally, while marine waters show no contribution (0.00%), consistent with their negligible role in terrestrial carbon accumulation.

With the case of carbon storage within the RES footprint, the results indicate an increase in low-carbon storage areas, rising from 44.09% in the initial phase to 46.02% under the prospective scenario. This trend reflects an expansion of areas with limited carbon sequestration capacity, likely associated with ongoing land degradation or intensification of land use. Medium carbon storage areas exhibit a slight decline, decreasing from 17.01% to 16.16%. Although the change is modest, it suggests a consistent reduction in intermediate carbon storage zones over time. High carbon storage areas also decrease, from 38.90% to 37.82%, indicating a gradual loss of the most carbon-rich habitats, such as forested or densely vegetated natural areas within the RES footprint.

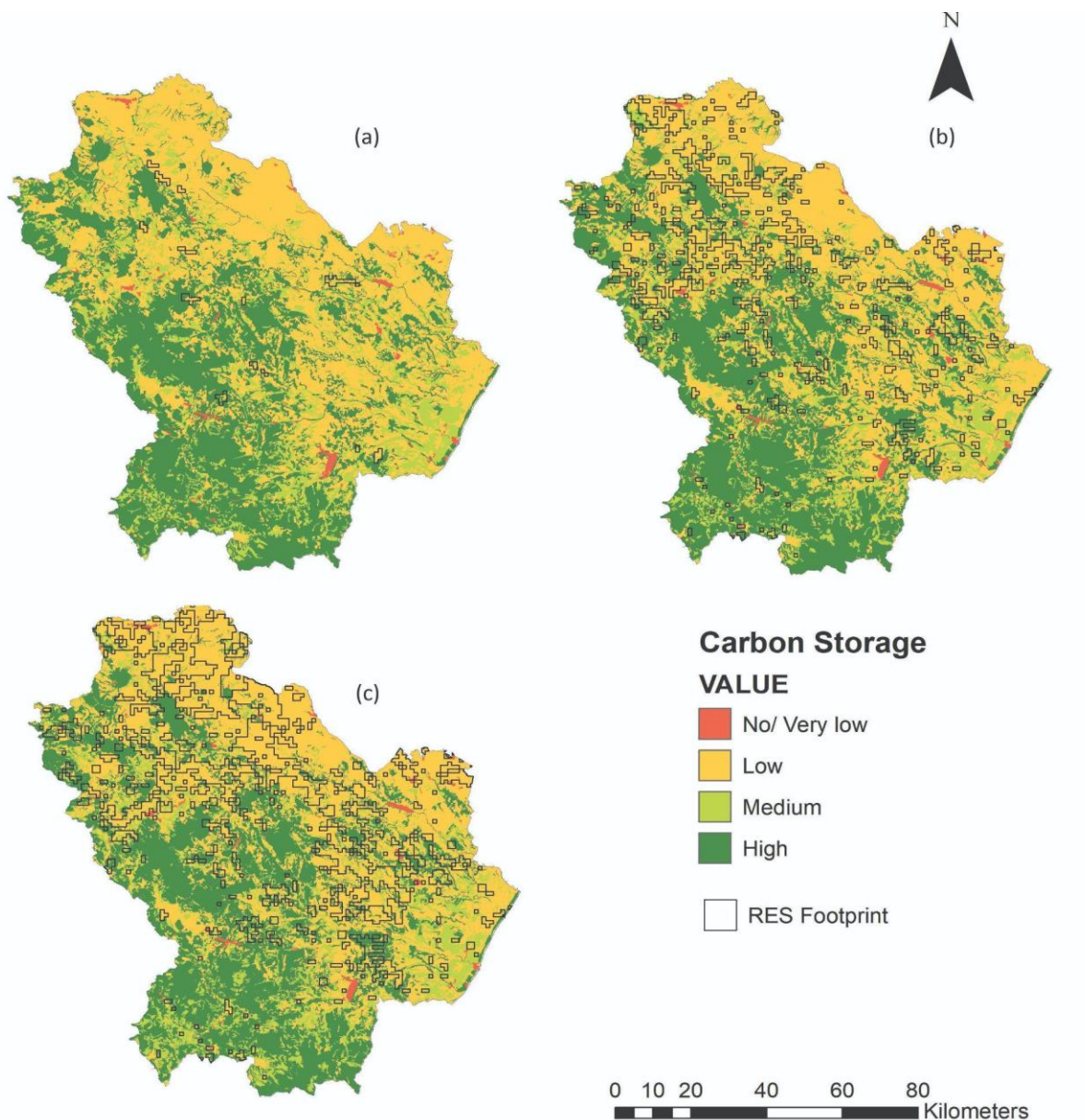


Fig.30. Carbon storage evaluation in Basilicata during three-time intervals. a) initial phase (2006-2008); b) mid-period (2008-2024); c) prospective scenario (2024-2030)

Crop pollination

The pollination maps depict the relative contribution of land-use classes to overall pollination potential within the RES footprint (Figure 31). When aggregated by land-use type, semi-natural habitats, particularly forests (18.93%) and scrub and herbaceous vegetation (19.45%), account for the largest share of the overall pollination potential, reflecting their spatial distribution and suitability for supporting pollinator populations. Agricultural areas collectively contribute moderate and more variable shares, generally ranging from approximately 3% to slightly above 10%, depending on crop type and management intensity. In contrast, artificial and heavily modified surfaces contribute marginally, with most values

below 4%, consistent with their limited capacity to support pollinators. Wetlands and marine-associated classes show relatively low contributions, mostly below 9%, indicating more localized and spatially constrained ecological roles. Overall, the results indicate that pollination potential within the footprint is primarily driven by semi-natural land covers, while agricultural and artificial areas provide more heterogeneous and generally weaker support.

Changes in pollination services within the RES footprint indicate an increase in low-pollination-potential areas, rising from 42.69% in the initial period to 44.08% in the prospective scenario. This pattern suggests an expansion of areas with limited capacity to support pollinators, likely reflecting continued degradation of habitat conditions favorable for pollination. Medium pollination potential areas decline from 23.13% to 21.60%, indicating a loss of intermediate-quality zones that are likely transitioning to lower pollination classes as a result of land-use pressures. High pollination potential areas remain largely stable, showing a marginal increase from 34.18% to 34.32%. Although the magnitude of change is minimal, this stability suggests that some high-quality pollination habitats persist within the RES footprint despite broader declining trends.

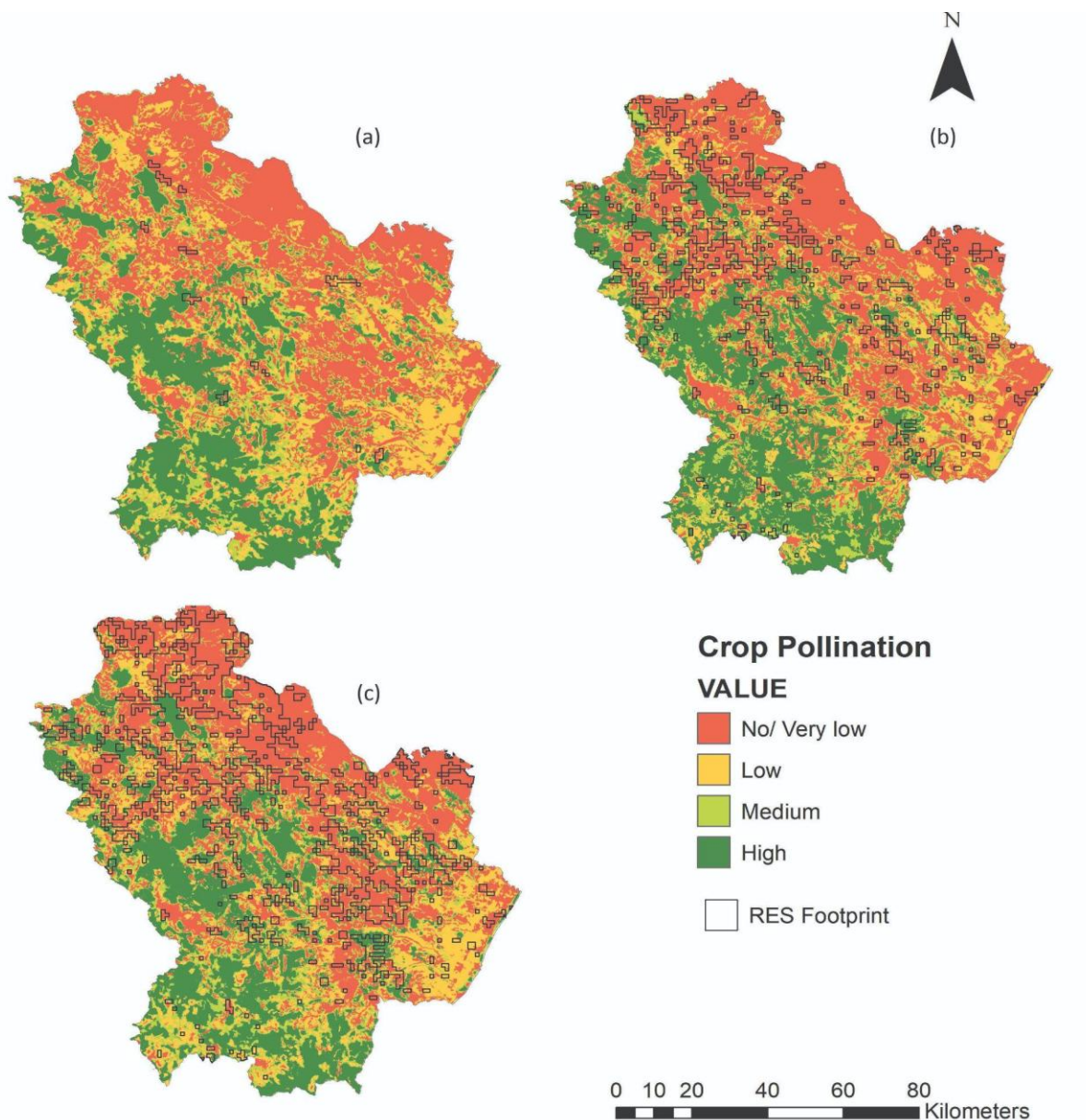


Fig.31. Crop pollination evaluation in Basilicata during three time intervals. a) initial phase (2006-2008); b) mid-period (2008-2024); c) prospective scenario (2024-2030)

Crop production

The crop production maps depict the relative contribution of land-use classes to total crop production within the RES footprint (Figure 32). When aggregated by land-use type, arable land accounts for the dominant share of overall production (56.87%), reflecting both its spatial extent and its role in regional agricultural systems, and thus represents the primary driver of provisioning services. Other agricultural land uses, including heterogeneous agricultural areas, pastures, and permanent crops, contribute more modestly, generally ranging between 2% and 5%, indicating lower but still relevant production functions. Artificial vegetated areas and inland wetlands also show comparatively higher contributions among

non-agricultural classes (9.0% and 9.91%, respectively), suggesting that in specific spatial contexts they can support measurable provisioning outputs. In contrast, natural vegetation types such as forests (0.71%) and scrub and herbaceous vegetation (2.14%) contribute minimally to total crop production within the footprint, highlighting their limited role in direct crop provisioning despite their importance for other ecosystem services. Overall, the results reveal a highly uneven distribution of crop production, strongly concentrated in arable land, with all other land-use classes contributing marginally.

Within the RES footprint, low crop production areas decline from 63.09% in the initial period to 60.89% in the prospective period, indicating a slight improvement in overall agricultural productivity, with fewer areas classified in the lowest production category. Medium crop production areas increase from 31.71% to 33.61%, suggesting a transition of some low-productivity lands toward moderate productivity levels, potentially driven by land-use changes or improved management practices. High crop production areas also exhibit a modest increase, rising from 5.20% to 5.49%. Although the magnitude of change is limited, it reflects a minor expansion of highly productive agricultural zones within the RES footprint.

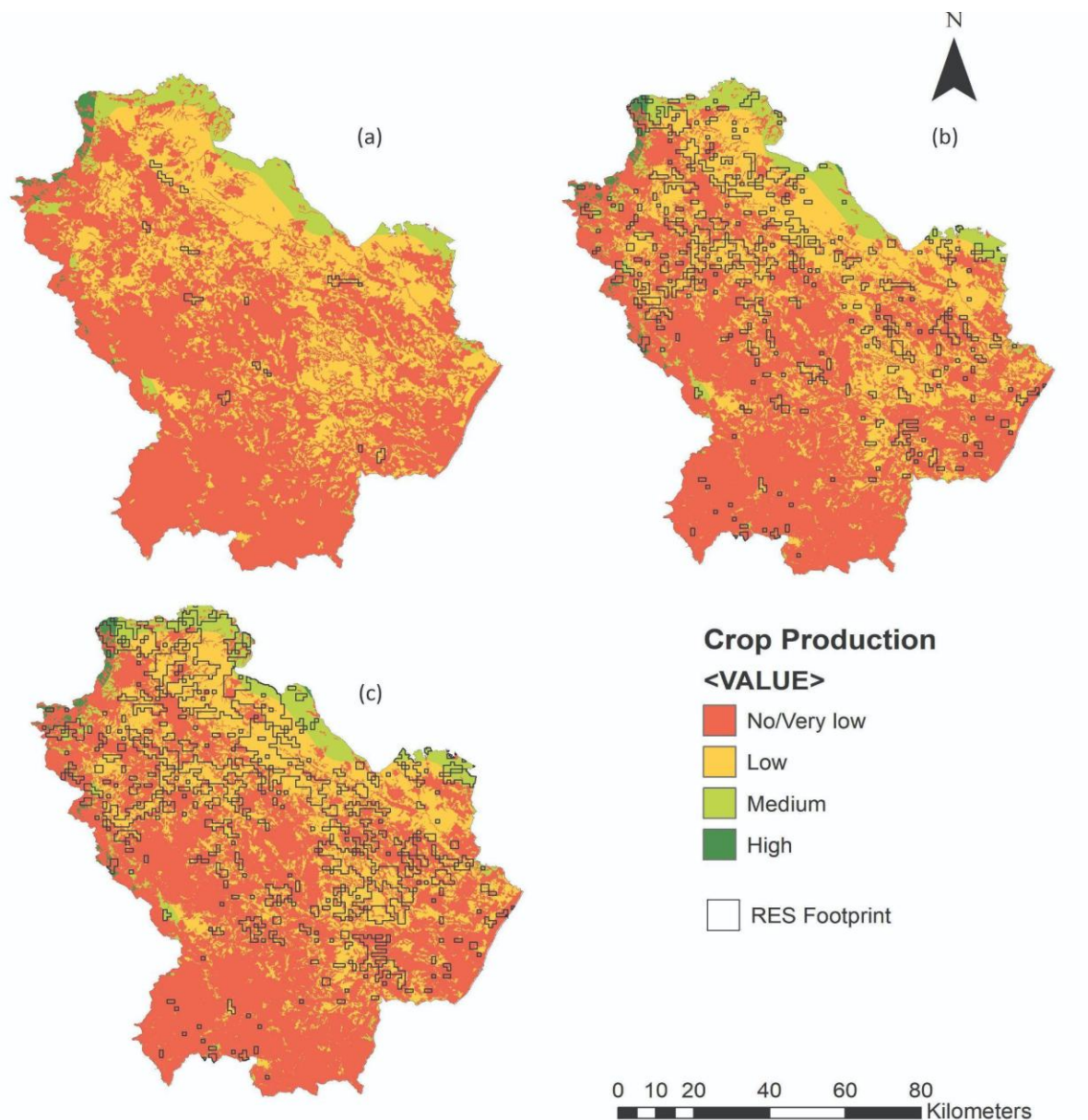


Fig.32. Crop production evaluation in Basilicata during three time intervals. a) initial phase (2006-2008); b) mid-period (2008-2024); c) prospective scenario (2024-2030)

4.3.2. Spatial characteristics and ecological implications of RES deployments

The spatial distribution of AHP scores and SOM clusters was subsequently mapped onto the regional extent of Basilicata. However, it should be noted that only grid cells within the RES footprint were considered and classified, while the remaining regional area represents a background context not directly involved in the analysis. Percentages reported for each cluster therefore refer to the proportion of the RES-affected area, rather than to the total regional surface.

