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Methods for the integrated assessment of environmental sustainability in agroecosystems

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Riassunto

In un contesto globale caratterizzato da una crescente domanda alimentare e da un incremento delle pressioni ambientali, è necessario disporre di strumenti in grado di valutare non solo l'efficienza dei sistemi agricoli, ma anche la loro capacità di sostenere o rigenerare il capitale naturale. L'agricoltura è il sistema umano più profondamente legato con gli ecosistemi e può quindi assumere un ruolo centrale in questa transizione, se adeguatamente sostenuta dalla ricerca e dall'innovazione.

In questo contesto si inserisce il presente lavoro, sviluppato in collaborazione con Guido Berlucchi & C., importante azienda dell'area vitivinicola della Franciacorta, che dispone di un vasto archivio pluriennale di dati agronomici e ambientali. La ricerca ha combinato metodi quantitativi, indicatori integrati, modelli statistici e strumenti di telerilevamento per analizzare gli impatti delle pratiche agronomiche e per costruire strumenti applicabili anche a situazioni operative di campo. L'approccio adottato si colloca all'interno della dimensione "Environmental Integrity" del framework SAFA della FAO, che considera la conservazione e la rigenerazione del capitale naturale come elementi centrali della sostenibilità.

Le attività di ricerca hanno considerato quattro dimensioni principali del capitale naturale: atmosfera, acqua, suolo e biodiversità. Per la dimensione "**atmosfera**", l'analisi dell'impronta carbonica in 25 aziende convenzionali e biologiche ha mostrato che le emissioni di gas serra non dipendono esclusivamente dal tipo di gestione. Sono invece influenzate dall'equilibrio tra input energetici, lavorazioni del suolo e uso di prodotti di sintesi, con differenze che riflettono il peso relativo delle singole pratiche. In relazione all'"**acqua**", l'analisi dell'impronta idrica di 38 vigneti non irrigui ha mostrato il ruolo determinante della densità d'impianto, della pendenza, delle caratteristiche pedologiche e varietali nel modulare la pressione delle pratiche sulle risorse idriche, confermando la natura dipendente dal contesto dei processi di impatto anche in assenza di irrigazione. La dimensione "**suolo**" è stata valutata attraverso lo sviluppo e l'applicazione del MISQ (Management Impact on Soil Quality), un indicatore integrato basato su cinque componenti chiave (riduzione del disturbo del terreno, rigenerazione della sostanza organica, protezione dall'ecotossicità da rame, efficienza d'uso dei nutrienti, protezione della

biodiversità edafica) che ha evidenziato l'importanza degli apporti di sostanza organica, degli inerbimenti e della gestione dei nutrienti nel mantenimento della qualità del suolo. Infine, per la dimensione relativa alla "**biodiversità**" sono stati considerati due approcci complementari. Da un lato, la valutazione comparativa di modelli di deep learning per la segmentazione delle coperture del suolo e la classificazione delle comunità di cover crops tramite immagini da drone ha mostrato come il telerilevamento sia efficace per mappare la biodiversità strutturale nelle aree agricole. Dall'altro, lo sviluppo e l'applicazione dell'indice FBS (Farmland Biodiversity Support), ha consentito di valutare la capacità dei paesaggi agricoli lombardi di sostenere la biodiversità, integrando elementi colturali e semi-naturali del mosaico rurale.

Nel loro complesso, le attività di ricerca hanno contribuito allo sviluppo di un sistema integrato di valutazione della sostenibilità ambientale negli agroecosistemi a diversa scala, dal paesaggio all'azienda fino al livello di campo, definendo strumenti operativi utili per valorizzare e rigenerare i capitali naturali.

Abstract

In a global context marked by rising food demand and increasing environmental pressures, it is necessary to use tools that can assess not only the efficiency of agricultural systems but also their ability to sustain or regenerate natural capital. Agriculture is the human system most deeply connected with ecosystems and can therefore play a central role in this transition, if adequately supported by research and innovation.

In this context, the present work was developed in collaboration with Guido Berlucchi & C., a major winery in the Franciacorta wine area, which has a large multi-year archive of agronomic and environmental data. The research combined quantitative methods, integrated indicators, statistical models, and remote-sensing tools to analyze the impacts of agronomic practices and to develop instruments applicable in the field. The adopted approach is in line with the "Environmental Integrity" dimension of the FAO SAFA framework, which considers the conservation and regeneration of natural capital as key elements of sustainability.

The research activities considered four main dimensions of natural capital: atmosphere, water, soil, and biodiversity. For the "**atmosphere**" dimension, the analysis of the carbon footprint in 25 conventional and organic farms showed that greenhouse gas emissions do not depend only on the management system. Instead, they are influenced by the balance among energy inputs, field operations, and the use of synthetic products, with differences reflecting the relative weight of each practice. Regarding "**water**", the analysis of the water footprint of 38 non-irrigated vineyards highlighted the key role of planting density, slope, and soil and varietal characteristics in shaping the pressure of practices on water resources, confirming the context-dependent nature of impact processes even in the absence of irrigation. The "**soil**" dimension was assessed through the development and application of MISQ (Management Impact on Soil Quality), an integrated indicator based on five key components: reduction of soil disturbance, regeneration of organic matter, protection from copper ecotoxicity, nutrient-use efficiency, and protection of soil biodiversity. The indicator highlighted the importance of organic matter inputs, cover cropping, and nutrient management in maintaining soil quality. Finally, for

the "**biodiversity**" dimension, two complementary approaches were considered. On one side, the comparative evaluation of deep learning models for soil-cover segmentation and cover-crop community classification using drone imagery showed that remote sensing is effective for mapping structural biodiversity in agricultural areas. On the other side, the development and application of the Farmland Biodiversity Support (FBS) index has allowed us to evaluate the ability of Lombardy's agricultural landscapes to support biodiversity by integrating cultural and semi-natural elements of the rural mosaic.

Taken together, the research activities contributed to the development of an integrated system for assessing environmental sustainability in agroecosystems at different scales, from the landscape to the farm and down to the field level, providing operational tools to enhance and regenerate natural capital.

1. Introduction

1.1. Sustainable agriculture and regeneration of natural capital

Since its origins, agriculture has been a driving force behind the unprecedented growth of the human population (Gignoux et al., 2011). By favoring the transition from a nomadic lifestyle to stable societies, it has provided a secure food supply and created conditions for cultural, technological, and demographic development. Today, covering more than one third of the Earth's land cover (FAO, 2025), it represents the largest human-engineered ecosystem. For thousands of years, the environment has changed in ways that fell within the limits of nature's ability to regenerate its natural capital (soil fertility, available water, biodiversity). In other words, nature was still able to reconstitute what was consumed or modified. Its self-regulating functions have maintained positive conditions for human development: relatively stable temperatures, access to fresh water and balanced biogeochemical cycles. However, the balance between human activity and the regenerative capacity of natural capital is facing increasing challenges. Rising reliance on finite resources and their excessive use are creating pressures that may affect the stability of the biophysical systems supporting planetary functioning (Rockström et al., 2009). In response, sustainability science has progressively shifted its focus from the issue of resource scarcity to the broader dynamics of global change and ecological limits, formalized through the concept of planetary boundaries, which define a safe operating space for humanity (Kallis et al., 2025). From 1960 to 2024, the world population grew from 3 to 8.1 billion people (World Bank Group, 2025). With the global population continuing to grow, demand on agroecosystems is increasing, challenging their capacity to remain sustainable. This requires meeting global food demand, minimizing losses along the supply chain, and ensuring equitable access to nutritious food, while respecting the ecological limits of the natural capital on which agriculture depends (Muhie, 2022). This challenge has generated several points of view on sustainable agriculture. According to the FAO, sustainable agricultural intensification is an approach that aims to increase the productivity of existing cultivated land while minimizing negative environmental impacts and

improving natural capital and ecosystem services (Cole and McCoskey, 2013; FAO, 2013; Garnett et al., 2013). This definition reflects a broader view of sustainability, which can generally be defined as the ability of a system to maintain itself indefinitely over time (Kuhlman and Farrington, 2010). However, sustainability is often simplified to the achievement of greater efficiency or the reduction of emissions in production processes; such a narrow interpretation fails to capture the full scope of the challenge (Fischer et al., 2023). Environmental improvements should be assessed in a broader framework that includes society, the economy and the ecosystem services that support them (Purvis et al. 2019). From this perspective, the ability to maintain a constant level of well-being over time depends on the relationship between natural capital and produced capital: growth can continue if technological progress or greater efficiency in the use of resources can compensate for their depletion. However, sustainability cannot be based solely on substitution or efficiency; it requires improving the regenerative capacity of natural capital, ensuring that human activities support its renewal rather than exceeding thresholds that can compromise system functioning (Bakshi et al., 2018; Solow, 1974). Natural capital can be defined more precisely as the extension of the economic idea to include environmental goods and services. Like all other forms of capital, it is a stock rather than a flow, consisting of "stocks of natural resources (e.g., soils, forests, bodies of water) that produce a flow of valuable ecosystem goods or services into the future" (Costanza and Daly, 1992). Natural capital represents the stock of renewable and non-renewable resources on Earth, plants, animals, air, water, soil and minerals, that provide benefits or "services" to people. These flows—agricultural outputs and ecosystem services—can both generate value for society and the economy (Jansson, 1994; Pearce et al., 1996). Agriculture and ecosystem services are closely interlinked. Agroecosystems act simultaneously as providers and users of ecosystem services (Zhang et al., 2007). They provide benefits such as food production, soil retention, and landscape, while simultaneously relying on functions supplied by natural ecosystems, including pollination, nutrient cycling, and water regulation. At the same time, agricultural practices can profoundly affect the quality and availability of ecosystem services originating from non-agricultural systems (Dale and Polasky, 2007). Agricultural

production itself is highly dependent on these ecosystem functions, particularly soil structure and fertility, water availability, pollination, and natural pest control, which collectively regulate crop growth and productivity (Power, 2010). Strengthening these interdependent processes, by enhancing soil health, promoting pollinator diversity, or fostering biological control, can help increase food supply while reducing agriculture's dependence on synthetic inputs, thereby mitigating the conflict between production goals and environmental sustainability (Dyer, 2014). However, when these relationships are perturbed, agriculture itself can become a cause of environmental degradation. Unsustainable practices lead to the loss of biodiversity and the decline of key ecosystem services resulting in overall ecosystem degradation (EASAC, 2022). To improve the sustainability and resilience of agricultural systems, an integrated approach is therefore required, which not only mitigates current impacts but also promotes the regeneration of natural capital in all its forms: atmosphere, water, soil and biodiversity. For this purpose, it is necessary to develop production systems that (i) maximize the closure of nutrient cycles, reducing losses; (ii) minimize emissions to the environment; (ii) reduce the use of non-renewable resources and external inputs; and (iv) integrate agricultural processes with the genesis and regulation of ecosystem services. In conclusion, to implement this vision it is necessary to quantify both the demand for ecosystem services generated by human activities and the ability of ecosystems to provide them (Bakshi et al., 2018). A regenerative approach to agriculture, grounded in soil health, biodiversity and crop diversity, can support high productivity while protecting nature and fostering its multifunctionality, therefore generating positive environmental, social and economic outcomes (Schreefel et al., 2020).

1.1.1. Atmosphere

The atmosphere serves as a reservoir of gases essential for life and as a regulator of global biogeochemical cycles (Schlesinger and Bernhardt, 2020). Agriculture depends closely on this dimension: vital processes such as photosynthesis and gas exchange rely on the availability of carbon dioxide, oxygen, and water vapor, while the atmospheric deposition of nutrients such as nitrogen and sulfur contributes to sustaining soil fertility (Krupa, 2003). At the same time, agricultural productivity is shaped by atmospheric conditions, including variations in solar radiation, temperature, precipitation, and soil moisture, which determines yields and quality of crop production. Clearly, the Earth's atmosphere has changed since the beginning of the last millennium, following the onset of the industrial era (Finlayson-Pitts and Jr, 1999). Transformations in atmospheric composition, with increasing concentrations of greenhouse gases such as CO_2, CH_4, and N_2O, are profoundly affecting crop growth, water requirements, and the plants interactions with pests and diseases (IPCC, 2022). These changes also disrupt the natural biogeochemical processes that help stabilize atmospheric composition, weakening the mechanisms that support climate and ecological regulation. Agriculture is a sector particularly exposed to the impacts of climate change and, at the same time, contributes significantly to the dynamics affecting the atmosphere. Estimates indicate that the agribusiness system is associated with about one third of global anthropogenic greenhouse gas emissions (FAO, 2024). In 2020, these emissions reached approximately 16 Gt CO_2eq, coming from three main components: agricultural and livestock production (farm-gate phase), which alone generated approximately 7.4 Gt CO_2eq, equal to 46–47% of the total; land use changes, responsible for approximately 3.1 Gt CO_2eq (19–20%); and the pre - and post-production phases, including processing, transport, distribution, consumption and management of food waste, which contributed about 5.6 Gt CO_2eq (34–35%). In addition to greenhouse gases, agriculture is also associated with the release of air pollutants. In particular, ammonia (NH_3) from livestock farming and fertilizer use is the main agricultural emission source in Europe and contributes to the formation of fine particulate matter ($PM_{2.5}$) and to eutrophication processes (EEA, 2020). Nevertheless, agriculture is not only a source of pressures but can also provide

important opportunities for mitigation and regulation. Agricultural soils represent a potential reservoir for organic carbon sequestration through management practices that enhance soil fertility and the resilience of cropping systems. According to FAO estimates (2022), this potential could offset up to 31.3% of net global agricultural emissions, making the conservation and enrichment of soil organic matter a crucial lever for the future sustainability of agrifood systems. This bidirectional relationship, in which agriculture depends on the atmosphere for its productivity while simultaneously altering its composition and quality, highlights the need to regard the atmosphere as natural capital to be preserved and managed within a sustainability perspective, by protecting the biogeochemical processes on which agroecosystems depend.

1.1.2. Water

Water is essential for life, for the functioning of biogeochemical cycles, and for agricultural productivity. Agriculture is both highly dependent on water resources and one of the main sources of pressure on them. Vital processes such as photosynthesis, transpiration, and crop growth require large amounts of water: it is estimated that over 90% of global freshwater consumed by human activities is devoted to food production, most of which is returned to the atmosphere through evapotranspiration (Mekonnen and Hoekstra, 2011). The distinction between green water (rainwater stored in the soil and used by vegetation) and blue water (surface and groundwater resources that can be taken for irrigation and other uses) is essential to understanding how agriculture interacts with freshwater resources. Green water accounts for about two-thirds of all accessible freshwater, while blue water often receives more attention because it is directly usable and subject to competition between the agricultural, industrial, and domestic sectors (Rockström and Barron, 2025). These water flows are influenced by two key stages in the hydrological cycle within the soil–vegetation system. The first occurs when precipitation reaches the soil surface, where it infiltrates or drains, potentially mobilizing sediment and nutrients. The second occurs within the soil profile, where infiltrated water can evaporate, be absorbed by plant roots and then stocked or transpirated, or percolate down beyond the root zone, contributing to groundwater flows. Both are relevant to the formation of green and blue water: infiltration into

the root zone and root uptake determine the fraction of green water available to vegetation, while percolation and runoff contribute to blue water resources. In both cases, farming practices largely determine the distribution and efficiency of water use (FAO, 1996). Globally, irrigated agriculture accounts for approximately 70% of freshwater withdrawal. According to several authors, in some regions current withdrawal levels may exceed the rate at which water resources are renewed, creating conditions of pressure and potential competition between sectors and territories (Giordano et al., 2019; Ünver and Mansur, 2019). In addition to quantitative aspects, agriculture also interacts with water quality. Leaching of fertilizers and plant protection products can contribute to widespread pollution, eutrophication, and groundwater contamination, while ammonia emissions from livestock farming and fertilizer use are a significant factor in the eutrophication and acidification processes of aquatic and terrestrial ecosystems (FAO, 1996; Mateo-Sagasta and Burke, 2011). At the same time, several studies highlight that agroecosystems can also contribute to water regulation. For example, rice paddies can store substantial volumes of water, reduce runoff, facilitate sediment retention, and promote groundwater recharge through controlled percolation, thus contributing to the regulation of water flows and improving water quality at the landscape scale (Chivenge et al., 2020). However rice cultivation is often considered environmentally contentious because of its high water demand and significant methane emissions, despite the important ecosystem services it provides—such as wetland habitat, biodiversity support, and cultural landscape value. While these dynamics are specific to flooded systems such as rice paddies, they illustrate how agricultural areas can influence water resource processes more broadly, depending on local soil conditions, management practices, and landscape configuration. This close interdependence highlights how water, while supporting agricultural productivity, can be sensitive to the dynamics that characterize the intensive use of water resources. Considering water as natural capital implies recognizing both its physical and qualitative limits and the need for careful management to ensure the continuity of the ecological and productive functions it supports. Proper water use—minimizing waste, avoiding unnecessary losses, and reducing leaching—allows most of the withdrawn resource to return to the

atmosphere through plant transpiration. In this sense, water withdrawn for agriculture can be viewed as a temporary loan from the system, reintegrated into the hydrological cycle without compromising the quality of the resource.