Expert-based scenarios

The expert-based approach referred to as AHP allowed integrating the geo-spatial and ES indicators into three alternative scenarios, combining them within a multicriteria decision-making framework (Figure 33). The definition of the AHP hierarchy and the weighting of criteria were carried out through a structured process of expert consultation involving academics with proven experience in spatial planning and industrial energy. The expert group included professors of urban and regional planning with expertise in multi-criteria analysis and applied GIS, as well as energy professors with extensive experience in research and technical consulting in heavy industry. Relative weights, expressed as percentages, were assigned to each indicator to reflect their importance under each scenario (Appendix, Figure E). To facilitate comparison across scenarios, values were classified using the natural breaks method into three classes: low (Class 1), medium (Class 2), and high (Class 3).

Scenario 1 is primarily driven by renewable energy infrastructure development, as indicated by the high weights assigned to visibility-related indicators, namely wind visibility (40.80%) and solar visibility (21.00%). In contrast, ecosystem services such as habitat quality (5.90%), carbon storage (4.50%), and agricultural services (crop production at 8.20% and crop pollination at 4.30%) receive lower relative importance, suggesting that this scenario prioritizes the visual aspects of energy development over ecological and agricultural considerations.

Scenario 2 emphasizes environmental conservation and ecosystem functionality. Habitat quality (33.30%) and carbon storage (23.34%) receive the highest weights, while visibility disturbances from wind (4.49%) and solar infrastructure (5.35%) are comparatively low. Crop production and crop pollination are assigned moderate weights, indicating a balanced approach that prioritizes ecological integrity while still supporting agricultural services.

Scenario 3 focuses on agricultural productivity as the primary objective. Crop production (35.07%) and crop pollination (25.69%) dominate this scenario, whereas visibility disturbances from wind (4.01%) and solar (6.01%) remain minimal. Habitat quality (10.65%) and carbon storage (13.00%) receive moderate weights, reflecting a trade-off between maximizing food production and maintaining environmental services.

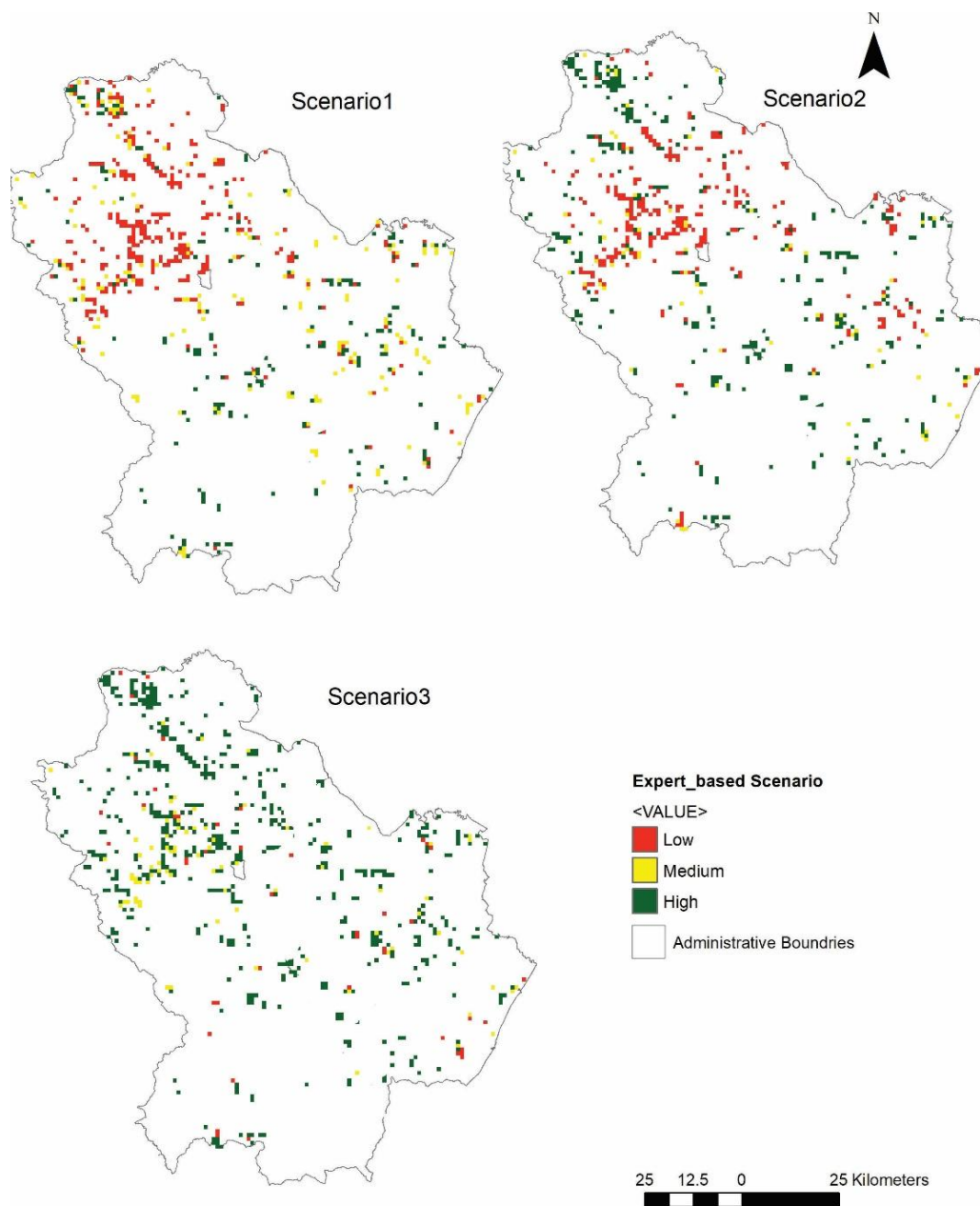


Fig.33. Three Expert-based scenarios.

Overall, the AHP results highlight the trade-offs among renewable energy development, ecosystem conservation, and agricultural productivity across the three scenarios. For all scenarios, the consistency ratio (CR) falls within acceptable limits, with values of 0.0778 for Scenario 1, 0.0354 for Scenario 2, and 0.0537 for Scenario 3.

Data-driven clusters

In parallel, an unsupervised learning approach based on SOM was applied to aggregate the geo-spatial and ES indicators. Unlike the AHP, no predefined weights were assigned; the SOM

autonomously organized the indicators based on inherent patterns in the data, allowing the analysis to reveal natural groupings and relationships within the RES footprint. This unsupervised, data-driven method provides a complementary perspective to the scenario-based, weighted results derived from the AHP, highlighting emergent structures and interactions among the indicators without imposing subjective priorities.

The SOM's heatmaps (Figure 34) provide a clear view of spatial patterns across the study area. Pollination potential is concentrated in the upper-left, with carbon storage showing a similar but slightly shifted high-value pattern, suggesting a positive spatial association between these two ecological services. Habitat quality is more localized in the lower-right, indicating that high-quality habitats do not strongly overlap with areas of high pollination or carbon storage. Crop production peaks in the upper-right, largely distinct from the main ecological hotspots, reflecting a spatial separation between intensive agriculture and key ecosystem services. Both wind and solar visibility are highest in the upper-left, partially coinciding with areas of high carbon and pollination, which may have implications for land-use planning and ecosystem service trade-offs. High fragmentation, indicated by the sprinkling index, occurs only in a few scattered points in the eastern corner, largely independent of other variables. Overall, these patterns highlight both the spatial clustering of related services and the partial segregation between ecological and anthropogenic indicators within the RES footprint.

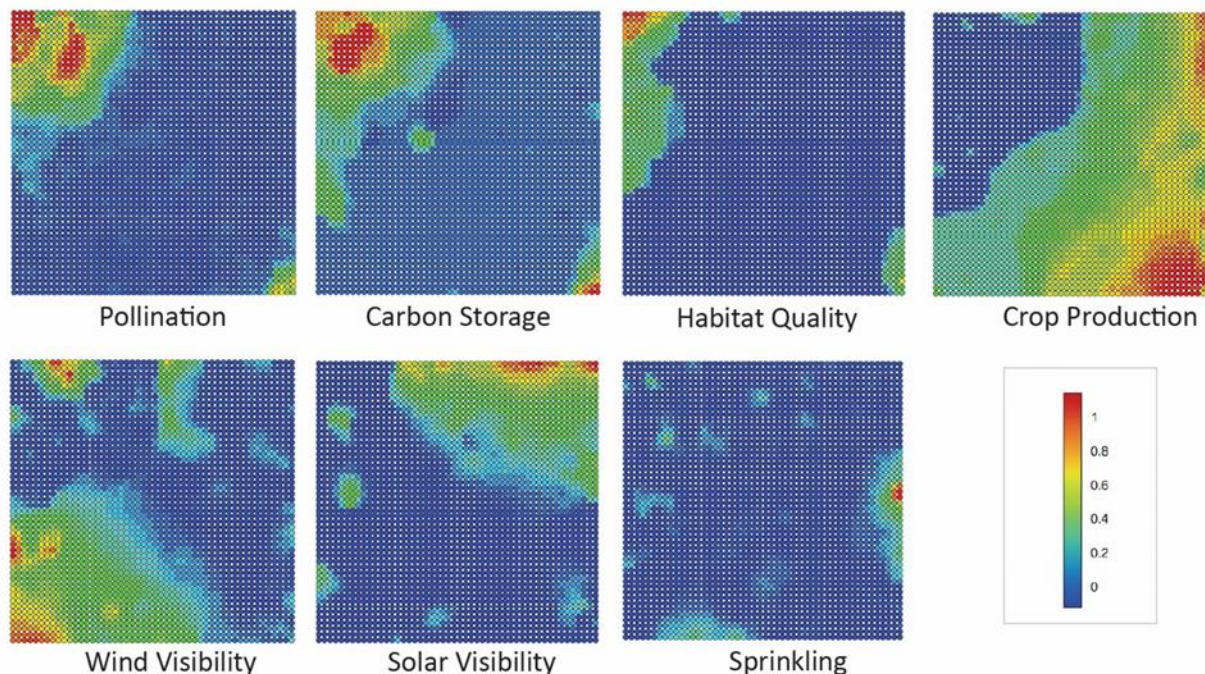


Fig.34 Heatmaps representing the pattern distribution of each variable across the SOM grid, expressed as scaled values in the range [0–1]

Units in the SOM's grid was finally aggregated into three main clusters, each representing a distinct landscape typology in terms of ecosystem service provision, agricultural productivity, and exposure to renewable energy infrastructure (Figure 35 and Table 15).

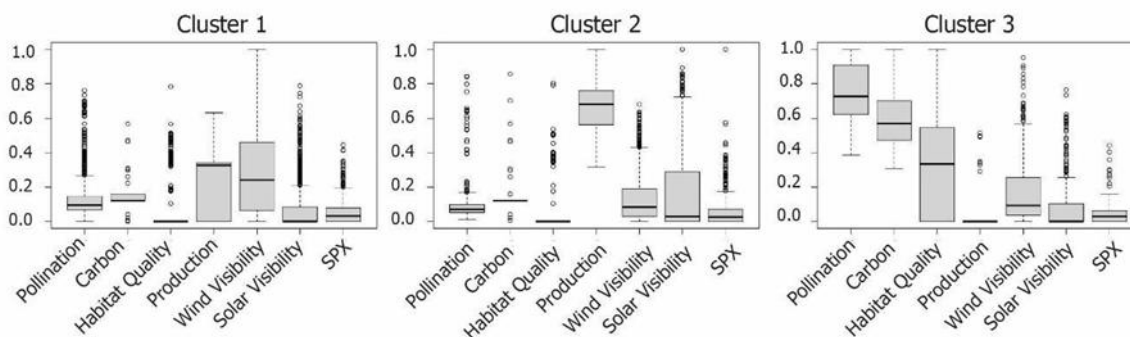


Fig.35. Boxplots of the distribution of variables expressed as scaled values in the range [0–1].

Tab.15 Labeling three SOM clusters.

CLUSTER	TABLE	PERSENTAGE
1	Agricultural Production Landscapes with High Visual Sensitivity	38.79%
2	Protected and Ecologically Sensitive Areas	43.43%
3	Ecosystem Service Priority Zones	17.78%

Cluster 1 (Agricultural production landscapes with high visual sensitivity) covers 38.79% of the study area and is characterized by a strong agricultural vocation combined with high visual exposure to renewable energy infrastructure. Box-plot analysis shows relatively high median values of crop production, together with elevated wind turbine visibility. In contrast, regulating and supporting ecosystem services, such as pollination, carbon storage, and habitat quality, exhibit consistently low values, with medians generally below 0.2. This cluster, therefore, represents productive rural landscapes with limited ecological multifunctionality, where renewable energy development may be feasible from a land-use perspective but is likely to generate substantial visual impacts, requiring careful landscape-sensitive planning and mitigation measures.

Cluster 2 (Highly productive agricultural areas with potential environmental risk) is the most extensive typology, accounting for 43.43% of the study area. It is distinctly defined by very

high crop production values, with the median and interquartile range concentrated at the upper end of the production scale, indicating intensive agricultural use. Other ecosystem service indicators show distributions broadly similar to Cluster 1, with generally low values for regulating and supporting services. While visual exposure to renewable energy infrastructure remains moderate, the dominant feature of this cluster is its high productive capacity. Consequently, further deployment of renewable energy systems in these areas may increase pressures related to soil degradation, pollution, and cumulative land-use impacts if not accompanied by adequate environmental safeguards.

Cluster 3 (Ecosystem service priority zones) represents 17.78% of the total study area and encompasses landscapes with high ecological and environmental value. This cluster is characterized by elevated median values of pollination, carbon storage, and habitat quality, while crop production remains consistently low, reflecting a limited role of intensive agriculture. Socio-spatial indicators related to renewable energy infrastructure, including SPX as well as solar and wind visibility, are close to zero, indicating minimal anthropogenic disturbance and low visual exposure. These areas function as ecosystem service hotspots and should therefore be considered priority zones for conservation, where the installation of new renewable energy infrastructure should be avoided or strictly limited to safeguard ecological integrity and ecosystem functionality. Figure 36 shows the overview of how these clusters are scattered in the area.

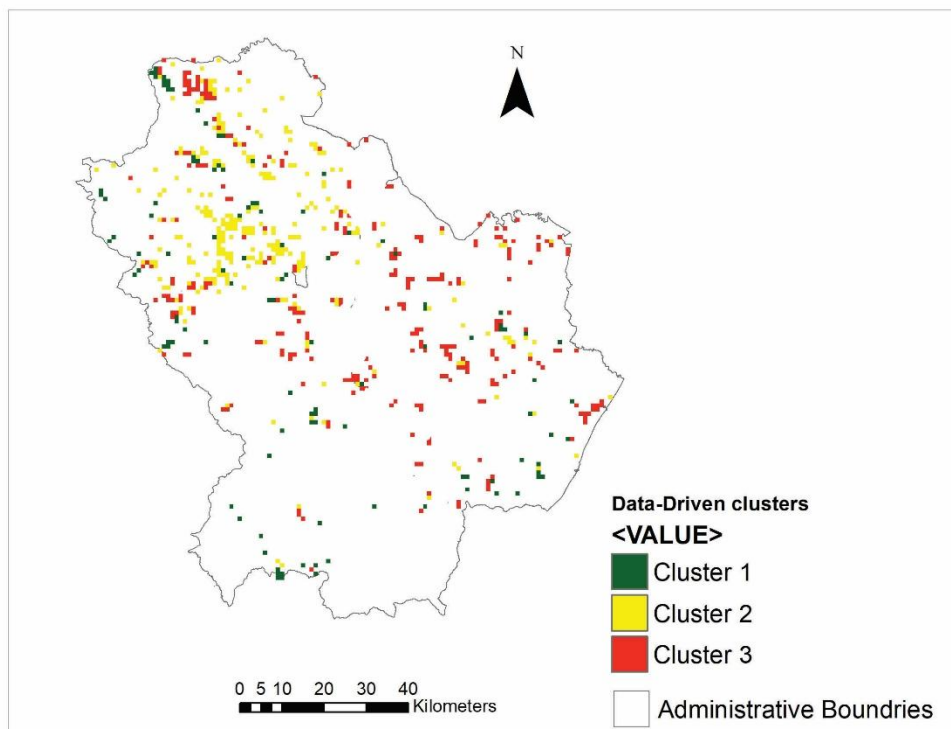


Fig.36. Three main data-driven cluster scattering in the Basilicata region.

4.4. Discussions

To assess the degree of consistency between the expert-knowledge-based and data-driven approaches, a comparative matrix was constructed to quantify the overlap between the three AHP scenarios and the SOM clusters within the RES footprint (Table 16). Given the discontinuous and selective nature of the analytical domain, this tabular comparison provides a robust and transparent alternative to traditional cartographic overlays, enabling a direct evaluation of methodological convergence and divergence.

Tab.16 Transitional comparison between three supervised scenarios and data SOM.

SCENARIO 1				
SOM		1	2	3
	1	0.64%	87.76%	11.60%
	2	0.41%	53.26%	46.33%
	3	0.20%	42.83%	56.97%
	SCENARIO 2			
	1	79.00%	21.00%	
	2	35.24%	64.76%	
	3	12.75%	74.90%	12.35%
	SCENARIO 3			
	1	19.45%	80.55%	
	2	10.03%	89.97%	
	3	8.76%	87.05%	4.18%

The results show strong agreement between AHP and SOM, especially for intermediate impact classes. In Scenario 1, Cluster 1 aligns mostly with the medium AHP class (87.76%), Cluster 2 also with medium (53.26%), and Cluster 3, the ecosystem service priority zone, with the high-impact class (56.97%). In Scenario 2, Cluster 1 remains medium (79.00%), while Clusters 2 and 3 increasingly align with high-impact classes (64.76% and 74.90%), reflecting scenario-specific weighting. Scenario 3 shows the strongest convergence: Cluster 1 is medium (80.55%), and Clusters 2 and 3 are highly consistent with high-impact (89.97% and 87.05%).

Despite different conceptual bases, AHP and SOM yield broadly consistent classifications. SOM clusters, particularly Cluster 3, are stable across scenarios, supporting their interpretation as robust landscape typologies. Variations across scenarios highlight the sensitivity of expert-based assessments and emphasize the value of integrating data-driven methods for transparent, evidence-based spatial planning. The integration of two methods

provides not only methodological insight but also a basis for spatially explicit policy guidance in the context of regional energy planning. The three identified clusters represent distinct landscape typologies that can support differentiated decision-making strategies aligned with frameworks such as the Basilicata Carbon Free law. In particular, Cluster 3, characterized by high habitat quality, carbon storage, and pollination potential, should be considered as areas of strict constraint or exclusion for future renewable energy development. In these zones, policy instruments should prioritize conservation objectives by limiting or conditioning financial incentives and reinforcing environmental protection measures. In contrast, Cluster 1 presents conditions where renewable energy deployment is feasible but requires landscape-sensitive planning approaches, including enhanced visual impact assessments, spatial optimization of installations, and the adoption of mitigation strategies such as screening or layout adjustments. Subsidy schemes in these areas could be designed to reward projects that minimize visual disturbance and improve integration with the surrounding landscape. Finally, Cluster 2 calls for a balanced and conditional development strategy, where renewable energy expansion is permitted but linked to safeguards that protect soil quality and ecosystem functionality. Policy measures in these zones may include promoting dual-use systems such as agrivoltaics, limiting land take, and tying financial incentives to the maintenance or enhancement of ecosystem services. Overall, these findings support a transition from uniform, technology-driven deployment toward spatially differentiated energy planning, in which regulatory constraints and subsidy allocation are explicitly aligned with the ecological and functional characteristics of the landscape. This approach enhances the capacity of regional policies to balance decarbonization goals with the preservation of ecosystem integrity and landscape quality.

4.5. Conclusion

In light of the findings presented, this research underscores the necessity of transitioning from traditional expert-based evaluation methods toward hybrid assessment frameworks that integrate both subjective and data-driven perspectives. By applying this dual methodology to the Basilicata region, the study demonstrates that the integration of the AHP and SOM provides a superior understanding of the spatial trade-offs inherent in renewable energy expansion. Methodologically, the AHP offers a structured approach for prioritizing regional goals based on expert judgment and predefined weights, yet it is inherently constrained by the subjectivity of the evaluators. In contrast, the SOM provides an unsupervised, data-driven exploration that uncovers latent spatial relationships and emergent clusters without the need for prior assumptions or human-defined hierarchies.

The synthesis of results through the transitional matrix reveals a significant degree of convergence between these two approaches, particularly in the identification of high-value ecosystem priority zones. These areas, characterized by high carbon storage and superior

habitat quality, were consistently flagged as high-sensitivity zones by both the expert-based AHP scenarios and the unsupervised SOM clustering. Such robustness in the findings confirms that certain landscape typologies are critically vulnerable to renewable energy encroachment regardless of the evaluation framework used. Specifically, the analysis highlights a worrying trend toward habitat degradation within the renewable energy footprint, with the modeling results suggesting a substantial increase in low-quality habitats from 3.92% in the current state to 18.72% in the 2030 scenario.

Furthermore, the study identifies distinct trade-offs in productive agricultural landscapes, where energy development often conflicts with visual sensitivity and vital ecosystem services such as pollination and crop production. By revealing these complex interactions through graphical SOM outputs, the proposed hybrid framework serves as a transparent Spatial Decision Support System for regional planners. It allows for the identification of critical zones where mitigation efforts are most urgent, ensuring that the advancement of regional decarbonization goals does not come at the expense of long-term ecosystem integrity. Ultimately, this approach facilitates a more nuanced and integrated spatial planning strategy that can balance the competing demands of energy production, landscape preservation, and social acceptance in the context of the green transition.

CHAPTER 5

Conclusion

The rapid expansion of renewable energy systems constitutes one of the most significant territorial transformations associated with the contemporary energy transition. Globally, wind and solar capacity is projected to more than double by 2030 under current policy trajectories, and in regions such as Basilicata, where over 2,100 wind turbines are already in operation and a further 780 structures are under development, the spatial pressure on landscapes and ecosystems is already acute. Although renewable technologies are widely regarded as essential for climate change mitigation and energy security, their deployment is not spatially neutral. Rather, it is embedded within landscapes, ecosystems, and social systems already shaped by multiple, often competing pressures, including agricultural land use, biodiversity conservation, cultural heritage, and local community interests. This doctoral research addresses these complexities by examining the interactions between renewable energy systems, landscapes, and ecosystem services across three interconnected dimensions: the visual and aesthetic impact of wind installations on culturally sensitive landscapes, the spatial suitability of sites for green hydrogen infrastructure in an industrial urban context, and the cumulative effects of solar and wind deployment on a broad set of ecosystem services at the regional scale. The overarching aim was to develop and test an integrated assessment framework to support more sustainable, informed spatial planning decisions in contexts where energy goals and territorial values are in tension.

The overarching objective of this thesis was to develop and test an integrated assessment framework that captures the spatial, ecological, and socio-cultural dimensions of renewable energy deployment. The research focused on the Basilicata region in southern Italy, a territory that offers a particularly instructive case study: it combines high environmental and cultural value, including the UNESCO World Heritage Site of Matera, 113 geosites, and extensive agricultural land, with a disproportionately high concentration of renewable energy infrastructure and a comparatively weak institutional capacity for spatial planning. With approximately 47% of its territory classified as mountainous and 56% of its land under agricultural use, Basilicata illustrates the spatial tensions typical of many Mediterranean regions navigating the energy transition. The research offers both context-specific insights into the cumulative landscape impacts of RES in this region and methodological contributions that are transferable to landscape-scale energy planning elsewhere in Italy and Europe.

Synthesis of the main findings

The three core studies presented in this thesis collectively demonstrate that the impacts of renewable energy systems cannot be adequately understood through single-dimensional or purely technical assessments. Each chapter addressed a distinct aspect of the RES–

landscape–ecosystem services relationship, yet all three converged on the same conclusion: robust and socially acceptable energy planning requires approaches that explicitly account for landscape values, ecosystem service dynamics, and spatial heterogeneity simultaneously. The key findings from each chapter are synthesized below.

Chapter 2 examined the aesthetic and visual impacts of wind energy installations in a cluster of seven municipalities in northern Basilicata (Livello, Montemilone, Venosa, Maschito, Palazzo San Gervasio, Banzi, and Forenza), emphasizing that landscape perception remains a central source of social concern and opposition, particularly in culturally and environmentally sensitive regions. By integrating expert-based landscape evaluation — grounded in the Naturalness (N), Environmental Quality (Q), and Constraint (V) indices — with the Scenic Quality Model implemented in InVEST, the analysis moved beyond conventional viewshed approaches to produce a composite landscape impact index (IP) that captures both the intrinsic value of the territory and the visual disturbance generated by installations. The findings revealed that under current conditions, approximately 60.35% of the study area falls into the highest visual impact category (Category 4), and this share is projected to rise to 65.10% once all authorized future installations become operational. These results are particularly critical given that 47% of the study area is already classified as having high or very high landscape value. Specifically, areas characterized by high naturalness (broadleaf forests, scrubland), high environmental quality, or historical and archaeological constraints were disproportionately affected by visual intrusion, even under relatively low turbine densities. The case of Basilicata illustrates how the accumulation of individually permitted installations can generate cumulative visual impacts that are far more significant than any single project assessment would suggest. These results highlight the importance of incorporating qualitative landscape values and compound visual sensitivity into spatial planning processes, rather than treating visual impacts as secondary or residual considerations.

Chapter 3 shifted the analytical focus from impact assessment to proactive site selection through the application of a GIS-based SMCA combined with the AHP to identify suitable locations for green hydrogen infrastructure in the municipality of Potenza. The case study of the Siderpotenza steel plant, an energy-intensive electric arc furnace facility with high electricity and water consumption, demonstrated how expert knowledge can be systematically operationalized into transparent and reproducible spatial suitability criteria. Seven criteria were evaluated through pairwise comparison matrices, including slope, solar radiation, road accessibility, proximity to the industrial site, distance to renewable energy sources, distance to gas pipelines, and land use. The AHP weighting assigned the highest importance to industry accessibility (28%), followed by land use (20%) and distance to renewable energy sources (18%), reflecting the locational logic of a hydrogen production

system that must serve a specific industrial consumer while minimizing land-use conflict. The resulting suitability maps indicated that only approximately 9% of the study area qualifies as highly suitable, with the most favorable zones concentrated in the vicinity of the Siderpotenza plant and existing industrial land uses. The three alternative planning scenarios, prioritizing technical, economic, and environmental criteria respectively, produced meaningfully different spatial outcomes, with the environmentally oriented Scenario 3 identifying a distinct area of approximately one hectare with high suitability near existing industrial sites. Importantly, a dual sensitivity analysis combining Monte Carlo simulation ($n = 10,000$) and One-at-a-Time perturbation confirmed that the ranking of top-priority sites was robust to weight variations of up to $\pm 20\%$, providing quantitative assurance about the reliability of the framework. These findings show that environmentally compatible pathways for industrial decarbonization are spatially feasible in Basilicata, provided that site selection integrates logistical, environmental, and infrastructure criteria within a well-documented multi-criteria framework.

Chapter 4 constituted the conceptual and methodological consolidation of the thesis by integrating expert-based assessment with data-driven unsupervised machine learning at the regional scale of Basilicata. Using a 1 km^2 grid covering the RES footprint of the entire region, the study combined six spatial and ecosystem service indicators — the sprinkling index, visual impact, habitat quality, carbon storage, crop pollination, and crop production — assessed across three temporal intervals (2006–2008, 2008–2024, and a 2024–2030 prospective scenario derived from Land Change Modeller simulations). Two parallel analytical approaches were applied: an Analytic Hierarchy Process that produced three expert-weighted scenarios prioritizing renewable energy visibility, ecological conservation, and agricultural productivity, respectively; and a Self-Organizing Map (SOM) trained on a 50×50 grid that autonomously clustered RES-affected cells into three landscape typologies. The SOM identified Cluster 1 (Agricultural Production Landscapes with High Visual Sensitivity, 38.79%), Cluster 2 (Highly Productive Agricultural Areas with Potential Environmental Risk, 43.43%), and Cluster 3 (Ecosystem Service Priority Zones, 17.78%). A key quantitative finding was the substantial increase in low-quality habitat within the RES footprint, rising from 3.92% in the initial phase to a projected 18.72% by 2030, alongside a decline in medium-quality habitat from 57.19% to 43.46%. Carbon-rich natural areas also showed a gradual erosion, with high carbon storage areas declining from 38.90% to 37.82%. A transitional comparison matrix between AHP scenarios and SOM clusters revealed strong convergence: Cluster 3, the ecosystem service priority zone, was consistently classified as high-impact across all three expert scenarios, with agreement rates of 56.97%, 74.90%, and 87.05%, respectively. This cross-validation confirmed that the most ecologically valuable areas are reliably identified as high-sensitivity zones regardless of which evaluation

approach is applied. Overall, the hybrid framework demonstrated clear advantages in terms of robustness, transparency, and interpretability compared to either method used alone, particularly in complex landscapes where multiple ecosystem services are simultaneously affected by energy infrastructure.

Methodological contributions

Beyond the individual case studies, this thesis contributes to the broader methodological discourse on assessing the impacts of renewable energy at the landscape scale. A first key contribution lies in the deliberate integration of expert-based and data-driven approaches, not as competing paradigms but as complementary tools that address different dimensions of uncertainty and knowledge. In Chapter 2, the combination of locally validated expert indices (N, Q, V) with the InVEST Scenic Quality Model produced a landscape impact assessment that is both spatially explicit and grounded in regulatory and cultural realities specific to the Italian context — an approach that standard viewshed analysis alone cannot achieve. In Chapter 3, the AHP-SMCA framework operationalized multi-stakeholder expert judgment through mathematically verifiable pairwise comparisons and quantified the sensitivity of outcomes through Monte Carlo and OAT analyses, making the decision logic fully transparent and reproducible. In Chapter 4, the SOM-AHP cross-validation demonstrated that data-driven clustering can independently confirm or challenge expert classifications, providing a principled basis for identifying where the two approaches converge (and thus where conclusions are most reliable) and where they diverge (signaling areas that warrant further investigation or stakeholder deliberation).

Expert-based methods remain indispensable in contexts where data availability is limited, where legal and cultural constraints play a decisive role, and where local knowledge provides insights that cannot be easily quantified. This was especially evident in Chapter 2, where decades of accumulated professional knowledge from environmental consultants at F4 s.r.l. were essential to assign ecologically and legally meaningful values to landscape features not captured by any single geospatial dataset. At the same time, data-driven and machine-learning techniques, specifically the SOM applied in Chapter 4, offer powerful means of identifying spatial patterns, reducing subjectivity, and revealing complex, nonlinear relationships between variables that AHP-based weighting might suppress or overlook. The SOM's ability to detect latent landscape clusters without prior assumptions was particularly valuable for characterizing ecosystem service trade-offs across the RES footprint, producing typologies that were both statistically meaningful and interpretable in planning terms. By combining these approaches within a single framework, this research demonstrates how their respective strengths can be leveraged while mitigating their individual limitations: the

subjectivity risk of purely expert-driven methods and the interpretability challenge of purely data-driven ones.

A second key methodological contribution is the explicit use of ecosystem services as an organizing framework for sustainability assessment, operationalized through the InVEST modelling suite across multiple temporal scenarios. Rather than focusing solely on environmental impacts in a narrow regulatory sense, the thesis adopts a multidimensional perspective that simultaneously quantifies habitat quality, carbon storage, crop pollination, and crop production within the RES footprint, alongside geospatial indicators of land fragmentation and visual disturbance. This multi-indicator approach makes trade-offs visible in concrete, spatially explicit terms. For example, the projected increase in low-quality habitat from 3.92% to 18.72% by 2030 within the RES footprint provides a specific, quantified target around which conservation and mitigation policies can be designed. Similarly, the identification that forested areas contribute 35.96% of total carbon storage within the footprint, despite covering a comparatively small share of the land, has direct implications for where new installations should be avoided or where compensation measures should be required. This approach shifts the planning discourse from minimizing discrete project-level damages toward understanding cumulative trade-offs and co-benefits across the landscape, thereby supporting more nuanced and context-sensitive decision-making at the regional scale.