1.1.3. Soil

As the physical support for agricultural production and provider of multiple ecosystem services, soil is a fundamental component of natural capital. Soil scientists describe soils using two key concepts: components and properties. Soil components include biogeochemical species (such as nitrates, NO_3^-) or their aggregates, which can be classified into four main categories: minerals, organic matter, liquids, and gases. Soil properties, on the other hand, are physical (e.g., porosity, texture), chemical (e.g., pH, available phosphates), and biological (e.g., microbial biomass) characteristics/features that can be measured, allowing to classify soils with comparative scales (Dominati et al., 2010). Soil is also home to extraordinary biodiversity, estimated at up to 60% of living species, which play a crucial role in the decomposition of organic matter, the mineralization of nutrients, and the formation of stable soil organic matter, thus ensuring the resilience and functionality of agroecosystems (Anthony et al., 2023). It mediates fundamental processes such as vegetation growth, surface runoff and water infiltration, soil use and management. It is therefore not surprising that soil quality is considered a primary indicator of land degradation: when the soil is degraded, so is the land (Rhodes, 2017). The main cause of soil degradation is erosion, which, in its water and wind forms, is responsible for 84% of the degraded surface area globally (56% water; 28% wind). According to the assessment by the International Soil Reference and Information Center, water erosion affects over 1,000 million hectares, wind erosion over 500 million, while chemical degradation processes (nutrient loss, salinization, pollution) and physical degradation processes (compaction) affect 239 and 83 million hectares globally, respectively (Oldeman cited in Rhodes, 2017). In addition to erosion, highly disruptive practices such as continuous plowing, irrigation without drainage (which promotes salinization), excessive use of mineral fertilizers and pesticides, and monoculture have accelerated compaction, contamination, and loss of organic matter (Alori et al., 2020). Mechanization can lead to a high risk of soil degradation, particularly due to compaction. Repeated

passes with heavy machinery can cause a significant reduction in agricultural yield of up to 50%, as well as damaging the structure and capacity of the soil to provide essential ecosystem services (Keller et al., 2019; Shaheb et al., 2021). The occurrence and severity of compaction are strongly influenced by tire characteristics: larger tires, or tracks, can distribute the load over a larger surface area, while a lower inflation pressure reduces the contact stress exerted on the ground, both helping to mitigate compaction (ten Damme et al., 2019). These processes reduce fertility, increase vulnerability to drought, pests, and weeds, and can compromise agricultural yields, leading to land abandonment (Rhodes, 2017). The intensive use of fungicides can cause soil contamination, significantly reducing soil microbial diversity, network stability, and soil biodiversity complexity, thereby compromising certain vital functions such as nutrient cycling and pest and disease control in agroecosystems (Komárek et al., 2010; Riedo et al., 2023; Zhang et al., 2024). Growing awareness of soil health has led to the introduction of new policies aimed at its protection. In particular, the European Union has developed regulatory frameworks, such as the European Soil Monitoring Law, to ensure sustainable management and promote the restoration of degraded soils (Kotschik et al., 2024). Several studies have shown that appropriate agricultural practices can help reverse these trends. Conservation agriculture, a system that avoids or minimizes mechanical soil disturbance (no-till/minimum-till) combined with soil cover and crop diversification, is considered a sustainable agroecological approach to agricultural production that conserves soil. In particular, conservation agronomic practices are based on permanent and total soil protection through species diversity and involve three key aspects: i) maintaining a protective layer of vegetation on the soil surface; ii) limiting mechanical disturbance caused by sowing or fertilizers distribution; iii) adopting an economically well-designed crop rotation to ensure an increase in the amount of organic matter on and in the soil, in order to provide surface protection and improve soil quality in terms of functionality and biodiversity (Corsi and Muminjanov, 2019). However, the absence or reduction of soil tillage can promote the accumulation of surface seeds and modify weed flora, making it necessary to adopt integrated weed control measures that combine cultivation and chemical techniques as a function of weed species composition and

local soil conditions (Derrouch et al., 2020). At the same time, reduced tillage generally decreases soil compaction and promotes the accumulation of organic carbon in the upper soil layers, contributing to improved soil structure and long-term fertility. Vegetation cover and the use of cover crops not only protect the soil from erosion and improve its structure, but also increase organic matter and promote microbial biodiversity, with positive effects on fertility and crop stability (Allam et al., 2023). Crops with particular functional traits, such as nitrogen-rich residues or extensive root systems, can positively influence organic carbon sequestration processes in soils, contributing to both fertility and climate change mitigation (García-Palacios et al., 2018). The application of organic fertilizers, such as animal manure or compost, has also proven effective in increasing organic carbon stocks, with average increases of 35% compared to conventional systems (Gross and Glaser, 2021; Maillard and Angers, 2014). As already highlighted in the *Atmosphere* section, certain farming practices reinforce the role of soil as one of the main terrestrial carbon sinks. Increasing the sequestration and stability of organic carbon storage through targeted agricultural management not only improves the fertility and resilience of cropping systems but also contributes substantially to climate change mitigation (FAO, 2022). In this perspective, maintaining and strengthening soil quality must be considered a strategic priority. Soil is not a renewable resource: it takes centuries or millennia to form, while degradation can occur in just a few years. Protecting and regenerating soil through conservation practices and sustainable use of resources are therefore essential for ensuring agricultural productivity, food security, and the stability of ecosystem services on a global scale.

1.1.4. Biodiversity

Biodiversity represents the variety and variability of life on Earth, at the genetic, species, and ecosystem levels. It constitutes a dynamic and interdependent system that supports the functioning of natural and anthropized ecosystems (Waterhouse et al., 2024). Each living organism has its own genetic and functional architecture that evolves over time. Genetic diversity is the basis of biological differences, both between species and between individuals of the same species. Because of genetic diversity, some individuals are better suited to survive and reproduce in certain

conditions and will be favored by natural selection. Genetic diversity increases the probability of species survival, especially during environmental changes, and is therefore essential for generating stability, resilience, and adaptation in ecological processes (GCWG, 2020). A multidimensional approach is needed to understand the links between biodiversity status and ecosystem functionality (Millennium Ecosystem Assessment, 2005). In this perspective, not only taxonomic aspects are important, but also functional ones: organisms perform complementary roles, from photosynthesis to decomposition to nitrogen fixation, and the loss of a key function can compromise the overall efficiency of the system, shifting the focus from the protection of indicator species alone to the protection of the ecological processes that generate ecosystem services (Hooper et al., 2006). Biodiversity and agriculture cannot be considered separately, since, as already highlighted, much of the land surface is now used for agricultural purposes, and farming has played a fundamental historical role in shaping landscapes and creating open environments capable of hosting a rich biological variety. During the second half of the 20th century, agricultural intensification, characterized by increased use of mineral fertilizers, synthetic pesticides, mechanization, and reduced crop diversity, led to increased productivity but also had a significant negative impact on biodiversity (Pretty, 2018). At the field level, fertilization, tillage, and pesticide use alter environmental conditions and reduce biological diversity (Jwaideh et al., 2022; Raven and Wagner, 2021). On a landscape scale, the disappearance of semi-natural environments on the edges of agricultural land, such as copses, permanent grasslands, hedges, and grass strips, has exacerbated the decline of plant and animal species (Marja et al., 2022; Prangel et al., 2023). The spatial homogenization of crops and the synchronization of agricultural practices (e.g., harvest or mowing dates) also contributed to reduce ecological complexity (Gepts, 2023). Furthermore, intensive agriculture in homogeneous landscapes favors the proliferation of pests and the resulting dependence on chemical inputs, while the simplification of landscapes can lead to a loss of biodiversity that is difficult to reverse. Climate change also amplifies these effects by altering crop areas and the life cycles of native species (Mennerat et al., 2010; Taylor, 2025). Nevertheless, no other activity can contribute to protect and promote biodiversity as much as agriculture, if geared towards targeted

management practices and more complex landscape management. Agricultural biodiversity includes domesticated varieties and breeds of plants and animals, beneficial microorganisms (soil bacteria, root symbionts), associated wild species (pollinators, natural predators, spontaneous flora), and landscape elements that connect agricultural and natural environments (hedges, rows of trees, dry stone walls, wetlands, copses) (FAO, 2005). In agroecosystems, we can distinguish between planned biodiversity, introduced directly through crop and livestock choices, and associated biodiversity, consisting of spontaneous organisms that colonize and support the agricultural system (Vandermeer and Perfecto, 1995). Agricultural practices such as crop rotation, organic fertilization, integrated pest management, and the maintenance of natural elements in the landscape can promote greater biological diversity and improve the overall ecological quality of agroecosystems. Heterogeneous landscapes, characterized by mosaics of crops and natural habitats, support a greater wealth of species than uniform landscapes. Elements such as hedges, flower borders, wetlands, and small wooded areas promote ecosystem connectivity by creating ecological corridors that enable migration, reproduction, and biological balance among species (Devictor and Jiguet, 2007). These landscape mosaics are therefore essential for the conservation of agricultural biodiversity compared to simplified landscapes, improving ecological connectivity and habitat quality. (Kratschmer et al., 2024; Staley et al., 2023). Agriculture that values biodiversity not only conserves species, but also regenerates natural capital, improves soil quality, reduces ecological risks, increases resilience to climate change, and optimizes the provision of ecosystem services by unlocking the multifunctional potential of agricultural systems.

1.2. A conceptual framework for integrated sustainability assessment oriented toward natural capital regeneration

To assess the effects of agricultural practices on natural capital and its capacity to regenerate, an integrated sustainability assessment approach is required—one that explicitly links agronomic management strategies to the state of natural capital. Among such tools, SAFA (Sustainability Assessment of Food and Agricultural

Systems), developed by the FAO, provides an international benchmark for evaluating sustainability in agri-food systems (Scialabba, 2013).

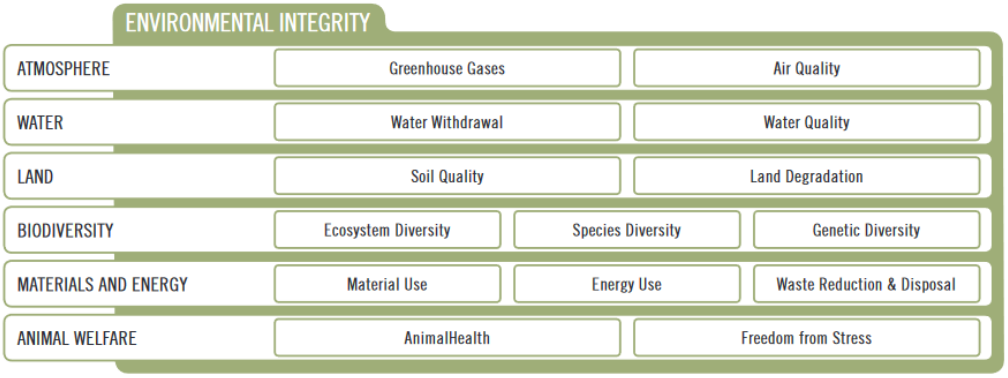


Figure 1 - Environmental Integrity dimension of SAFA

The framework adopts a holistic approach, divided into four fundamental dimensions: Good Governance, Environmental Integrity, Economic Resilience, and Social Well-being. The SAFA structure is organized hierarchically, comprising 21 themes, 58 sub-themes, and 116 indicators. The four dimensions constitute the highest level of the model and reflect the main areas of economic, environmental, social, and institutional sustainability. The themes represent the strategic objectives of each dimension, while the sub-themes translate the principles into operational objectives, such as reducing greenhouse gas emissions, promoting community investment, or protecting worker safety. Overall, SAFA provides a coherent and integrated structure for comparing sustainability performance across the entire agri-food supply chain, offering an internationally shared reference framework. The use of SAFA has grown steadily over the years, with a strong concentration of studies in Italy and Switzerland, countries that stand out for their commitment to sustainable production models. About half of the applications involved direct sustainability assessments, while other research used SAFA as a basis for creating new tools. Among the main strengths are the model's comprehensiveness, flexibility, and adaptability to different geographical and production contexts (Zarbà et al., 2025).

This PhD project explored the most relevant topics related to the Environmental Integrity dimension of SAFA (Figure 1). Within this dimension, several themes,

such as soil quality, biodiversity protection, water conservation and greenhouse gas mitigation, directly relate to the regenerative capacity of natural capital. In particular, the topics of Atmosphere, Water, Soil, and Biodiversity were considered. For environmental impact assessment, the most immediate approach is normally based on direct measurements in the field. This solution is feasible in experimental farms, but its application to commercial farms for routine measurements presents practical problems, as the surveys are costly and time-consuming (Sharpley, 1995). In this context, indicators provide an alternative or complementary approach when direct measurements are not feasible, costly, or insufficient on their own. According to the classical definition, an indicator is a variable that provides information on other variables that are difficult to measure directly (Gras et al., 1990). A comprehensive review of the literature has shown that the methods for assessing sustainability topic in agricultural systems has grown impressively over the years (Fig. 2, Fig. 3).

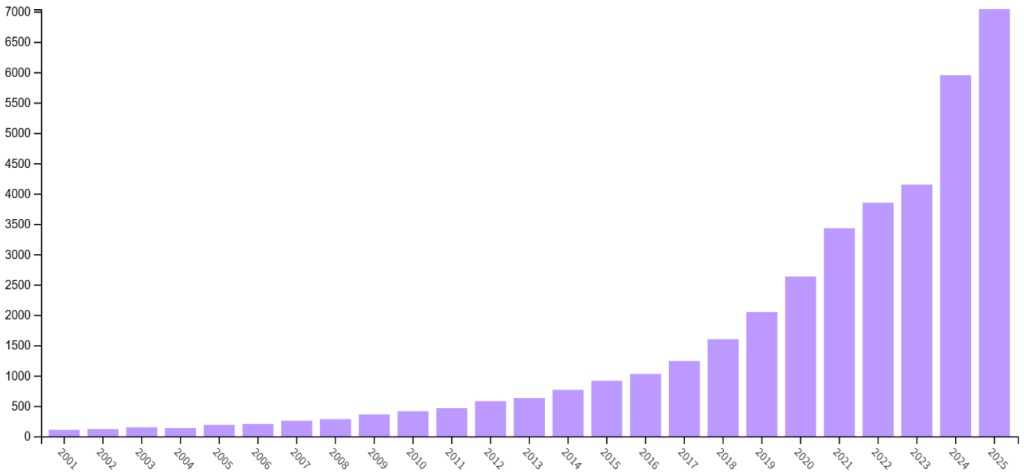


Figure 2 - No. of publications indexed in Web of Science on sustainability assessment methods in agroecosystems (2001–2025). The graph shows an exponential growth in scientific interest in the topic over the last twenty years.

To help navigate this vast array of tools available in the literature, this work focused in particular on three groups of indicators, as identified by Bockstaller et al. (2008):

1. Indicators constructed using only one variables obtained without direct measurements, from surveys, databases, or other indirect sources. Some of them also take environmental characteristics into account (e.g., soil,

climate). They may be based on a single variable or on elementary combinations, such as balances or ratios (e.g., of nutrients).

2. Calculated indicators, which integrate multiple factors (e.g., agricultural practices and soil conditions). This category includes a wide variety of tools of varying complexity, ranging from emission factors used in life cycle assessment (LCA) to mechanistic simulation models of cropping systems.
3. Indicators based on one or more direct measurements. This category includes, for example, biodiversity indices such as the QBS-ar index for the study of arthropod communities.

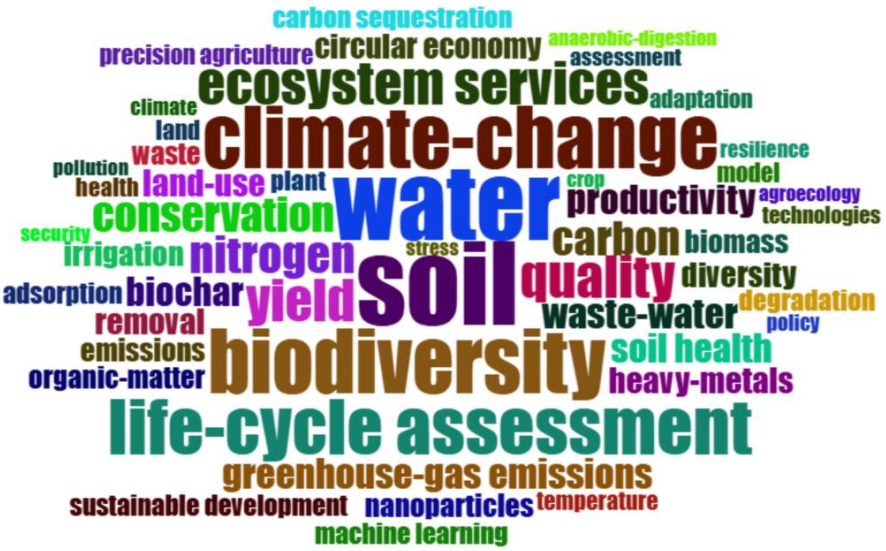


Figure 3 - Most common keywords in publications indexed in Web of Science on sustainability assessment methods in agroecosystems. Word cloud highlights dominant themes in recent literature, including soil, water, biodiversity, climate change, and life-cycle assessment.