Implications for planning and policy

The findings of this research carry several important implications for spatial planning, environmental assessment, and energy policy. First, they highlight the limitations of fragmented and sectoral approaches to renewable energy planning. When energy objectives are pursued in isolation from landscape and ecosystem considerations, the risk of cumulative impacts, social conflict, and irreversible land-use change increases significantly. In Basilicata, the cumulative effect of individually permitted installations has already pushed approximately 65% of the landscape in the most wind-intensive municipalities into the highest visual impact category, a level that would not have been predictable from any single project's Environmental Impact Assessment. This underscores the urgent need to shift from project-by-project permitting toward strategic area-based planning, in which cumulative thresholds for visual impact, habitat fragmentation, and ecosystem service loss are defined at the regional or landscape scale before individual authorizations are granted.

Second, the results emphasize the value of early-stage spatial screening and scenario analysis. The GIS-AHP framework developed in Chapter 3 demonstrated that a fully integrated multi-criteria suitability analysis can reduce the search space for green hydrogen infrastructure from a 728 km² study area to a limited set of high-suitability zones

concentrated near existing industrial land and road infrastructure, doing so in a way that is transparent, reproducible, and sensitive to different planning priorities. More broadly, Decision Support Systems that integrate landscape sensitivity maps, ecosystem service indicators, and infrastructure requirements can help identify suitable locations before project-level conflicts arise. Such preventive planning approaches are particularly relevant in regions like Basilicata, where the 2018 regional law on “Decarbonisation and Regional Policies on Climate Change” sets ambitious targets but where high environmental value coexists with economic vulnerability and limited institutional capacity for long-range spatial planning.

Third, the research supports the need for greater transparency in decision-making processes. Explicitly documenting assumptions, criteria weights, and methodological choices not only improves the technical quality of assessments but also enhances their legitimacy in the eyes of stakeholders and the public. This thesis demonstrated this in two concrete ways: in Chapter 3, the Monte Carlo sensitivity analysis provided quantitative evidence that the suitability rankings were stable across plausible ranges of expert weight configurations (with industry accessibility retaining the first rank in 81.3% of 10,000 simulations), turning what is typically an opaque expert judgment into a verifiable and communicable result; and in Chapter 4, the transitional matrix between AHP scenarios and SOM clusters provided a structured basis for comparing the outputs of expert knowledge and automated analysis, making areas of methodological agreement and disagreement explicit rather than obscured. In this regard, hybrid expert–data-driven frameworks offer promising pathways for bridging the gap between technical analysis and participatory planning, and for building the kind of procedural trust that is increasingly necessary for social acceptance of renewable energy projects.

Limitations and future research directions

Moreover, while the thesis focuses on wind energy, solar installations, and green hydrogen infrastructure, the proposed framework is potentially transferable to other renewable technologies and territorial contexts. Applying the approach across different regions and governance settings would help test its generalizability and refine its components. The proposed framework, although developed and applied to the Basilicata region, presents a structure that is inherently scalable and transferable to other contexts. From a scalability perspective, the methodology is based on modular components, including GIS-based spatial analysis, multi-criteria evaluation, ecosystem service indicators, and data-driven techniques, which can be applied across different spatial scales. The use of standardized datasets and widely adopted tools allows the framework to be extended from local case

studies to broader regional or national applications without substantial methodological changes.

In terms of transferability, the framework is designed to be adaptable to different socio-environmental conditions. While the selection of indicators and their weighting reflects the specific characteristics of Basilicata, the overall methodological structure remains applicable to other Italian regions and beyond. Adjustments can be made to account for variations in environmental constraints, land-use patterns, planning regulations, and socio-economic priorities, ensuring that the model remains context-sensitive. However, the application of the framework in different contexts requires careful calibration. The availability and quality of spatial data, as well as the integration of local expertise, play a critical role in ensuring the reliability of the results. For this reason, although the framework is transferable, its implementation should be supported by context-specific adaptation of indicators, weighting schemes, and validation procedures. This adaptability enhances its potential as a decision-support tool for sustainable renewable energy planning in diverse territorial settings.

About limitations, several boundaries of the present research should be acknowledged to guide future work. First, the integration of ecosystem service demand-side dynamics, governance structures, and socio-economic distributional effects remains an open challenge. The InVEST models used in Chapter 4 quantify the supply of ecosystem services but do not assess who benefits from them or how those benefits are distributed across the population. Addressing these dimensions, for instance, by incorporating indicators of agricultural household income, tourism revenue from landscape quality, or health co-benefits of carbon sequestration, would further strengthen the capacity of integrated assessment frameworks to support just and inclusive energy transitions. Second, from a methodological perspective, the data-driven approaches adopted in this research are strongly dependent on the quality, spatial resolution, and temporal updating of input data. Corine Land Cover, while harmonized at the European scale, is updated only every six years and at a resolution of 100 metres, which means it may fail to capture recent land-use changes associated with the most recent wave of RES installations or the fine-scale heterogeneity of peri-urban and mountain landscapes. Future versions of the framework should explore the integration of higher-resolution land cover products, such as those derived from Sentinel-2 imagery, to improve the spatial accuracy of ecosystem service assessments. Third, the expert-based components of the framework (the landscape value indices in Chapter 2 and the AHP weights in Chapters 3 and 4) were calibrated through consultation with professionals working in Basilicata. While this ensures local relevance, it also means that the specific indicator values and weight configurations require recalibration when the framework is applied to other regional contexts. Protocols for structured expert

elicitation and validation should be developed to facilitate this transferability in a rigorous and reproducible manner.

Concluding remarks

In conclusion, this doctoral research demonstrates that the sustainability of renewable energy systems cannot be assessed solely in terms of energy output or emission reductions. It must be evaluated through a broader lens that accounts for landscape integrity, ecosystem service provision, spatial equity, and the cumulative territorial consequences of deployment at scale. The three empirical studies presented in this thesis, on wind turbine visual impact, green hydrogen infrastructure siting, and regional ecosystem service assessment, collectively show that such a broader evaluation is not only conceptually necessary but technically feasible. The tools and methods assembled here, the InVEST Scenic Quality Model paired with expert landscape valuation, the GIS-AHP-SMCA framework with dual sensitivity analysis, and the SOM-AHP hybrid classification- can each be applied independently, but their greatest analytical power lies in their combination. By developing and applying this integrated, landscape-scale assessment framework, this thesis contributes to a more holistic understanding of renewable energy impacts and offers practical, evidence-based tools that can directly inform regional planning, environmental impact assessment, and energy policy at the local, regional, and national levels.

In a context where the urgency of climate action often risks overshadowing territorial considerations, this work argues for a more balanced approach, one that recognizes renewable energy not only as a technological solution but as a spatial and ecological intervention with long-term and irreversible consequences. Basilicata's experience is instructive in this regard: a region that hosts more than 2,100 wind turbines, has some of the highest per-capita renewable energy production in Italy, and yet still lacks a comprehensive landscape-scale planning framework to manage the cumulative impacts of this expansion. The findings of this thesis suggest that the tools to build such a framework already exist; what is needed is the institutional will to apply them systematically and the methodological capacity to do so in a way that is transparent, inclusive, and adaptive. Supporting the energy transition, therefore, requires not only accelerating deployment but also improving the quality, rigor, and territorial awareness of the planning decisions that shape our landscapes and ecosystems for generations to come.

Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declaration of generative AI and AI-assisted technologies in the

During the writing process and the preparation of this work, the authors used ChatGPT 3.5 in order to improve the readability of parts of the text. After using this service, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

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References

- Abe, J.O., Popoola, A.P.I., Ajenifuja, E., Popoola, O.M., 2019. Hydrogen energy, economy and storage: Review and recommendation. *Int. J. Hydrog. Energy* 44, 15072–15086. <https://doi.org/10.1016/j.ijhydene.2019.04.068>
- Abels, A., Lenaerts, T., Trianni, V., Nowé, A., 2023. Dealing with expert bias in collective decision-making. *Artif. Intell.* 320, 103921. <https://doi.org/10.1016/j.artint.2023.103921>
- Abrantes, P., Marques Da Costa, E., Gomes, E., 2023. Towards a typology of agri-urban patterns to support spatial planning: evidence from Lisbon, Portugal. *Landsc. Res.* 48, 88–106. <https://doi.org/10.1080/01426397.2022.2136366>
- Aksoy, G., 2024. Service time thresholds at barrier-operated freeway exit toll booths. *Heliyon* 10, e35923. <https://doi.org/10.1016/j.heliyon.2024.e35923>
- Al Garni, H.Z., Awasthi, A., 2017. Solar PV power plant site selection using a GIS-AHP based approach with application in Saudi Arabia. *Appl. Energy* 206, 1225–1240. <https://doi.org/10.1016/j.apenergy.2017.10.024>
- Ali, F., Bennui, A., Chowdhury, S., Techato, K., 2022. Suitable Site Selection for Solar-Based Green Hydrogen in Southern Thailand Using GIS-MCDM Approach. *Sustainability* 14, 6597. <https://doi.org/10.3390/su14116597>
- Amrani, S.-E., Alami Merrouni, A., Touili, S., Dekhissi, H., 2023. A multi-scenario site suitability analysis to assess the installation of large scale photovoltaic-hydrogen production units. Case study: Eastern Morocco. *Energy Convers. Manag.* 295, 117615. <https://doi.org/10.1016/j.enconman.2023.117615>
- Angeloni, M., Perrella, G., Caminiti, N.M., 2007. GENERAL COORDINATION AND EDITING: Atlaimpianti portale: Mappa degli impianti energetici GSE [WWW Document], 2021. URL <https://www.gse.it/dati-e-scenari/atlaimpianti> (accessed 1.15.26).
- Bäckstrand, K., 2022. Towards a Climate-Neutral Union by 2050? The European Green Deal, Climate Law, and Green Recovery, in: Bakardjieva Engelbrekt, A., Ekman, P., Michalski, A., Oxelheim, L. (Eds.), *Routes to a Resilient European Union: Interdisciplinary European Studies*. Springer International Publishing, Cham, pp. 39–61. https://doi.org/10.1007/978-3-030-93165-0_3
- Balotari-Chiebáo, F., Byholm, P., 2024. Quantifying land impacts of wind energy: a regional-scale assessment in Finland. *Environ. Dev. Sustain.* 28, 1467–1480. <https://doi.org/10.1007/s10668-024-05048-9>
- Barzehkar, M., Parnell, K.E., Mobarghaee Dinan, N., Brodie, G., 2021. Decision support tools for wind and solar farm site selection in Isfahan Province, Iran. *Clean Technol. Environ. Policy* 23, 1179–1195. <https://doi.org/10.1007/s10098-020-01978-w>
- Bashir, M.F., Pata, U.K., Shahzad, L., 2025. Linking climate change, energy transition and renewable energy investments to combat energy security risks: Evidence from top energy consuming economies. *Energy* 314, 134175. <https://doi.org/10.1016/j.energy.2024.134175>
- Bateman, I.J., Mace, G.M., Fezzi, C., Atkinson, G., Turner, K., 2011. Economic Analysis for Ecosystem Service Assessments. *Environ. Resour. Econ.* 48, 177–218. <https://doi.org/10.1007/s10640-010-9418-x>
- Batlles, F.J., Bosch, J.L., Tovar-Pescador, J., Martínez-Durbán, M., Ortega, R., Miralles, I., 2008. Determination of atmospheric parameters to estimate global radiation in areas of complex topography: Generation of global irradiation map. *Energy Convers. Manag.* 49, 336–345. <https://doi.org/10.1016/j.enconman.2007.06.012>
- Bedle, H., Garneau, C.R.H., Vera-Arroyo, A., 2023. Clustering energy support beliefs to reveal unique sub-populations using self-organizing maps. *Heliyon* 9, e18351. <https://doi.org/10.1016/j.heliyon.2023.e18351>
- Bentivenga, M., Pescatore, E., Piccarreta, M., Gizzi, F.T., Masini, N., Giano, S.I., 2024. Geoheritage and Geoconservation, from Theory to Practice: The Ghost Town of Craco (Matera District, Basilicata Region, Southern Italy). *Sustainability* 16. <https://doi.org/10.3390/su16072761>
- Bhatti, U.A., Bhatti, M.A., Tang, H., Syam, M.S., Awwad, E.M., Sharaf, M., Ghadi, Y.Y., 2024. Global production patterns: Understanding the relationship between greenhouse gas emissions, agriculture greening and climate variability. *Environ. Res.* 245, 118049. <https://doi.org/10.1016/j.envres.2023.118049>
- Bishop, I.D., 2002. Determination of Thresholds of Visual Impact: The Case of Wind Turbines. *Environ. Plan. B Plan. Des.* 29, 707–718. <https://doi.org/10.1068/b12854>
- Bishop, I.D., Miller, D.R., 2007. Visual assessment of off-shore wind turbines: The influence of distance, contrast, movement and social variables. *Renew. Energy* 32, 814–831. <https://doi.org/10.1016/j.renene.2006.03.009>
- Blaydes, H., Whyatt, J.D., Carvalho, F., Lee, H.K., McCann, K., Silveira, J.M., Armstrong, A., 2025. Shedding light on land use change for solar farms. *Prog. Energy* 7, 033001. <https://doi.org/10.1088/2516-1083/adc9f5>

- Bøe, V., Holden, E., Linnerud, K., 2023. Measuring renewables' impact on biosphere integrity: A review. *Ecol. Indic.* 156, 111135. <https://doi.org/10.1016/j.ecolind.2023.111135>
- Casali, Y., Aydin, N.Y., Comes, T., 2022. Machine learning for spatial analyses in urban areas: a scoping review. *Sustain. Cities Soc.* 85, 104050. <https://doi.org/10.1016/j.scs.2022.104050>
- Casas, G.L., Scorza, F., Murgante, B., Las Casas, G., 2019. Razionalità a-priori: una proposta verso una pianificazione antifrangibile. *Sci. Reg.* <https://doi.org/10.14650/93656>
- Cassatella, C., 2011. Assessing Visual and Social Perceptions of Landscape, in: Cassatella, C., Peano, A. (Eds.), *Landscape Indicators*. Springer Netherlands, Dordrecht, pp. 105–140. https://doi.org/10.1007/978-94-007-0366-7_6
- Catalogo Dati [WWW Document], 2013. URL https://rsdi.regione.basilicata.it/Catalogo/srv/ita/search?hl=ita#|r_basili:20EA8E87-F903-D62F-467F-BBB44D422FA1 (accessed 1.15.26).
- Catalogo RSDI [WWW Document], 2018. URL https://rsdi.regione.basilicata.it/geonetwork/srv/ita/catalog.search#/metadata/r_basili:DA9315ED-261F-0153-7C98-110255FA4D61 (accessed 1.15.26).
- Censimento Agricoltura [WWW Document], 2020. URL <https://esploradati.istat.it/databrowser/#/it/censimentoagricoltura> (accessed 1.15.26).
- change, C., 2023. Review of the Eighth National Communication (NC8) and the Fifth Biennial Report (BR5) under the United Nations Framework Convention on Climate Change [WWW Document]. ISPRA Ist. Super. Prot. E Ric. Ambient. URL <https://www.isprambiente.gov.it/en/archive/news-and-other-events/ispra-news/2023/10/review-of-the-eighth-national-communication-nc8-and-the-fifth-biennial-report-br5-under-the-united-nations-framework-convention-on-climate-change> (accessed 2.8.26).
- Cherp, A., Jewell, J., 2014. The concept of energy security: Beyond the four As. *Energy Policy* 75, 415–421. <https://doi.org/10.1016/j.enpol.2014.09.005>
- Codemo, A., Favargiotti, S., Albatici, R., 2021. Fostering the climate-energy transition with an integrated approach: Synergies and interrelations between adaptation and mitigation strategies. *TeMA - J. Land Use Mobil. Environ.* 14, 5–20. <https://doi.org/10.6092/1970-9870/7157>
- Cogato, A., Marinello, F., Pezzuolo, A., 2023a. Soil Footprint and Land-Use Change to Clean Energy Production: Implications for Solar and Wind Power Plants. *Land* 12. <https://doi.org/10.3390/land12101822>
- Cogato, A., Marinello, F., Pezzuolo, A., 2023b. Soil Footprint and Land-Use Change to Clean Energy Production: Implications for Solar and Wind Power Plants. *Land* 12, 1822. <https://doi.org/10.3390/land12101822>
- Commission Assessment of the Final Updated National Energy and Climate Plan of Italy - European Commission [WWW Document], 2024. URL https://commission.europa.eu/publications/commission-assessment-final-updated-national-energy-and-climate-plan-italy_en (accessed 4.23.26).
- COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS An EU Strategy to harness the potential of offshore renewable energy for a climate neutral future, 2020.
- COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE EUROPEAN COUNCIL, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS A Green Deal Industrial Plan for the Net-Zero Age, 2023.
- COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE EUROPEAN COUNCIL, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS REPowerEU Plan, 2022.
- Copernicus Land Monitoring Service [WWW Document], 2018. URL <https://land.copernicus.eu/en> (accessed 1.15.26).
- Dagdougui, H., Ouammi, A., Sacile, R., 2011. A regional decision support system for onsite renewable hydrogen production from solar and wind energy sources. *Int. J. Hydrog. Energy, Fuel Cell Technologies: FUCETECH* 2009 36, 14324–14334. <https://doi.org/10.1016/j.ijhydene.2011.08.050>
- Dale, V.H., Kline, K.L., Parish, E.S., Eichler, S.E., 2019a. Engaging stakeholders to assess landscape sustainability. *Landsc. Ecol.* 34, 1199–1218. <https://doi.org/10.1007/s10980-019-00848-1>
- Dale, V.H., Kline, K.L., Parish, E.S., Eichler, S.E., 2019b. Engaging stakeholders to assess landscape sustainability. *Landsc. Ecol.* 34, 1199–1218. <https://doi.org/10.1007/s10980-019-00848-1>
- De Montis, A., Serra, V., Ganciu, A., Ledda, A., 2020. Assessing Landscape Fragmentation: A Composite Indicator. *Sustainability* 12, 9632. <https://doi.org/10.3390/su12229632>