1.3. Research activities at the company Guido Berlucchi & C. and aims of the thesis

The PhD project is co-financed by Guido Berlucchi & C. and the PNRR – National Recovery and Resilience Plan, as part of the European NextGeneration EU program. The funding of the PNRR is part of Mission 4 “Education and Research”, Component 2 “From Research to Enterprise”, which promotes the strengthening of doctoral programs aimed at technology transfer and collaboration between universities and businesses. The main research topic concerns the development of

integrated systems for assessing the impacts of management practices on natural capital, providing companies with tools to improve the environmental performance of production. The research activities were carried out in close collaboration with Guido Berlucchi, located in Franciacorta, a wine-growing area in the province of Brescia renowned for the production of high-quality sparkling wines. The company manages over 70 hectares of vineyards and numerous local winegrowers for grape supply. With a production of over 4 million bottles per year, it represents one of the main Italian wine companies. Guido Berlucchi holds a vast archive of agronomic and technical data, including soil analysis, environmental monitoring, and multi-year sampling. The research project involved company technicians and managers, with the aim of promoting knowledge exchange, developing a conceptual framework for integrated sustainability assessment, and sharing the results.

During the PhD, research activities led to the publication of scientific results, some of which were based on data made available by Guido Berlucchi. Additional research activities were carried out through complementary studies conducted in the Italian context. This document presents the research activities implemented, many of which have already been published or are currently being reviewed by international journals.

The overall research was structured through a combination of case study contributions and methodological developments, each addressing specific topics within the main dimensions of natural capital—atmosphere, water, soil, and biodiversity. Figure 4 provides a schematic representation of this organization, illustrating how the different research activities conducted during the PhD intersect these dimensions, distinguishing between case-based analyses and methodological approaches, and highlighting the analytical scales at which each contribution operates. The following chapters present these studies in detail.

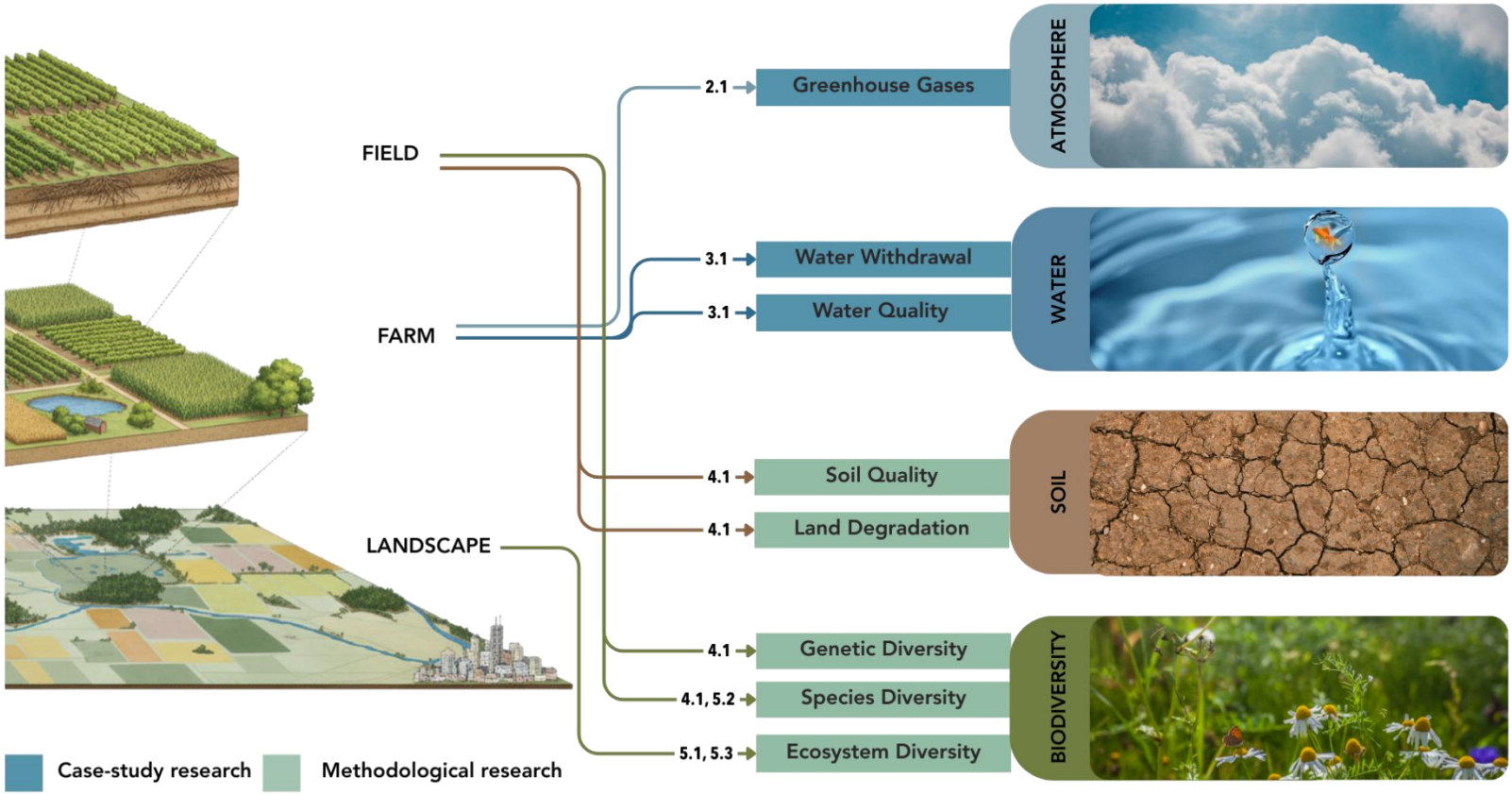


Figure 4 - Schematic representation of the different natural capitals addressed in the PhD research (atmosphere, water, soil, and biodiversity), including the specific topics investigated within each dimension. The figure illustrates how the individual studies composing the thesis intersect these domains across different scales of analysis. Contributions are organized by scale and color-coded: blue denotes case-study-based research providing interpretative results on the agroecosystem, while green indicates methodological studies. Numbers preceding each topic (e.g., 2.1) identify the thesis chapters where that topic is discussed.

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2. Atmosphere

2.1. Comparing the carbon footprint of conventional and organic vineyards in northern Italy

Chapter 2 has been published in Sustainability https://doi.org/10.3390/su15065252

Abstract: The carbon footprint is an index used to assess the impact of an activity in terms of greenhouse gas emissions. Viticulture contributes to greenhouse gas emissions due to the use of fuels, fertilizers, pesticides, and soil erosion. Organic viticulture differs from conventional one mainly because of the absence of synthetic products, the soil tillage, and the level of organic carbon in soil. The purpose of the study was to determine the actual differences between conventional and organic vineyard management in terms of greenhouse gas emissions, comparing multiannual data from 25 wineries in northern Italy. No statistically significant differences were found between the overall mean values of conventional and organic management. In organically farmed vineyards, a higher incidence of fuel consumption was observed, while in conventionally farmed vineyards higher emissions were observed due to the use of such products as pesticides and fertilizers. No differences were found between the two management systems in terms of emissions resulting from direct fertilizing. Further assessment of the potential sequestration of organic fertilizer would be necessary.

Keywords: Viticulture; Organic vs. conventional management; Carbon Footprint; Greenhouse gas (GHG); Sustainable viticulture

Introduction

The Carbon Footprint (CF) is an indicator of global warming (IPCC, Geneva, Switzerland, 2022). The CF expresses the amount of greenhouse gas emissions (GHGs) generated during the production or consumption of goods and converted into CO_2 equivalent (CO_2-eq) according to their global warming potential (Röös et al., 2013). It can be considered a simplified LCA focusing on global warming as the only impact category (Pattara et al., 2012). CF can be assessed either at the corporate level, according to the ISO 14064 standard (2018) and the GHG Protocol

for organizations (2004 and 2011), or at the product level, according to the ISO 14067 standard (2018) and the GHG Protocol for products (2011). The corporate CF method consists of calculating direct and indirect GHG emissions that a company generates over one year while performing its activities. Direct emissions are generated from sources controlled by a company, while indirect emissions are a consequence of the activities of a company (Borsato et al., 2020). All company products are included in the assessment of the corporate CF, only one company product is assessed in the product CF (Navarro et al., 2017a). Corporate CF is therefore a method used to assess the sustainability of a company according to the impact of its production activities on global warming. Viticulture contributes to GHG emissions due to the use of fertilizers, pesticides, water and fuels, soil erosion and degradation, not to mention the production of a significant amount of organic waste (Bandinelli et al., 2020). In particular, the impact of fossil fuels in the carbon footprint of the vineyard stage is always particularly relevant in all flat vineyard systems. (F. Gierling and Blanke, 2021) Also the production of synthetic products used in viticulture can result in significant emissions due to high resource and energy consumption. In addition to the high emissions from the production of fertilizers, particularly nitrogen fertilizers (Menegat et al., 2022), there are also emissions from the production of synthetic pesticides, such as fungicides and insecticides, which can be particularly high in viticulture (Cech et al., 2022). Even though viticulture leads to carbon sequestration by the vines and all cover crops, intensive vineyard cultivation needs to be correctly managed to reduce GHG emissions (Chiriacò et al., 2019). In this perspective, many wineries are now gearing towards sustainable grape-growing practices (Tsalidis et al., 2022). The key sustainable measures contemplate innovation and improvement in terms of energy and water consumption, the restricted use of environmentally harmful products, such as pesticides and fertilizers, and the limitation of other pollutants potentially released in the ecosystem (Volanti et al., 2022). Among the certifications considering sustainable viticultural practices, the certification of organic wine is considered the most widespread (Letamendi et al., 2022). In the European Union, this certification can be obtained if the vine grower complies with specific organic farming rules set forth by the European Parliament and Council Regulation

2018/848/EU. As compared to conventional management, organic viticulture management does not use synthetic products, such as fertilizers and pesticides, applies different soil tillage practices and leads to a different level of organic carbon sequestered in croplands (Ahrens et al., 2022). The wineries certified to sustainable organic viticulture tend to be perceived as realities with a generally beneficial impact on the environment compared to those adopting conventional viticulture (Baiano, 2021). The FAO has highlighted that both conventional and organic agriculture are key models to address global warming (FAO, 2007). The question arises as to whether conventional and organic viticulture has an impact in terms of GHG emissions. Some authors have highlighted that organic practices may not necessarily lead to a reduction in CF values compared to conventional ones. The lower yields, the possible increase in the consumption of fuels necessary for the greater number of phytosanitary treatments, the need of adopting mechanical weeding, the high number of soil management interventions (Litskas et al., 2020) and the transport of a large amount of manure and organic fertilizers could generate higher GHG emissions than conventional farming (Venkat, 2012). Furthermore, a number of studies have shown that conventional systems maximizing productivity have a reduced environmental impact according to several indicators, including the CF (Korsaeth, 2008).

The current literature shows little knowledge of the real differences in the amount of greenhouse gas emissions in the organic versus conventional management of vineyards. It emerges the need for an environmental assessment that takes into account the distinctive features of the two systems, based on a large sample of wineries with different characteristics over several years. This paper aims to obtain a comparative overview of organic and conventional vineyard management, focusing on the main categories of carbon dioxide emissions. The approach used is the corporate carbon footprint, involving 25 wineries in northern Italy over nine different vintages. The numerosity of the dataset of the present study, both in terms of wineries and in terms of years, allows obtaining a real comparison on the effects of organic and conventional viticulture strategies over the long term.

Materials and Methods

Geographical location and years of study

Table 2.1 *Information about vineyard areas per: number of case studies involved, years of data collection, management system and administrative region.*

Administrative Region	Management	Years of data collection	Number of case studies	Vineyard surface area (ha)	
				Mean	[min; max]
Friuli-Venezia Giulia	CONV	2012, 2013, 2015, 2017	4	69.31	[38.85; 83.65]
Lombardy	ORG	2009, 2010, 2011, 2014, 2015, 2016, 2017	9	49.24	[3.41; 84.65]
	CONV	2009, 2010, 2011, 2012, 2013, 2014, 2016	34	57.37	[9.22; 180.63]
Piedmont	CONV	2010	1	93.01	[93.01; 93.01]
Veneto	ORG	2012, 2013	2	17.19	[17.18; 17.19]
Overall			50	55.96	[3.41; 180.63]

The study involved 25 wineries, located in four administrative regions of northern Italy. Six wineries adopting organic management practices (ORG) were certified according to EU Regulation 2018/848, or, while not certified, did not use synthetic products in plant protection, weed management, fertilization, or other practices. Nineteen wineries were conventionally managed (CONV), so they used synthetic products for at least one phase of grape production. The data collected refers to the 2009-2017 years. A case study represents the overall data collected in one year in one farm. For the years 2009, 2010, 2011, 2014 and 2016, it was possible to collect more case studies for both management systems. Table 2.1 shows the administrative

regions, the years and the average vineyard surface area managed, with maximum and minimum values, by each winery available for CONV and ORG for the number of case studies.

System boundaries and description of viticultural practices

Figure 2.1 describes the processes associated with organic and conventional vineyard management. According to specific European Parliament and Council rules on organic agriculture (Regulation 2018/848/EU), ORG differs from CONV in a number of agronomic aspects: i) control of weeds and pests is allowed only with the application of mechanical and physical methods, ii) the exclusive use of natural or natural-derived substances, such as organic or mineral low-solubility fertilizers, iii) the exclusive use of natural or mineral products for pest control, such as sulfur and copper for fungal treatments and plant-extracted pyrethrins. for insecticide treatments with specific restrictions (EC, 2021; EP, EC, 2018). In this study, a cradle-to-gate approach is adopted, therefore the system boundaries include all the main sources of GHG emissions during the production processes (in accordance with ISO 14064, 2018). The production process was considered from post-harvest operations to the delivery of the following year's grapes to the winery, regardless of the post-agricultural life cycle stages, as described in Figure 2.1.

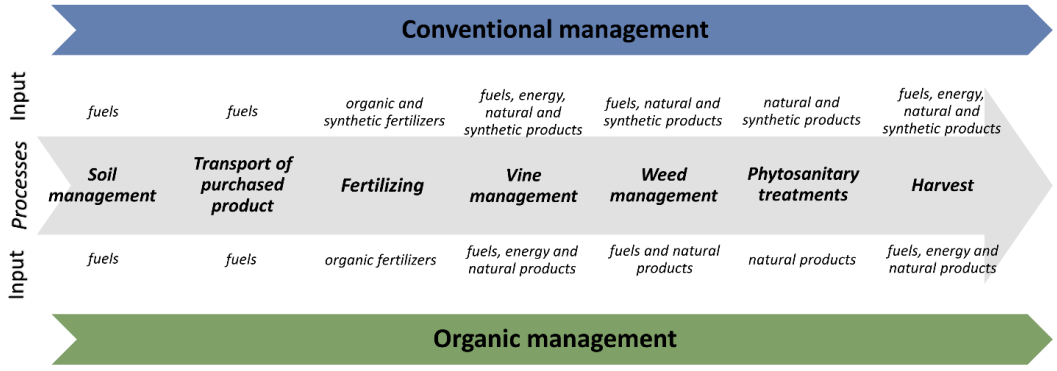


Figure 2.1 *Description of the grape production system, processes, and inputs in conventional and organic management.*

All inputs related to the stages of grape production shown in Figure 1 were included. According to other studies (Villanueva-Rey et al., 2014), co-products from grape production (e.g. pruning waste) do not fall within the production system boundaries.

Regarding direct emissions, this study did not consider specific mechanical soil cultivation, due to the lack of information on each individual vineyard. Indirect GHG emissions from machinery, infrastructure (including vineyard planting) and vehicles were excluded because they were considered negligible compared to the overall impact (D'Ammaro et al., 2021). Emissions generated from waste management were also considered negligible as, unlike wine-making or bottling operations, they are not relevant during grape production (ANPA, 2001). No complete data was available on irrigation water and energy required by the pumps for vineyard irrigation; therefore, these sources of emissions were neglected. The vine nursery phase was also excluded from the study considering that the average number of vines replaced on an annual basis is low (Villanueva-Rey et al., 2014).

Primary data acquisition

A survey was prepared and submitted to wineries in order to obtain the primary data necessary for CF calculation: type of management (conventional/organic), total vineyard surface area managed (ha), type and quantity of fertilizers consumed, type and quantity of pesticides consumed, transport of purchased products, fuel consumption of vehicles owned by the winery, rented, or owned by agricultural contractors. Data on fuel consumptions related to the use of farming machinery owned by the winery or agricultural contractors were collected directly as the amount of fuel consumed (e.g., kilos of diesel and petrol); whereas fuel consumptions related to the use of vehicles for other activities, such as off-road vehicles, were collected as mileage traveled. For fuel consumption, aggregate data from the use of tractors and other vehicles were considered without separation in single operation. As envisaged in the latest version of the ISO 14064 standard, the transport of the purchased products was calculated by determining the weight of the products and the mileage covered upstream of the supply chain. Workers' commuting trips were not considered due to lack of data. The amount of specific active principle was collected for the mineral or synthetic fertilizers, pesticides, and herbicides. The concentration stated on the label was used to determine the amount in kg of nitrogen contained in synthetic fertilizers. In the case of organic fertilizers (e.g. manure, compost, solid fraction of digestate), the nitrogen content was

determined using data on organic matrices collected in several Italian geographical areas during the LIFE VITISOM Project (Valenti et al., 2019).