- Delafield, G., Smith, G.S., Day, B., Holland, R.A., Donnison, C., Hastings, A., Taylor, G., Owen, N., Lovett, A., 2024. Spatial context matters: Assessing how future renewable energy pathways will impact nature and society. *Renew. Energy* 220, 119385. <https://doi.org/10.1016/j.renene.2023.119385>
- Di Febbraro, M., Sallustio, L., Vizzarri, M., De Rosa, D., De Lisio, L., Loy, A., Eichelberger, B.A., Marchetti, M., 2018. Expert-based and correlative models to map habitat quality: Which gives better support to conservation planning? *Glob. Ecol. Conserv.* 16, e00513. <https://doi.org/10.1016/j.gecco.2018.e00513>
- Di Leo, S., Pietrapertosa, F., Salvia, M., Cosmi, C., 2021. Contribution of the Basilicata region to decarbonisation of the energy system: results of a scenario analysis. *Renew. Sustain. Energy Rev.* 138, 110544. <https://doi.org/10.1016/j.rser.2020.110544>
- Diffendorfer, J.E., Dorning, M.A., Keen, J.R., Kramer, L.A., Taylor, R.V., 2019. Geographic context affects the landscape change and fragmentation caused by wind energy facilities. *PeerJ* 7, e7129. <https://doi.org/10.7717/peerj.7129>
- Directive 2001/77/EC of the European Parliament and of the Council of 27 September 2001 on the promotion of electricity produced from renewable energy sources in the internal electricity market, 2001. , OJ L.
- D’Onofrio, C., 2024. Land Change Modeler. *Geospatial Anal.* URL <https://www.clarku.edu/centers/geospatial-analytics/terrset-liberagis-features/land-change-modeler/> (accessed 1.11.26).
- Dramstad, W.E., Tveit, M.S., Fjellstad, W.J., Fry, G.L.A., 2006. Relationships between visual landscape preferences and map-based indicators of landscape structure. *Landsc. Urban Plan.* 78, 465–474. <https://doi.org/10.1016/j.landurbplan.2005.12.006>
- E W Colglazier Jr, Deese, D.A., 1983. Energy and Security in the 1980s. *Annu. Rev. Environ. Resour.* 8, 415–449. <https://doi.org/10.1146/annurev.eg.08.110183.002215>
- Ecosystem Accounts for China: Report of the NCAVES project | System of Environmental Economic Accounting [WWW Document], 2021. URL <https://seea.un.org/node/2808> (accessed 1.21.26).
- Elkhatat, A., Al-Muhtaseb, S., 2024. Climate Change and Energy Security: A Comparative Analysis of the Role of Energy Policies in Advancing Environmental Sustainability. *Energies* 17, 3179. <https://doi.org/10.3390/en17133179>
- Espécie, M.D.A., De Carvalho, P.N., Pinheiro, M.F.B., Rosenthal, V.M., Da Silva, L.A.F., Pinheiro, M.R.D.C., Espig, S.A., Mariani, C.F., De Almeida, E.M., Sodré, F.N.G.A.D.S., 2019a. Ecosystem services and renewable power generation: A preliminary literature review. *Renew. Energy* 140, 39–51. <https://doi.org/10.1016/j.renene.2019.03.076>
- Espécie, M.D.A., De Carvalho, P.N., Pinheiro, M.F.B., Rosenthal, V.M., Da Silva, L.A.F., Pinheiro, M.R.D.C., Espig, S.A., Mariani, C.F., De Almeida, E.M., Sodré, F.N.G.A.D.S., 2019b. Ecosystem services and renewable power generation: A preliminary literature review. *Renew. Energy* 140, 39–51. <https://doi.org/10.1016/j.renene.2019.03.076>
- Esteves, N.B., Sigal, A., Leiva, E.P.M., Rodríguez, C.R., Cavalcante, F.S.A., de Lima, L.C., 2015. Wind and solar hydrogen for the potential production of ammonia in the state of Ceará – Brazil. *Int. J. Hydrog. Energy* 40, 9917–9923. <https://doi.org/10.1016/j.ijhydene.2015.06.044>
- European Environment Agency, European Commission, 2025. Natura 2000 (vector) - version end 2024. <https://doi.org/10.2909/91357F39-7866-41CE-B447-43905C364EC8>
- European Hydrogen Backbone: Boosting EU Resilience and Competitiveness, 2024. . Gas Infrastruct. Eur. URL <https://www.gie.eu/press/european-hydrogen-backbone-boosting-eu-resilience-and-competitiveness/> (accessed 1.21.26).
- Fagerholm, N., Käyhkö, N., Ndumbaro, F., Khamis, M., 2012. Community stakeholders’ knowledge in landscape assessments – Mapping indicators for landscape services. *Ecol. Indic.* 18, 421–433. <https://doi.org/10.1016/j.ecolind.2011.12.004>
- Ferrari, G., Ioverno, F., Sozzi, M., Marinello, F., Pezzuolo, A., 2021. Land-Use Change and Bioenergy Production: Soil Consumption and Characterization of Anaerobic Digestion Plants. *Energies* 14. <https://doi.org/10.3390/en14134001>
- Finland, G., 2025. Gasgrid publishes first hydrogen information package to foster the development of the hydrogen market. Gasgrid. URL <https://gasgrid.fi/en/2025/09/05/gasgrid-publishes-first-hydrogen-information-package-to-foster-the-development-of-the-hydrogen-market/> (accessed 1.21.26).
- Fishburn, P.C., 1967. Letter to the Editor—Additive Utilities with Incomplete Product Sets: Application to Priorities and Assignments. *Oper. Res.* 15, 537–542. <https://doi.org/10.1287/opre.15.3.537>

- Flora, F.M.I., 2025. A GIS-based on application of Monte Carlo and multi-criteria decision-making approach for site suitability analysis of solar-hydrogen production: Case of Cameroon. *Heliyon* 11, e41541. <https://doi.org/10.1016/j.heliyon.2024.e41541>
- Florio, P., Peronato, G., Perera, A.T.D., Di Blasi, A., Poon, K.H., Kämpf, J.H., 2021. Designing and assessing solar energy neighborhoods from visual impact. *Sustain. Cities Soc.* 71, 102959. <https://doi.org/10.1016/j.scs.2021.102959>
- Franz, M., Dumke, H., 2025. Evolution of patterns of specific land use by free-field photovoltaic power plants in Europe from 2006 to 2022. *Energy Sustain. Soc.* 15, 12. <https://doi.org/10.1186/s13705-024-00504-w>
- FuntanaElighe, L., Mncdnl, C.F., 2013. REGIONE AUTONOMA SARDEGNA PROVINCIA DI SASSARI Comune di Nule.
- Galparsoro, I., Menchaca, I., Garmendia, J.M., Borja, Á., Maldonado, A.D., Iglesias, G., Bald, J., 2022. Reviewing the ecological impacts of offshore wind farms. *Npj Ocean Sustain.* 1, 1. <https://doi.org/10.1038/s44183-022-00003-5>
- Ganter, A., Gabrielli, P., Sansavini, G., 2024. Near-term infrastructure rollout and investment strategies for net-zero hydrogen supply chains. *Renew. Sustain. Energy Rev.* 194, 114314. <https://doi.org/10.1016/j.rser.2024.114314>
- Gao, Y., Feng, Z., Wang, Y., Liu, J.-L., Li, S.-C., Zhu, Y.-K., 2014. Clustering Urban Multifunctional Landscapes Using the Self-Organizing Feature Map Neural Network Model. *J. Urban Plan. Dev.* 140, 05014001. [https://doi.org/10.1061/\(ASCE\)UP.1943-5444.0000170](https://doi.org/10.1061/(ASCE)UP.1943-5444.0000170)
- Garegnani, G., Geri, F., Zambelli, P., Grilli, G., Sacchelli, S., Paletto, A., Curetti, G., Ciolli, M., Vettorato, D., 2015. A new open source DSS for assessment and planning of renewable energy: r.green. ITA.
- Gayen, D., Chatterjee, R., Roy, S., 2024. A review on environmental impacts of renewable energy for sustainable development. *Int. J. Environ. Sci. Technol.* 21, 5285–5310. <https://doi.org/10.1007/s13762-023-05380-z>
- Genger, T.K., Luo, Y., Hammad, A., 2021. Multi-criteria spatial analysis for location selection of multi-purpose utility tunnels. *Tunn. Undergr. Space Technol.* 115, 104073. <https://doi.org/10.1016/j.tust.2021.104073>
- Gennatas, E.D., Friedman, J.H., Ungar, L.H., Pirracchio, R., Eaton, E., Reichmann, L.G., Interian, Y., Luna, J.M., Simone, C.B., Auerbach, A., Delgado, E., van der Laan, M.J., Solberg, T.D., Valdes, G., 2020. Expert-augmented machine learning. *Proc. Natl. Acad. Sci.* 117, 4571–4577. <https://doi.org/10.1073/pnas.1906831117>
- Genovese, M., Schlüter, A., Scionti, E., Piraino, F., Corigliano, O., Fragiaco, P., 2023. Power-to-hydrogen and hydrogen-to-X energy systems for the industry of the future in Europe. *Int. J. Hydrog. Energy* 48, 16545–16568. <https://doi.org/10.1016/j.ijhydene.2023.01.194>
- Gerden, T., 2018. The Adoption of the Kyoto Protocol of the United Nations Framework Convention on Climate Change. *Contrib. Contemp. Hist.* 58, 160–189. <https://doi.org/10.51663/pnz.58.2.07>
- Ghasempour, R., Nazari, M.A., Ebrahimi, M., Ahmadi, M.H., Hadiyanto, H., 2019. Multi-Criteria Decision Making (MCDM) Approach for Selecting Solar Plants Site and Technology: A Review. *Int. J. Renew. Energy Dev.* 8, 15–25. <https://doi.org/10.14710/ijred.8.1.15-25>
- Gizzi, F.T., Proto, M., Potenza, M.R., 2019. The Basilicata region (Southern Italy): a natural and ‘human-built’ open-air laboratory for manifold studies. Research trends over the last 24 years (1994–2017). *Geomat. Nat. Hazards Risk* 10, 433–464. <https://doi.org/10.1080/19475705.2018.1527786>
- Goldthau, A., 2011. Governing global energy: existing approaches and discourses. *Curr. Opin. Environ. Sustain., Energy Systems* 3, 213–217. <https://doi.org/10.1016/j.cosust.2011.06.003>
- Haase, D., Frantzeskaki, N., Elmqvist, T., 2014. Ecosystem Services in Urban Landscapes: Practical Applications and Governance Implications. *AMBIO* 43, 407–412. <https://doi.org/10.1007/s13280-014-0503-1>
- Hancock, K.J., Vivoda, V., 2014. International political economy: A field born of the OPEC crisis returns to its energy roots. *Energy Res. Soc. Sci.* 1, 206–216. <https://doi.org/10.1016/j.erss.2014.03.017>
- Hemming, V., Burgman, M.A., Hanea, A.M., McBride, M.F., Wintle, B.C., 2018. A practical guide to structured expert elicitation using the IDEA protocol. *Methods Ecol. Evol.* 9, 169–180. <https://doi.org/10.1111/2041-210X.12857>
- Herrero-Jiménez, C.M., 2012. An expert system for the identification of environmental impact based on a geographic information system. *Expert Syst. Appl.* 39, 6672–6682. <https://doi.org/10.1016/j.eswa.2011.10.019>
- Hossain, M.S., Chowdhury, S.R., Das, N.G., Rahaman, M.M., 2007. Multi-criteria evaluation approach to GIS-based land-suitability classification for tilapia farming in Bangladesh. *Aquac. Int.* 15, 425–443. <https://doi.org/10.1007/s10499-007-9109-y>

- Hosseini Dehshiri, S.J., Zanjirchi, S.M., 2022. Comparative analysis of multicriteria decision-making approaches for evaluation hydrogen projects development from wind energy. *Int. J. Energy Res.* 46, 13356–13376. <https://doi.org/10.1002/er.8044>
- Huguet Ferran, P., Heijungs, R., Vogtländer, J.G., 2018. Critical Analysis of Methods for Integrating Economic and Environmental Indicators. *Ecol. Econ.* 146, 549–559. <https://doi.org/10.1016/j.ecolecon.2017.11.030>
- Iamarino, M., D'Angola, A., 2025. Trends, Challenges, and Viability in Green Hydrogen Initiatives. *Energies* 18, 4476. <https://doi.org/10.3390/en18174476>
- İnci, M., 2022. Future vision of hydrogen fuel cells: A statistical review and research on applications, socio-economic impacts and forecasting prospects. *Sustain. Energy Technol. Assess.* 53, 102739. <https://doi.org/10.1016/j.seta.2022.102739>
- Ioannidis, R., Koutsyiannis, D., 2020. A review of land use, visibility and public perception of renewable energy in the context of landscape impact. *Appl. Energy* 276, 115367. <https://doi.org/10.1016/j.apenergy.2020.115367>
- Jager, H.I., Efromson, R.A., McManamay, R.A., 2021. Renewable energy and biological conservation in a changing world. *Biol. Conserv.* 263, 109354. <https://doi.org/10.1016/j.biocon.2021.109354>
- Johnson, M.S., Adams, V.M., Byrne, J.A., 2024. Understanding how landscape value and climate risk discourses can improve adaptation planning: Insights from Q-method. *Environ. Sci. Policy* 162, 103947. <https://doi.org/10.1016/j.envsci.2024.103947>
- Kazak, J.K., Mrówczyńska, M., Skiba, M., Bazan-Krzywoszańska, A., Świąder, M., Tokarczyk-Dorociak, K., Szwerański, S., 2021. A Decision Support System for the Planning of Hybrid Renewable Energy Technologies. *IOP Conf. Ser. Earth Environ. Sci.* 701, 012012. <https://doi.org/10.1088/1755-1315/701/1/012012>
- Kenter, J.O., 2016. Editorial: Shared, plural and cultural values. *Ecosyst. Serv.*, Shared, plural and cultural values 21, 175–183. <https://doi.org/10.1016/j.ecoser.2016.10.010>
- Khalifa, S.A.M., Elshafiey, E.H., Shetaia, A.A., El-Wahed, A.A.A., Algethami, A.F., Musharraf, S.G., AlAjmi, M.F., Zhao, C., Masry, S.H.D., Abdel-Daim, M.M., Halabi, M.F., Kai, G., Al Naggar, Y., Bishr, M., Diab, M.A.M., El-Seedi, H.R., 2021. Overview of Bee Pollination and Its Economic Value for Crop Production. *Insects* 12, 688. <https://doi.org/10.3390/insects12080688>
- Kiesecker, J.M., Nagaraju, S.K., Oakleaf, J.R., Ortiz, A., Lavista Ferres, J., Robinson, C., Krishnaswamy, S., Mehta, R., Dodhia, R., Evans, J.S., Heiner, M., Priyadarshini, P., Chandran, P., Sochi, K., 2023. The Road to India's Renewable Energy Transition Must Pass through Crowded Lands. *Land* 12, 2049. <https://doi.org/10.3390/land12112049>
- Kinley, R., 2017. Climate change after Paris: from turning point to transformation. *Clim. Policy* 17, 9–15. <https://doi.org/10.1080/14693062.2016.1191009>
- Kishore, T.S., Kumar, P.U., Ippili, V., 2025. Review of global sustainable solar energy policies: Significance and impact. *Innov. Green Dev.* 4, 100224. <https://doi.org/10.1016/j.igd.2025.100224>
- Kohonen, T., 2013. Essentials of the self-organizing map. *Neural Netw.* 37, 52–65. <https://doi.org/10.1016/j.neunet.2012.09.018>
- Kuhnert, P.M., Martin, T.G., Griffiths, S.P., 2010. A guide to eliciting and using expert knowledge in Bayesian ecological models. *Ecol. Lett.* 13, 900–914. <https://doi.org/10.1111/j.1461-0248.2010.01477.x>
- Kuo, T., Chen, M.-H., 2023. On using pairwise comparison in the analytic hierarchy process: Validity is goal while consistency is means. *Inf. Sci.* 648, 119630. <https://doi.org/10.1016/j.ins.2023.119630>
- Lam, T.Y.M., 2019. A sustainable procurement approach for selection of construction consultants in property and facilities management. *Facilities* 38, 98–113. <https://doi.org/10.1108/F-12-2018-0147>
- Landfill Siting Using Geographic Information Systems: A Demonstration, 1996. . *J. Environ. Eng.* 122, 515–523. [https://doi.org/10.1061/\(ASCE\)0733-9372\(1996\)122:6\(515\)](https://doi.org/10.1061/(ASCE)0733-9372(1996)122:6(515))
- Levelised Cost of Hydrogen Maps – Data Tools [WWW Document], 2024. . IEA. URL <https://www.iea.org/data-and-statistics/data-tools/levelised-cost-of-hydrogen-maps> (accessed 1.21.26).
- Li, L., Carter, J., 2025. Exploring the relationship between urban green infrastructure connectivity, size and multifunctionality: a systematic review. *Landsc. Ecol.* 40, 61. <https://doi.org/10.1007/s10980-025-02069-1>
- Liladhar Rane, N., Purushottam Choudhary, S., Saha, A., Srivastava, A., Pande, C.B., Alshehri, F., Roy, R., Katipoğlu, O.M., Abdo, H.G., 2024. Delineation of environmentally sustainable urban settlement using GIS-based MIF and AHP techniques. *Geocarto Int.* 39, 2335249. <https://doi.org/10.1080/10106049.2024.2335249>
- Lothian, A., 1999. Landscape and the philosophy of aesthetics: is landscape quality inherent in the landscape or in the eye of the beholder? *Landsc. Urban Plan.* 44, 177–198. [https://doi.org/10.1016/S0169-2046\(99\)00019-5](https://doi.org/10.1016/S0169-2046(99)00019-5)

- Louis, F.R.B. of S., 1977. May 1977. Review (Federal Reserve Bank of St. Louis). <https://doi.org/10.20955/r.59.2-12.cdy>
- Mah, A.X.Y., Ho, W.S., Hassim, M.H., Hashim, H., Muis, Z.A., Ling, G.H.T., Ho, C.S., 2022. Spatial optimization of photovoltaic-based hydrogen-electricity supply chain through an integrated geographical information system and mathematical modeling approach. *Clean Technol. Environ. Policy* 24, 393–412. <https://doi.org/10.1007/s10098-021-02235-4>
- Maitland, E., Sammartino, A., 2015. Decision making and uncertainty: The role of heuristics and experience in assessing a politically hazardous environment. *Strateg. Manag. J.* 36, 1554–1578. <https://doi.org/10.1002/smj.2297>
- Martens, M.L., Carvalho, M.M., 2016. Sustainability and Success Variables in the Project Management Context: An Expert Panel. *Proj. Manag. J.* 47, 24–43. <https://doi.org/10.1177/875697281604700603>
- Martínez-Martínez, Y., Dewulf, J., Casas-Ledón, Y., 2022. GIS-based site suitability analysis and ecosystem services approach for supporting renewable energy development in south-central Chile. *Renew. Energy* 182, 363–376. <https://doi.org/10.1016/j.renene.2021.10.008>
- Martínez-Medina, R., Gil-Meseguer, E., Gómez-Espín, J.M., 2025. Changes in Land Use Due to the Development of Photovoltaic Solar Energy in the Region of Murcia (Spain). *Land* 14. <https://doi.org/10.3390/land14051083>
- Martínez-Sastre, R., Ravera, F., González, J.A., López Santiago, C., Bidegain, I., Munda, G., 2017. Mediterranean landscapes under change: Combining social multicriteria evaluation and the ecosystem services framework for land use planning. *Land Use Policy* 67, 472–486. <https://doi.org/10.1016/j.landusepol.2017.06.001>
- Mazzola, E., 2025. The role of renewable energies in landscape transformation. Methodological proposal and application to the Valdagno case study. *TeMA - J. Land Use Mobil. Environ.* 18, 203–218. <https://doi.org/10.6093/1970-9870/11145>
- Medeiros, A., Fernandes, C., Gonçalves, J.F., Farinha-Marques, P., 2021a. Research trends on integrative landscape assessment using indicators – A systematic review. *Ecol. Indic.* 129, 107815. <https://doi.org/10.1016/j.ecolind.2021.107815>
- Medeiros, A., Fernandes, C., Gonçalves, J.F., Farinha-Marques, P., 2021b. Research trends on integrative landscape assessment using indicators – A systematic review. *Ecol. Indic.* 129, 107815. <https://doi.org/10.1016/j.ecolind.2021.107815>
- Meraj, G., Singh, S.K., Kanga, S., Islam, Md.N., 2022. Modeling on comparison of ecosystem services concepts, tools, methods and their ecological-economic implications: a review. *Model. Earth Syst. Environ.* 8, 15–34. <https://doi.org/10.1007/s40808-021-01131-6>
- Messaoudi, D., Settou, N., Negrou, B., Settou, B., 2019. GIS based multi-criteria decision making for solar hydrogen production sites selection in Algeria. *Int. J. Hydrog. Energy* 44, 31808–31831. <https://doi.org/10.1016/j.ijhydene.2019.10.099>
- Miljkovic, D., 2017. Brief review of self-organizing maps, in: 2017 40th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO). Presented at the 2017 40th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), IEEE, Opatija, Croatia, pp. 1061–1066. <https://doi.org/10.23919/MIPRO.2017.7973581>
- Millennium Ecosystem Assessment (Program) (Ed.), 2005. Ecosystems and human well-being: synthesis. Island Press, Washington, DC.
- Minelli, A., Marchesini, I., Taylor, F.E., De Rosa, P., Casagrande, L., Cenci, M., 2014. An open source GIS tool to quantify the visual impact of wind turbines and photovoltaic panels. *Environ. Impact Assess. Rev.* 49, 70–78. <https://doi.org/10.1016/j.eiar.2014.07.002>
- Monfreda, C., Ramankutty, N., Foley, J.A., 2008. Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Glob. Biogeochem. Cycles* 22, 2007GB002947. <https://doi.org/10.1029/2007GB002947>
- Morgan, M.G., 2014. Use (and abuse) of expert elicitation in support of decision making for public policy. *Proc. Natl. Acad. Sci.* 111, 7176–7184. <https://doi.org/10.1073/pnas.1319946111>
- Moussaoui, F., Cherrared, M., Kacimi, M.A., Belarbi, R., 2018. A genetic algorithm to optimize consistency ratio in AHP method for energy performance assessment of residential buildings—Application of top-down and bottom-up approaches in Algerian case study. *Sustain. Cities Soc.* 42, 622–636. <https://doi.org/10.1016/j.scs.2017.08.008>

- Mozaffari, M., Bemani, A., Erfani, M., Yarami, N., Siyahati, G., 2023. Integration of LCSA and GIS-based MCDM for sustainable landfill site selection: a case study. *Environ. Monit. Assess.* 195, 510. <https://doi.org/10.1007/s10661-023-11112-0>
- Mrabet, M., Sliti, M., 2024. Integrating machine learning for the sustainable development of smart cities. *Front. Sustain. Cities* 6, 1449404. <https://doi.org/10.3389/frsc.2024.1449404>
- Murgante, B., Annunziata, A., Tonini, M., 2025. Developing a taxonomy framework for assessing human capital provision: A case study of Southern Italian municipalities. *Appl. Geogr.* 179, 103640. <https://doi.org/10.1016/j.apgeog.2025.103640>
- Murgante, B., Borruso, G., Lapucci, A., 2011. Sustainable Development: Concepts and Methods for Its Application in Urban and Environmental Planning, in: Murgante, B., Borruso, G., Lapucci, A. (Eds.), *Geocomputation, Sustainability and Environmental Planning*. Springer, Berlin, Heidelberg, pp. 1–15. https://doi.org/10.1007/978-3-642-19733-8_1
- Muzzillo, V., Pilogallo, A., Saganeiti, L., Santarsiero, V., Scorza, F., Murgante, B., 2020. Impact of Renewable Energy Installations on Habitat Quality, in: Gervasi, O., Murgante, B., Misra, S., Garau, C., Blečić, I., Tanar, D., Apduhan, B.O., Rocha, A.M.A.C., Tarantino, E., Torre, C.M., Karaca, Y. (Eds.), *Computational Science and Its Applications – ICCSA 2020, Lecture Notes in Computer Science*. Springer International Publishing, Cham, pp. 636–644. https://doi.org/10.1007/978-3-030-58814-4_50
- Next Generation EU e il Piano Nazionale di Ripresa e Resilienza [WWW Document], 2023. . Agenzia Coesione Territ. URL https://www.agenziacoesione.gov.it/dossier_tematici/nextgenerationeu-e-pnrr/ (accessed 1.21.26).
- Nobrega, A., Barroca Filho, I., 2025. Analysis of Machine Learning Performance in Spatial Interpolation of Rainfall Data. *IEEE Access* PP, 1–1. <https://doi.org/10.1109/ACCESS.2025.3569261>
- Omer, A.M., 2008. Energy, environment and sustainable development. *Renew. Sustain. Energy Rev.* 12, 2265–2300. <https://doi.org/10.1016/j.rser.2007.05.001>
- Özkan, B., Özceylan, E., Sariççek, İ., 2019. GIS-based MCDM modeling for landfill site suitability analysis: A comprehensive review of the literature. *Environ. Sci. Pollut. Res.* 26, 30711–30730. <https://doi.org/10.1007/s11356-019-06298-1>
- Palermo, A., Chieffallo, L., Virgilio, S., 2024. Re-generate resilience to deal with climate change: A data-driven pathway for a liveable, efficient and safe city. *TeMA - J. Land Use Mobil. Environ.* 11–28. <https://doi.org/10.6093/1970-9870/9969>
- Palm, V., Larsson, M., 2007. Economic instruments and the environmental accounts. *Ecol. Econ.*, Special Issue on Environmental Accounting: Introducing the System of Integrated Environmental and Economic Accounting 2003 61, 684–692. <https://doi.org/10.1016/j.ecolecon.2006.01.015>
- Paulvannan Kanmani, A., Obringer, R., Rachunok, B., Nateghi, R., 2020. Assessing Global Environmental Sustainability Via an Unsupervised Clustering Framework. *Sustainability* 12, 563. <https://doi.org/10.3390/su12020563>
- Pelczar, S., 2025. Development of photovoltaic power plants in the context of their impact on the agricultural production space. *Int. Agrophysics* 39, 175–189. <https://doi.org/10.31545/intagr/200377>
- Picchi, P., Van Lierop, M., Geneletti, D., Stremke, S., 2019a. Advancing the relationship between renewable energy and ecosystem services for landscape planning and design: A literature review. *Ecosyst. Serv.* 35, 241–259. <https://doi.org/10.1016/j.ecoser.2018.12.010>
- Picchi, P., Van Lierop, M., Geneletti, D., Stremke, S., 2019b. Advancing the relationship between renewable energy and ecosystem services for landscape planning and design: A literature review. *Ecosyst. Serv.* 35, 241–259. <https://doi.org/10.1016/j.ecoser.2018.12.010>
- Pilogallo, A., Nolè, G., Amato, F., Saganeiti, L., Bentivenga, M., Palladino, G., Scorza, F., Murgante, B., Casas, G.L., 2019. Geotourism as a Specialization in the Territorial Context of the Basilicata Region (Southern Italy). *Geoheritage* 11, 1435–1445. <https://doi.org/10.1007/s12371-019-00396-9>
- Pilogallo, A., Saganeiti, L., 2023. Energy Transition and Spatial Transformation: Looking for a Suitable Trade-Off, in: Gervasi, O., Murgante, B., Rocha, A.M.A.C., Garau, C., Scorza, F., Karaca, Y., Torre, C.M. (Eds.), *Computational Science and Its Applications – ICCSA 2023 Workshops, Lecture Notes in Computer Science*. Springer Nature Switzerland, Cham, pp. 3–15. https://doi.org/10.1007/978-3-031-37120-2_1
- Pomerol, J.-C., 2022. What is the added value of expert groups for decision making? *J. Decis. Syst.* 1–12. <https://doi.org/10.1080/12460125.2022.2156556>