Corporate carbon footprint method

Table 2.2 Breakdown of primary data and sources of emission factors used (EFs).

Categories according to ISO 14064	Subcategories according to ISO 14064	Entries	Emission factor sources
Direct GHG emissions	Direct emissions from mobile combustion	Fuels for field operations, Fuels for other vehicles	DEFRA - Department for Environment, Food Rural Affairs, 2021
	Direct fugitive emissions arising from the release of GHGs in anthropogenic systems	Synthetic fertilizing Organic fertilizing (manure, compost, digestate)	For nitrous oxide emissions from fertilizing: Joint Research Centre (JRC), the European Commission's science and knowledge service provides scientific evidence throughout the whole policy cycle. (Zampori and Pant, 2019a) For carbon dioxide emissions from urea use: Intergovernmental Panel on climate Change (IPCC, 2019, 2006)
Indirect GHG emissions from transportation	Indirect emissions from upstream transport for goods	Transport of purchased goods	DEFRA - Department for Environment, Food Rural Affairs, 2021
Indirect GHG emissions from products and services used by organization	Indirect emissions from purchased goods, which are associated with product manufacturing activities	Synthetic fertilizers Organic fertilizers, Fungicides, Herbicides, Insecticides	ADEME's Bilan Carbone database, ADEME 2020 The ecoinvent database (Frischknecht and Rebitzer, 2005)
	Indirect emissions from mobile combustion	Fuels for rental or non-owned vehicles Fuels for agricultural contractors.	DEFRA - Department of the Environment, Food Rural Affairs, 2021

Primary data were aggregated and classified into three categories and five subcategories according to ISO 14064:2018. A total of twelve entries were defined

based on data collected from questionnaires submitted to wineries (Table 2.2). Starting from the wineries' primary data, the corporate CF was determined adopting Ita.Ca.® (Italian Wine Carbon Calculator), a tool for calculating greenhouse gas emissions specifically for the Italian wine sector. Ita.Ca ® protocol is based on the OIV-GHG (Organisation Internationale de la Vigne et du Vin-Greenhouse Gas) emissions calculator, which is publicly available (on the OIV website) and built on the International Wine Carbon Calculator (IWCC) guidance (Corbo et al., 2014). In addition, the Ita.Ca ® carbon calculator complies with ISO14064 standard (ISO 14064, 2018). The carbon footprint can be quantified using the following equation: $CF = \Sigma\ (Pd_i \cdot EF_i)$ where $\boldsymbol{Pd_i}$ is the *primary datum* quantifying a *specific process* ***(i)*** and $\boldsymbol{EF_i}$ is the *emission factor* of the *specific process* ***(i).***

Ita.Ca.® provides the use of specific Emission Factors (EFs) derived from the main LCA databases, including the UK Department for Environment, Food and Rural Affairs (DEFRA, 2022), French ADEME, Agence de l'environnement et de la maîtrise de l'énergie, Bilan Carbone database (ADEME, 2020), and Ecoinvent database, as well as publications of the Joint Research Centre (JRC), the European Commission's science and knowledge service and the Intergovernmental Panel on Climate Change (IPCC). An example of emission computation with Ita.Ca ® is shown in Figure S1 of Supplementary Materials.

The adoption of different databases allows to increase accuracy and specificity of emission factors (Rugani et al., 2013). In Table 2, EFs used for direct emissions from the use of vehicle fuels include indirect emissions related to the production and transportation of fuels. A specific EF has been used for each type of fuel or vehicle (e.g., diesel, LPG, petrol), derived by DEFRA (2022). In case of plant protection products, specific EFs found in the Ecoinvent, and Bilan Carbone databases were used, when available, otherwise an average EF value was applied. For herbicides, the glyphosate emission factor was used (Ponstein et al., 2019). In the case of urea, it was considered that during fertilizing, CO_2 is also released into the atmosphere in addition to N_2O emissions (IPCC, 2006). The allocation of the environmental impact of organic fertilizers can be a controversial issue in agricultural systems (Villanueva-Rey et al., 2014; Vázquez-Rowe et al., 2012; Luo

et al., 2009). As to manure, digestate and the waste from other production systems, the approach proposed by several author was adopted, which only includes the impact directly related to viticultural practices, such as the transport and direct fertilizing concerning the release into the atmosphere of GHGs, such as nitrous oxide, into the atmosphere (Bathia et al., 2011; D'Ammaro et al., 2021; Navarro et al., 2017b). As indicated by Zampori and Pant (Zampori and Pant, 2019b), N_2O direct and indirect emissions must be estimated taking into account 0.022 kg of N_2O emitted into the atmosphere for each kg of synthetic N fertilizer and organic fertilizer applied.

Data analysis

An Analysis of Variance (ANOVA) was conducted to assess whether the total impact per hectare differed significantly between the two types of management, CONV and ORG. The relevance of the crop years was also tested given that different agronomic practices may have been adopted due to climatic conditions and pest pressure. Therefore, the effects of management and winery, management, and year (two-way ANOVA) and the combination of management, winery, and year (three-way ANOVA) were tested (function aov and TukeyHSD, R software). The second stage of analysis focused on the difference between the CF of direct and indirect emission subcategories according to management type. The non-parametric Wilcoxon rank sum test for two independent groups of samples was used (function Wilcox. Test, R software).

Results

Inventory data for vineyard inputs

Table 2.3. shows the mean, standard deviation, minimum and maximum values obtained for the key inputs in vineyard according to the management systems (ORG or CONV).

Table 2.3 Mean, standard deviation (SD), minimum and maximum values of vineyard inputs by surface area (ha) in organic and conventional vineyards. (a.s.): active substance.

Vineyard inputs	**Organic**		**Conventional**	
	Mean (± SD)	**[min; max]**	**Mean (± SD)**	**[min; max]**
Fuels for field work (kg ha^{-1})	324.31 (± 97.44)	[216.44; 475.32]	237.1 (± 125.12)	[0; 500.81]
Fuel for other vehicles (km ha^{-1})	169.22 (± 197.45)	[0; 459.28]	139.14 (± 221.24)	[0; 693.86]
Manure (q ha^{-1})	3659.09 (± 6115.74)	[0; 16738.65]	2098.3 (± 3456.63)	[0; 13731.48]
Compost (q ha^{-1})	562.33 (± 1735.34)	[0; 5781.81]	78.62 (± 361.03)	[0; 2029.78]
Nitrous-based fertilizers (kg N ha^{-1})	-	-	8.07 (± 15.15)	[0; 72.59]
Urea-based synthetic fertilizers (kg ha^{-1})	-	-	5.99 (± 10)	[0; 45.08]
Phospho-potassium fertilizers and others (kg a.s. ha^{-1})	-	-	20.43 (± 23.81)	[0; 167.72]
Sulphur-based fungicides (kg a.s. ha^{-1})	125.07 (± 65.92)	[38.16; 225.39]	47.63 (± 48.94)	[0; 210.06]
Copper-based fungicides (kg a.s. ha^{-1})	4.66 (± 0.86)	[3.68; 5.76]	3.43 (± 2.75)	[0; 10.44]
Unspecific fungicides (kg a.s. ha^{-1})	-	-	9.84 (± 20.05)	[0; 116.31]
Herbicides (kg a.s. ha^{-1})	-	-	0.73 (± 0.88)	[0; 3.38]
Insecticides (kg a.s. ha^{-1})	-	-	0.46 (± 0.46)	[0; 2.05]
Natural insecticides (kg a.s. ha^{-1})	0.59 (± 1.17)	[0; 3.92]	0.25 (± 0.62)	[0; 2.43]
Fuels for rental or non-owned vehicles (km ha^{-1})	21.32 (± 28.38)	[0; 73.99]	2.37 (± 7.72)	[0; 37.02]
Fuels for agricultural contractors (kg ha^{-1})	238.91 (± 534.52)	[0; 1440.00]	1213.02 (± 2596.32)	[0; 9489.15]