- Rabelo, M.C., Tonini, M., Silvestri, N., 2023. Dynamics of agricultural land systems in western Mediterranean areas: a clustering approach based on the self-organizing map. *Ital. J. Agron.* 18, 2199. <https://doi.org/10.4081/ija.2023.2199>
- Raman, R., Nair, V.K., Prakash, V., Patwardhan, A., Nedungadi, P., 2022. Green-hydrogen research: What have we achieved, and where are we going? Bibliometrics analysis. *Energy Rep.* 8, 9242–9260. <https://doi.org/10.1016/j.egy.2022.07.058>
- Ramondetti, L., 2025. Heterogeneous energy landscapes and the challenges for spatial planning: the Port of Ravenna and its hinterland. *Sustain. Sci.* <https://doi.org/10.1007/s11625-025-01635-5>
- Ransikarbum, K., Zadek, H., Janmontree, J., 2024. Evaluating Renewable Energy Sites in the Green Hydrogen Supply Chain with Integrated Multi-Criteria Decision Analysis. *Energies* 17, 4073. <https://doi.org/10.3390/en17164073>
- Ravestein, P., van der Schrier, G., Haarsma, R., Scheele, R., van den Broek, M., 2018. Vulnerability of European intermittent renewable energy supply to climate change and climate variability. *Renew. Sustain. Energy Rev.* 97, 497–508. <https://doi.org/10.1016/j.rser.2018.08.057>
- Ren, X., Mi, Z., Georgopoulos, P.G., 2020. Comparison of Machine Learning and Land Use Regression for fine-scale spatiotemporal estimation of ambient air pollution: Modeling ozone concentrations across the contiguous United States. *Environ. Int.* 142, 105827. <https://doi.org/10.1016/j.envint.2020.105827>
- Resniova, E., Ponomarenko, T., 2021. Sustainable Development of the Energy Sector in a Country Deficient in Mineral Resources: The Case of the Republic of Moldova. *Sustainability* 13, 3261. <https://doi.org/10.3390/su13063261>
- Riera, J.A., Lima, R.M., Knio, O.M., 2023. A review of hydrogen production and supply chain modeling and optimization. *Int. J. Hydrog. Energy* 48, 13731–13755. <https://doi.org/10.1016/j.ijhydene.2022.12.242>
- Roseland, M., 2000. Sustainable community development: integrating environmental, economic, and social objectives. *Prog. Plan.* 54, 73–132. [https://doi.org/10.1016/S0305-9006\(00\)00003-9](https://doi.org/10.1016/S0305-9006(00)00003-9)
- Saaty, R. W., 1987. The analytic hierarchy process—what it is and how it is used. *Math. Model.* 9, 161–176. [https://doi.org/10.1016/0270-0255\(87\)90473-8](https://doi.org/10.1016/0270-0255(87)90473-8)
- Saaty, R.W., 1987. The analytic hierarchy process—what it is and how it is used. *Math. Model.* 9, 161–176. [https://doi.org/10.1016/0270-0255\(87\)90473-8](https://doi.org/10.1016/0270-0255(87)90473-8)
- Saaty, T., 2008. Decision making with the Analytic Hierarchy Process. *Int J Serv. Sci. Int J Serv. Sci.* 1, 83–98. <https://doi.org/10.1504/IJSSCI.2008.017590>
- Saaty, T.L., Vargas, L.G., 1980. Hierarchical analysis of behavior in competition: Prediction in chess. *Behav. Sci.* 25, 180–191. <https://doi.org/10.1002/bs.3830250303>
- Saganeiti, L., Favale, A., Pilogallo, A., Scorza, F., Murgante, B., 2018. Assessing Urban Fragmentation at Regional Scale Using Sprinkling Indexes. *Sustainability* 10, 3274. <https://doi.org/10.3390/su10093274>
- Saganeiti, L., Pilogallo, A., Faruolo, G., Scorza, F., Murgante, B., 2020. Territorial Fragmentation and Renewable Energy Source Plants: Which Relationship? *Sustainability* 12, 1828. <https://doi.org/10.3390/su12051828>
- Salak, B., Hunziker, M., Grêt-Regamey, A., Spielhofer, R., Wissen Hayek, U., Kienast, F., 2024. Shifting from techno-economic to socio-ecological priorities: Incorporating landscape preferences and ecosystem services into the siting of renewable energy infrastructure. *PLOS ONE* 19, e0298430. <https://doi.org/10.1371/journal.pone.0298430>
- Salunkhe, S., Nandgude, S., Tiwari, M., Bhange, H., Chavan, S.B., 2023a. Land Suitability Planning for Sustainable Mango Production in a Vulnerable Region Using Geospatial Multi-Criteria Decision Model. *Sustainability* 15, 2619. <https://doi.org/10.3390/su15032619>
- Salunkhe, S., Nandgude, S., Tiwari, M., Bhange, H., Chavan, S.B., 2023b. Land Suitability Planning for Sustainable Mango Production in Vulnerable Region Using Geospatial Multi-Criteria Decision Model. *Sustainability* 15, 2619. <https://doi.org/10.3390/su15032619>
- Santarsiero, V., Nolè, G., Lanorte, A., Tucci, B., Cillis, G., Murgante, B., 2022. Remote Sensing and Spatial Analysis for Land-Take Assessment in Basilicata Region (Southern Italy). *Remote Sens.* 14, 1692. <https://doi.org/10.3390/rs14071692>
- Santos, F.E.D.O., Silva, M.A.S.D., Matos, L.N., Moura, F.R.D., Dompieri, M.H.G., 2021. Self-Organizing Map approach to cluster Brazilian agricultural spatiotemporal diversity, in: *Anais Da XXI Escola Regional de Computação Bahia, Alagoas e Sergipe (ERBASE 2021)*. Presented at the Escola Regional de Computação Bahia, Alagoas e Sergipe, Sociedade Brasileira de Computação - SBC, Brasil, pp. 65–73. <https://doi.org/10.5753/erbase.2021.20058>

- Scheidel, A., Sorman, A.H., 2012. Energy transitions and the global land rush: Ultimate drivers and persistent consequences. *Glob. Environ. Change, Global transformations, social metabolism and the dynamics of socio-environmental conflicts* 22, 588–595. <https://doi.org/10.1016/j.gloenvcha.2011.12.005>
- Schüpbach, B., Roesch, A., Herzog, F., Szerencsits, E., Walter, T., 2020a. Development and application of indicators for visual landscape quality to include in life cycle sustainability assessment of Swiss agricultural farms. *Ecol. Indic.* 110, 105788. <https://doi.org/10.1016/j.ecolind.2019.105788>
- Schüpbach, B., Roesch, A., Herzog, F., Szerencsits, E., Walter, T., 2020b. Development and application of indicators for visual landscape quality to include in life cycle sustainability assessment of Swiss agricultural farms. *Ecol. Indic.* 110, 105788. <https://doi.org/10.1016/j.ecolind.2019.105788>
- Science for policy - The Joint Research Centre: EU Science Hub [WWW Document], 2025. URL https://joint-research-centre.ec.europa.eu/index_en (accessed 1.11.26).
- Scorza, F., Las Casas, G.B., Murgante, B., 2016. SPATIALIZING OPEN DATA FOR THE ASSESSMENT AND THE IMPROVEMENT OF TERRITORIAL AND SOCIAL COHESION. *ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci.* IV-4/W1, 145–151. <https://doi.org/10.5194/isprs-annals-IV-4-W1-145-2016>
- Scorza, F., Pilogallo, A., Saganeiti, L., Murgante, B., 2020a. Natura 2000 Areas and Sites of National Interest (SNI): Measuring (un)Integration between Naturalness Preservation and Environmental Remediation Policies. *Sustainability* 12, 2928. <https://doi.org/10.3390/su12072928>
- Scorza, F., Pilogallo, A., Saganeiti, L., Murgante, B., Pontrandolfi, P., 2020b. Comparing the territorial performances of renewable energy sources' plants with an integrated ecosystem services loss assessment: A case study from the Basilicata region (Italy). *Sustain. Cities Soc.* 56, 102082. <https://doi.org/10.1016/j.scs.2020.102082>
- Scorza, F., Pilogallo, A., Saganeiti, L., Murgante, B., Pontrandolfi, P., 2020c. Comparing the territorial performances of renewable energy sources' plants with an integrated ecosystem services loss assessment: A case study from the Basilicata region (Italy). *Sustain. Cities Soc.* 56, 102082. <https://doi.org/10.1016/j.scs.2020.102082>
- Shaw, B.J., Van Vliet, J., Verburg, P.H., 2020. The peri-urbanization of Europe: A systematic review of a multifaceted process. *Landsc. Urban Plan.* 196, 103733. <https://doi.org/10.1016/j.landurbplan.2019.103733>
- Shukla, P.R., Skea, J., Reisinger, A.R., IPCC (Eds.), 2022. Climate change 2022: mitigation of climate change. IPCC, Geneva.
- Siksnylyte-Butkiene, I., Streimikiene, D., Agnusdei, G.P., Balezentis, T., 2023. Energy-space concept for the transition to a low-carbon energy society. *Environ. Dev. Sustain.* 25, 14953–14973. <https://doi.org/10.1007/s10668-022-02697-6>
- SNAM [WWW Document], 2024. URL <https://www.snam.it/it/i-nostri-business/trasporto/piani-decennali/piano-decennale-Snam-Rete-Gas/2025-2034.html> (accessed 1.21.26).
- Solecka, I., 2019. The use of landscape value assessment in spatial planning and sustainable land management — a review. *Landsc. Res.* 44, 966–981. <https://doi.org/10.1080/01426397.2018.1520206>
- Solecka, I., Rinne, T., Caracciolo Martins, R., Kytta, M., Albert, C., 2022. Important places in landscape – investigating the determinants of perceived landscape value in the suburban area of Wrocław, Poland. *Landsc. Urban Plan.* 218, 104289. <https://doi.org/10.1016/j.landurbplan.2021.104289>
- Stürck, J., Verburg, P.H., 2017. Multifunctionality at what scale? A landscape multifunctionality assessment for the European Union under conditions of land use change. *Landsc. Ecol.* 32, 481–500. <https://doi.org/10.1007/s10980-016-0459-6>
- Sun, H., He, C., Wang, H., Zhang, Y., Lv, S., Xu, Y., 2017. Hydrogen station siting optimization based on multi-source hydrogen supply and life cycle cost. *Int. J. Hydrog. Energy* 42, 23952–23965. <https://doi.org/10.1016/j.ijhydene.2017.07.191>
- Taoufik, M., Fekri, A., 2023. A GIS-based multi-criteria decision-making approach for site suitability analysis of solar-powered hydrogen production in the Souss-Massa Region, Morocco. *Renew. Energy Focus* 46, 385–401. <https://doi.org/10.1016/j.ref.2023.08.004>
- Tarquini, S., Isola, I., Favalli, M., Battistini, A., Dotta, G., 2023. TINITALY, a digital elevation model of Italy with a 10 meters cell size, version 1.1. <https://doi.org/10.13127/TINITALY/1.1>
- Territorio e cartografia [WWW Document], 2024. URL <https://www.istat.it/statistiche-per-temi/ambiente-e-territorio/territorio-e-cartografia/> (accessed 1.11.26).
- Tonini, M., Yu, J., Hagen-Zanker, A., 2025. Redefining Swiss Territorial Typologies: An Unsupervised Learning Approach to the Rural–Urban Continuum. *J. Geovisualization Spat. Anal.* 9, 24. <https://doi.org/10.1007/s41651-025-00226-3>

- Tran, T.H., Egermann, M., 2022. Land-use implications of energy transition pathways towards decarbonisation – Comparing the footprints of Vietnam, New Zealand and Finland. *Energy Policy* 166, 112951. <https://doi.org/10.1016/j.enpol.2022.112951>
- Tuncel, G., Gunturk, B., 2024. A Fuzzy Multi-Criteria Decision-Making Approach for Agricultural Land Selection. *Sustainability* 16, 10509. <https://doi.org/10.3390/su162310509>
- Van Eldik, M.A., Vahdatikhaki, F., Dos Santos, J.M.O., Visser, M., Doree, A., 2020. BIM-based environmental impact assessment for infrastructure design projects. *Autom. Constr.* 120, 103379. <https://doi.org/10.1016/j.autcon.2020.103379>
- Virah-Sawmy, D., Sturmberg, B., 2025. Socio-economic and environmental impacts of renewable energy deployments: A review. *Renew. Sustain. Energy Rev.* 207, 114956. <https://doi.org/10.1016/j.rser.2024.114956>
- Vrana, I., Vaníček, J., Kovář, P., Brožek, J., Aly, S., 2012. A group agreement-based approach for decision-making in environmental issues. *Environ. Model. Softw.* 36, 99–110. <https://doi.org/10.1016/j.envsoft.2011.12.007>
- Wang, J., Biljecki, F., 2022. Unsupervised machine learning in urban studies: A systematic review of applications. *Cities* 129, 103925. <https://doi.org/10.1016/j.cities.2022.103925>
- Wang, J., Li, C., Deng, Z., Carr, J., Stringer, L.C., Li, K., Hu, Y., Zeng, C., Huang, K., Peng, S., Wang, Z., 2025. Biodiversity Impacts of Land Occupation for Renewable Energy Infrastructure in a Globally Connected World. *Environ. Sci. Technol.* 59, 9529–9539. <https://doi.org/10.1021/acs.est.4c11453>
- Wang, Y., Yuan, F., Cammarano, D., Liu, X., Tian, Y., Zhu, Y., Cao, W., Cao, Q., 2025. Integrating machine learning with spatial analysis for enhanced soil interpolation: Balancing accuracy and visualization. *Smart Agric. Technol.* 11, 101032. <https://doi.org/10.1016/j.jatech.2025.101032>
- Wang, Z., Ren, F., 2025. Developing a decision support system for sustainable urban planning using machine learning-based scenario modeling. *Sci. Rep.* 15, 13210. <https://doi.org/10.1038/s41598-025-90057-5>
- Wehbi, H., 2024. Powering the Future: An Integrated Framework for Clean Renewable Energy Transition. *Sustainability* 16, 5594. <https://doi.org/10.3390/su16135594>
- Wehrens, R., Buydens, L.M.C., 2007. Self- and Super-organizing Maps in R: The kohonen Package. *J. Stat. Softw.* 21, 1–19. <https://doi.org/10.18637/jss.v021.i05>
- Wehrens, R., Kruisselbrink, J., 2018. Flexible Self-Organizing Maps in kohonen 3.0. *J. Stat. Softw.* 87, 1–18. <https://doi.org/10.18637/jss.v087.i07>
- World Energy Outlook, 2023.
- Wosiek, M., 2020. Rural?urban divide in human capital in Poland after 1988. *Oeconomia Copernic.* 11, 183–201. <https://doi.org/10.24136/oc.2020.008>
- Wright, J.R., Wiggins, L.L., Jain, R.K., Kim, T.J. (Eds.), 1993. *Expert Systems in Environmental Planning*. Springer, Berlin, Heidelberg. <https://doi.org/10.1007/978-3-642-77870-4>
- Wróżyński, R., Sojka, M., Pyszny, K., 2016. The application of GIS and 3D graphic software to visual impact assessment of wind turbines. *Renew. Energy* 96, 625–635. <https://doi.org/10.1016/j.renene.2016.05.016>
- Wüstenhagen, R., Wolsink, M., Bürer, M.J., 2007. Social acceptance of renewable energy innovation: An introduction to the concept. *Energy Policy* 35, 2683–2691. <https://doi.org/10.1016/j.enpol.2006.12.001>
- Zardo, L., Granceri Bradaschia, M., Musco, F., Maragno, D., 2023a. Promoting an integrated planning for a sustainable upscale of renewable energy. A regional GIS-based comparison between ecosystem services tradeoff and policy constraints. *Renew. Energy* 217, 119131. <https://doi.org/10.1016/j.renene.2023.119131>
- Zardo, L., Granceri Bradaschia, M., Musco, F., Maragno, D., 2023b. Promoting an integrated planning for a sustainable upscale of renewable energy. A regional GIS-based comparison between ecosystem services tradeoff and policy constraints. *Renew. Energy* 217, 119131. <https://doi.org/10.1016/j.renene.2023.119131>
- Zeng, Q., Chen, X., 2023. Identification of urban-rural integration types in China – an unsupervised machine learning approach. *China Agric. Econ. Rev.* 15, 400–415. <https://doi.org/10.1108/CAER-03-2022-0045>

List of Figures

Fig.1. The general framework of the core of the study.

Fig.2. Methodology framework.

Fig.3. The thematic map offers a strategic visualization of the conceptual landscape.

Fig.4. The location of the case study in Basilicata, Italy.

Fig.5. Transforming CLC codes to N, Q, and V indexes.

Fig.6. a) Landscape value map for the study area. b) landscape value percentage for each class.

Fig.7. Comparison between current and future scenarios of the visibility index.

Fig. 8. a) VI and VP relation with IP. b) Comparison of VI and VP impact on landscape value changes.

Fig. 9. Flowchart of the proposed methodology.

Fig. 10. Selection of the study area and identification of Available areas.

Fig. 11. OAT Sensitivity

Fig. 12. Level of suitability based on the Slope sub-criterion.

Fig. 13. Level of Suitability of available areas based on solar radiation sub-criterion.

Fig. 14. Road Accessibility map.

Fig. 15. Siderpotenza industry accessibility map.

Fig. 16. Level of Suitability of available areas based on Distance from RES.

Fig.17. Level of Suitability of available areas based on Distance from the gas pipeline.

Fig. 18. Level of Suitability of available areas resulting from impact on Land use.

Fig.19. Land Suitability map.

Fig.20. Land Suitability under Scenario 1.

Fig. 21. Land Suitability under Scenario 2.

Fig. 22. Land Suitability under Scenario 3.

Fig. 23. Model Builder architecture.

Fig.24. Basilicata location in southern Italy.

Fig. 25. Flowchart of the methodology framework.

Fig.26. Sprinkling index trends evaluated for RES in Basilicata during three time intervals: a) initial phase (2006-2008); b) mid-period (2008-2024); c) prospective scenario (2024-2030).

Fig.27. The visibility index evaluation for solar panels in Basilicata during three time intervals. a) initial phase (2006-2008); b) mid-period (2008-2024); c) prospective scenario (2024-2030).

Fig.28. The visibility index evaluation for wind turbines in Basilicata during three-time intervals. a) initial phase (2006-2008); b) mid-period (2008-2024); c) prospective scenario (2024-2030)

Fig.29. Habitat quality evaluation in Basilicata during three-time intervals. a) initial phase (2006-2008); b) mid-period (2008-2024); c) prospective scenario (2024-2030).

Fig.30. Carbon storage evaluation in Basilicata during three-time intervals. a) initial phase (2006-2008); b) mid-period (2008-2024); c) prospective scenario (2024-2030).

Fig.31. Crop pollination evaluation in Basilicata during three-time intervals. a) initial phase (2006-2008); b) mid-period (2008-2024); c) prospective scenario (2024-2030).

Fig.32. Crop production evaluation in Basilicata during three-time intervals. a) initial phase (2006-2008); b) mid-period (2008-2024); c) prospective scenario (2024-2030).

Fig.33. Three Expert-based scenarios.

Fig.34. Heatmaps representing the pattern distribution of each variable across the SOM grid, expressed as scaled values in the range [0–1].

Fig.35. Boxplots of the distribution of variables expressed as scaled values in the range [0–1].

Fig.36. Three main data-driven cluster scattering in the Basilicata region.

List of Tables

Tab. 1: Input data information.

Tab. 2: Main information of bibliometric analysis.

Tab. 3: Index of Naturalness and classes of land use.

Tab. 4: Index of Environmental Quality.

Tab. 5: Index of constraints.

Tab. 6: Landscape value impacted by wind turbines

Tab. 7: Comparison of spatial multi-criteria approaches for green hydrogen siting.

Tab. 8: Saaty semantic scale.

Tab. 9: RCI values.

Tab. 10: Descriptions and sources of the layers used in the spatial analysis.

Tab. 11: Selection and assessment of criteria and sub-criteria based on relevant literature.

Tab. 12: Pairwise comparison matrix and weights of sub-criteria.

Tab. 13: Rank stability of AHP criteria across 10,000 Monte Carlo simulations.

Tab. 14: consistency check.

Tab. 15: The weights of sub-criteria for different scenarios.

Tab.16: Labeling three SOM clusters.

Tab.17: Transitional comparison between three supervised scenarios and data SOM.

Appendix

Table A: Standardization and Scoring Scheme for Weighted Criteria.

Criterion	Sub-criterion	Measurement / Class	Value Range or Class Description	Suitability Score	Basis for Threshold Selection
	Slope	%	> 15%	Excluded	Engineering feasibility limits; high construction and stability risk
			13–15%	1 (Very low)	High earthworks and accessibility constraints
			9–13%	2 (Low)	Moderate construction difficulty
			3–9%	3 (Moderate)	Acceptable terrain for industrial facilities
			1–3%	4 (High)	Favorable construction conditions
			0–1%	5 (Very high)	Optimal terrain conditions
Technical	Solar radiation	kWh/m ² /year	< 900	Excluded	Minimum threshold for PV feasibility
			900–1000	1 (Very low)	Low energy yield
			1000–1200	2 (Low)	Marginal PV performance
			1200–1400	3 (Moderate)	Acceptable PV generation
			1400–1600	4 (High)	High solar potential
			> 1600	5 (Very high)	Optimal solar resource
Economic	Road accessibility	Travel time (min)	> 25 min	1 (Very low)	High logistics and transport cost
			20–25 min	2 (Low)	Reduced accessibility
			15–20 min	3 (Moderate)	Acceptable access
			10–15 min	4 (High)	Good accessibility
			5–10 min	5 (Very high)	Optimal logistics efficiency
			> 25 min	1 (Very low)	High delivery and operational cost
Economic	Industry accessibility	Travel time (min)	20–25 min	2 (Low)	Reduced supply efficiency
			15–20 min	3 (Moderate)	Acceptable supply conditions
			> 25 min	1 (Very low)	High delivery and operational cost

			10–15 min	4 (High)	Efficient supply
			5–10 min	5 (Very high)	Optimal proximity to demand
Economic	Distance to RES	Linear distance (m)	> 5000 m	1 (Very low)	High transmission losses
			3000–5000 m	2 (Low)	Increased connection cost
			1500–3000 m	3 (Moderate)	Acceptable distance
			500–1500 m	4 (High)	Efficient energy supply
			< 500 m	5 (Very high)	Optimal RES integration
Economic	Distance to gas pipeline	Linear distance (m)	> 5000 m	1 (Very low)	High infrastructure cost
			3000–5000 m	2 (Low)	Increased connection complexity
			1500–3000 m	3 (Moderate)	Acceptable distance
			500–1500 m	4 (High)	Favorable integration
			< 500 m	5 (Very high)	Optimal network access
Environmental	Land use	CORINE classes	Natural / protected areas	1 (Very low)	Environmental protection priorities
			Agricultural land	2 (Low)	Competing land use
			Mixed-use areas	3 (Moderate)	Conditional compatibility
			Industrial / brownfield	4 (High)	Reduced environmental impact
			Abandoned / degraded land	5 (Very high)	Preferred for sustainable development

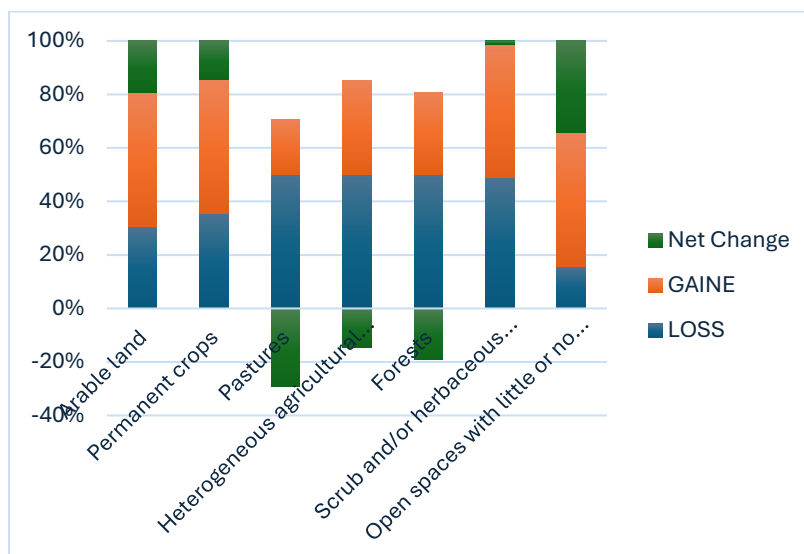


Fig.A.1 Main Giane and Loss percentages from 2006 to 2012

Highlight both losses and gains across major land-use classes, with the most significant change being the conversion of heterogeneous agricultural areas into arable land (20,910 ha), reflecting agricultural intensification. Concurrently, approximately 10,520 ha of arable land were converted into heterogeneous agricultural areas, indicating diversification, while additional conversions from forests and scrublands to arable land illustrate pressures on natural landscapes.

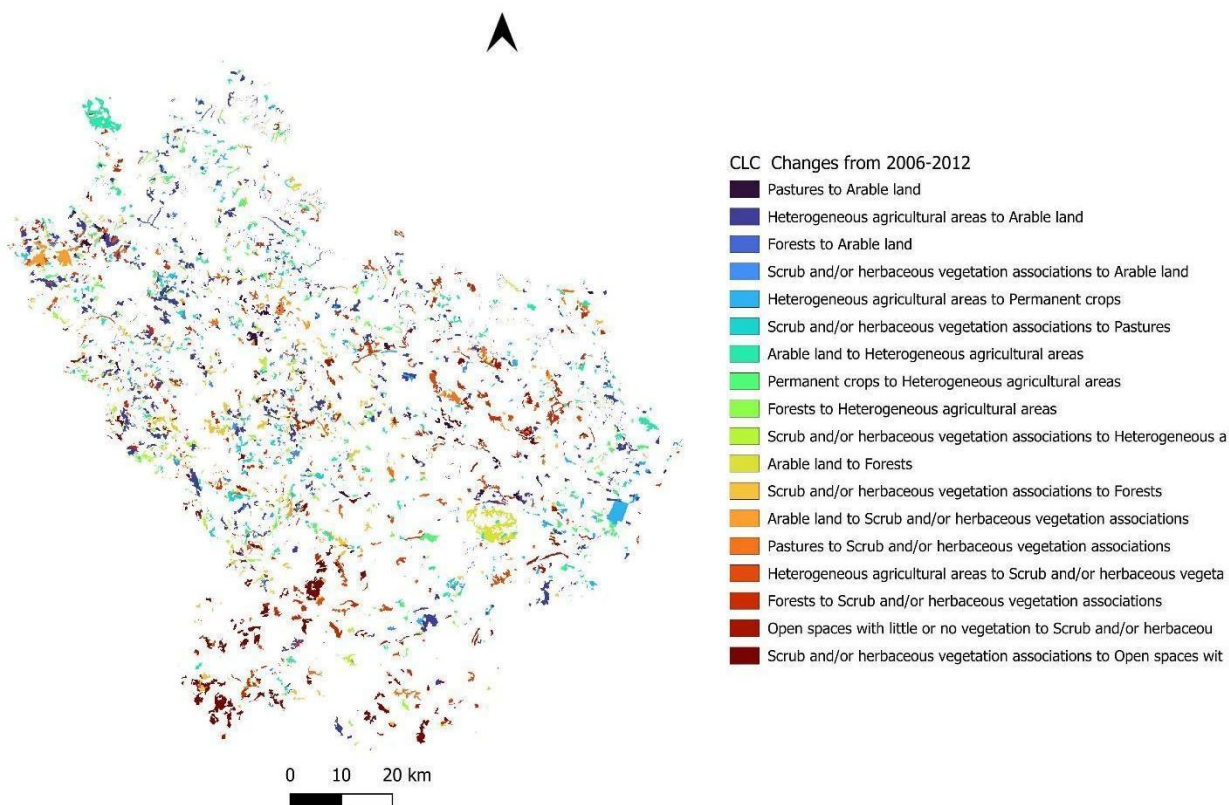


Fig.A.2 Gains and Losses between 2006-2012 CLC

The threats examined in this study, identified in the literature as primary factors contributing to habitat degradation, include both intensive and extensive agriculture, urbanization, roads, industrial infrastructure, mining sites, wind turbines, and solar panels. The mapping of these threats is carried out using open-source data provided by OpenStreetMap (OSM) in shapefile format. These shapefiles are clipped according to the study area's boundaries, rasterized, and saved as .tiff files in the Threat raster directory.

For each identified threat, the Threat Table (Tab.B.1) specifies the impact weight, the maximum distance within which the threat can influence a habitat, the decay function, and the location of the raster file representing each threat within the Threat Raster directory. The values for impact weight and maximum distance are adopted from the literature review.

Tab.B.1 Threat table for habitat quality

Threat	Weight	Max_dist	Decay	Source
Agriculture	0.5	1	linear	[68],[69],[70], [71], [72], [73], [74], [75], and [76]
Urban	1	10	exponential	
Industrial	1	7	exponential	
Mine	0.8	4	exponential	
Road	1	2	linear	
Wind Turbines	1	1.5	linear	
Solar Panels	1	1.5	linear	

In the Sensitivity Table, each LULC class is assigned a series of scores between 0 and 1, reflecting its habitat potential (column “HABITAT”) and its vulnerability to each of the threats analyzed (columns titled with the names of the threats). The values in the Sensitivity table are also derived from the literature review.

Tab.B.2 Sensitivity table for habitat quality

lulc	HABITAT	Agriculture	Urban	Industry	Mine	Road	Wind turbines	Solar panels
1	0.2	0	0	0.1	0.1	0	0	0
2	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0
5	0.6	0.3	0.5	0.7	0.7	0.2	0.7	0.7
6	0.5	0.1	0.3	0.5	0.2	0.4	0.2	0.5
7	0.4	0.5	0.8	0.4	0.4	0.5	0.8	0.9
8	0.4	0.3	0.6	0.4	0.5	0.3	0.4	0.4

9	1	0.8	0.8	0.7	0.5	0.7	0.5	0.5
10	0.8	0.5	0.8	0.6	0.6	0.6	0.6	0.6
11	0.2	0	0.6	0.6	0.6	0.3	0.6	0.6
12	0.2	0	0.6	0.6	0.6	0.3	0.6	0.6
13	0.2	0	0.6	0.6	0.6	0.3	0.6	0.6
14	0.3	0.2	0.3	0	0.5	0.1	0.3	0.3

Table C is a sample of a carbon pool table that is applied in the InVEST model for the Basilicata region. Data for individual pools are extrapolated from various sources, such as: i. Italian National Forest Inventory (IFI); ii. ORNL DAAC; iii. Institute for Environmental Protection and Research (ISPRA).

Tab.C Biophysical table for each land use used to compute carbon storage in Invest

lucode	LULC_NAME	C_above	C_below	C_soil	C_dead
1	Urban fabric	0	0.5	3	0
2	Industrial, commercial, and transport units	0	0	1	0
3	Mine, dump, and construction sites	0	0	2	0
4	Artificial, non-agricultural vegetated areas	7	4	2	0
5	Arable land	5	1	3	0
6	Permanent crops	7	1	2	0
7	Pastures	3.7	0.65	3	0
8	Heterogeneous agricultural areas	17	58	2	0
9	Forests	31.7	119	13	0
10	Scrub and/or herbaceous vegetation associations	17.6	50	10	0
11	Open spaces with little or no vegetation	19.1	35	8	0
12	Inland wetlands	0	20	7	0
13	Maritime wetlands	0	0	2	0
14	Marine waters	0	0	0	0

A biophysical table (Table.D.1) mapping each LULC class to nesting availability and floral abundance data for each substrate and season in that LULC class. Values are extracting from JRC report of pollinators in Italy. Although Guild Table (Table.D.2) mapping each pollinator species or guild of interest to its pollination-related parameters.

Tab.D.1 Biophysical Table for each land use used to compute pollination in Invest

lucod e	LULC_NAM E	floral_resources_s ummer_index	nesting_cavity_ava ilability_index	nesting_ground_av ailability_index	floral_resources_ spring_index
1	Urban fabric	0.05	0.1	0.1	0.05
2	Industrial, commercial, and transport units	0.25	0.3	0.3	0.25
3	Mine, dump, and construction sites	0	0.1	0.1	0
4	Sport and leisure facilities	0.05	0.3	0.3	0.05
5	Arable land	0.2	0.2	0.2	0.2
6	Permanent crops	0.6	0.3	0.3	0.6
7	Pastures	0.2	0.3	0.3	0.2
8	Heterogen eous agricultural areas	0.5	0.4	0.4	0.5
9	Forests	0.6	0.8	0.8	0.6
10	Scrub and/or herbaceou s vegetation associations	0.75	0.8	0.8	0.75
11	Open spaces with little or no vegetation	0.35	0.3	0.3	0.35
12	Inland wetlands	0.75	0.3	0.3	0.55
13	Maritime wetlands	0	0	0	0
14	Inland waters	0	0	0	0

Tab.D.2 Guild Table for each land use used to compute carbon storage in Invest

species	nesting_suitability_cavity_index	foraging_activity_spring_index	nesting_suitability_ground_index	foraging_activity_summer_index	alpha	relative_abundance
Apis mellifera	1	1	1	1	200	1
Bombus spp	0.8	0.9	1	0.85	180	0.9
Apis solitariae	0.7	0.8	0.9	0.75	150	0.7
Cetonia aurata	0.5	0.4	0.3	0.5	120	0.4
Aglais io	0	0.7	0.6	0.8	100	0.6
Anthocharis cardamines	0	0.8	0.7	0.7	110	0.5
Xylocopa spp.	1	0.9	0	0.8	190	0.8
Osmia spp.	1	0.8	0	0.85	170	0.75

Tab.E weights indicators for different scenarios

Indicators	Scenario 1	Scenario 2	Scenario 3
SPX	15.2 %	6.36 %	5.56 %
Wind Visibility	40.80 %	4.49 %	4.01 %
Solar Visibility	21 %	5.35 %	6.01 %
Habitat quality	5.9 %	33.30 %	10.65 %
Carbon storage	4.5 %	23.34 %	13 %
Crop production	8.2 %	15.24 %	35.07 %
Crop pollination	4.3 %	11.92 %	25.69 %