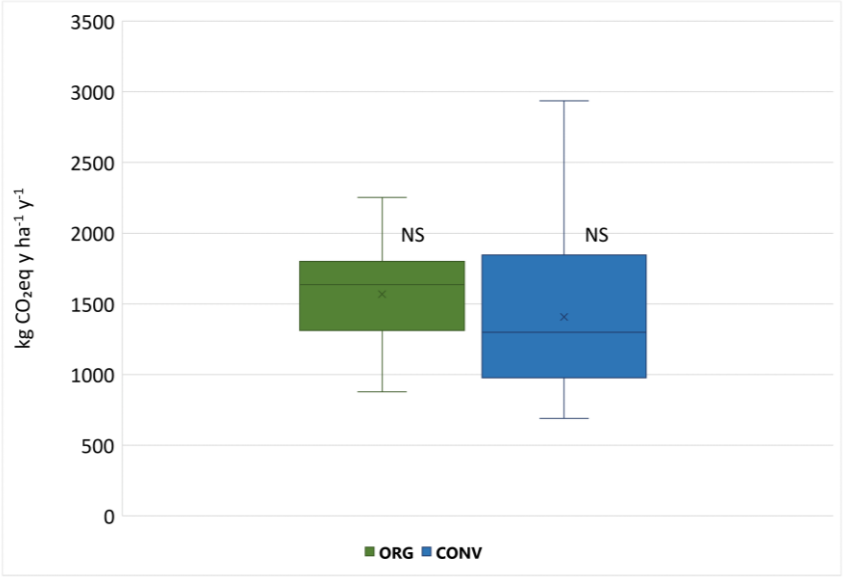
Inputs for fertilizers, fungicides, insecticides, and herbicides are reported as active substances. Some inputs considered in categories of fertilizers, fungicides, herbicides, and insecticides are not considered in the case of ORG system (-) because they cannot be used in organic agriculture based on the specific rules and regulations set forth by the European Parliament and Council Regulation 2018/848/EU. The minimum value recorded in case of fuels (direct and indirect emissions) is zero because some wineries carry out farming operations using owned vehicles only (direct emissions) or, conversely, using only rented or farm contractor vehicles only (indirect emissions).

Overall organic and conventional viticulture carbon footprint results

As shown in Table 2.4, the overall emissions from the wineries considered range between 690.39 and 2937.03 kg CO_2-eq ha^{-1} y^{-1}. The median carbon footprint is 1408.34 and 1568.77 kg CO_2-eq ha^{-1} y^{-1} for CONV and ORG wineries, respectively. Data analysis (Figure 2.2) reveals a high variability of data in the ORG system, even higher in the CONV system. The mean values of the overall impacts in the CONV and ORG systems show no significant differences. Comparison of mean values of overall impacts by management by single year also shows no significant differences, in any year of the study.

Table 2.4 Mean, standard deviation (SD), minimum and maximum estimates of overall GHG emissions (kg CO_2-eq ha^{-1} y^{-1}) in ORG and CONV wineries.

Management	**GHG emissions Mean (± SD)**	**GHG emissions [min/max]**
ORG	1568.77 (± 396.80)	[876.99; 2253.34]
CONV	1408.34 (± 535.27)	[690.39; 2937.03]
ALL	1443.63 (± 508.76)	[690.39; 2937.03]



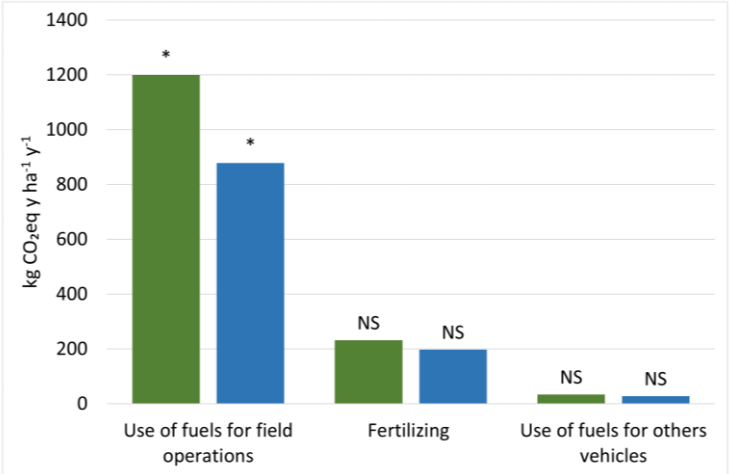
**** p-value < 0.001; ** p-value < 0.01; * p-value < 0.05; NS not significant.*

Figure 2.2 Box plots showing variability of CFs in ORG and CONV systems and the results obtained by ANOVA analysis: NS not significant differences.

3.3. Direct emissions in organic and conventional management

As shown in Figure 2.3, emissions from "Use of fuels for field operations" show a high range of variability. This category represents the main contribution to direct emissions for both ORG and CONV systems, with a mean value of 1199.48 kg CO_2-eq ha^{-1} y^{-1} in the case of organic management and 878.72 kg CO_2-eq ha^{-1} y^{-1} in the case of conventional management. Direct nitrogen emissions generated by fertilizer distribution (Fertilizing) show an overall average value of 205.42 kg CO_2-eq ha^{-1} y^{-1}; these emissions together with the consumption of fuels represent the greatest contribution to the value of direct emissions.

In Figure 2.3, the category "Use of fuels for field operations" refers to emissions from the use of own agricultural machinery; while the category "Use of fuels for other vehicles" refers to cars and vehicles, other than own agricultural machinery. The emissions due to "Use of fuels for field operations" resulted statistically significant (p-value <0.01) between ORG and CONV, while not statistically significance is detected for Fertilizing and Use of fuels for other vehicles (Figure 2.3).



	Mean (± SD)	[min/max]	Mean (± SD)	[min/max]	Mean (± SD)	[min/max]
ORG	**1199.48** (± 361.55)	[798.61; 1755.37]	**232.27** (± 39.74)	[0; 877.78]	**34.22** (± 318.82)	[0; 91.17]
CONV	**878.72** (± 463.09)	[0; 1867.9]	**197.84** (± 203.24)	[0; 859.5]	**28.28** (± 45.27)	[0; 142.34]

**** p-value < 0.001; ** p-value < 0.01; * p-value < 0.05; NS not significant.*

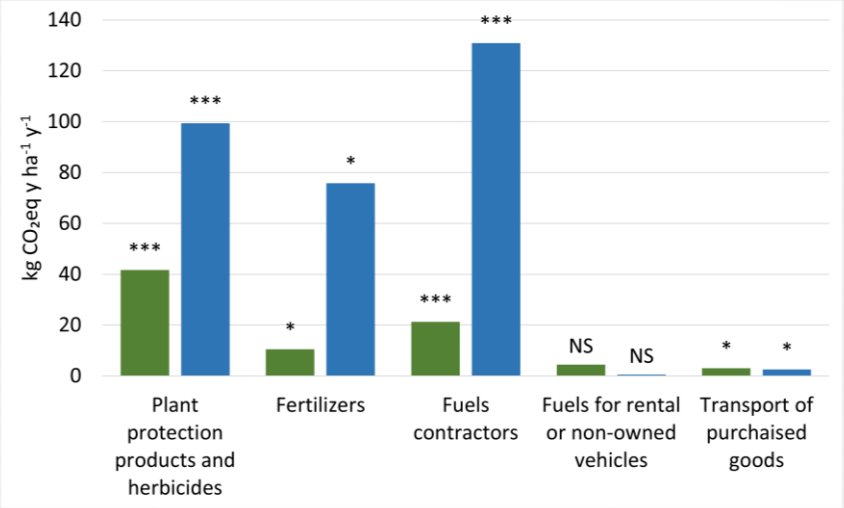
Figure 2.3 Results comparing ORG and CONV systems in terms of direct emissions

3.4. Indirect emissions in organic and conventional management

Under the categories “Fertilizers” and “Plant protection products and herbicides” indirect emissions (Figure 4) in CONV where higher than those in ORG. The lower value in the “Fertilizers” category for ORG vs CONV is due to the exclusion of indirect emissions for manure and digestate, whose production emissions are excluded as waste from other production systems. Emissions from the transport of goods purchased account for less than 1% of overall indirect emissions, both in CONV and ORG systems.

Wilcoxon test (Figure 2.4) confirmed the existence of statistically significant differences between CONV and ORG. The indirect emissions due to Fertilizers, Plant protection products and herbicides, and Fuels for contractors in CONV are higher than those associated with ORG (p-values < 0.01, < 0.001, < 0.001, respectively).

Indirect emissions from transport of goods purchased are higher for the ORG system (p-value < 0.001). No significant differences are found for "Fuels for rental or not-owned vehicles”.



	Plant protection products and herbicides		Fertilizers		Fuels contractors		Fuels for rental or non-owned vehicles		Transport of purchaised goods	
	Mean (± SD)	[min/ max]	Mean (± SD)	[min/ max]	Mean (± SD)	[min/ max]	Mean (± SD)	[min/ max]	Mean (± SD)	[min/ max]
ORG	**41.64** (± 14.5)	[22.74 ; 61.94]	**10.46** (± 21.98)	[0 ; 69.15]	**21.33** (± 47.72)	[0 ; 128.56]	**4.46** (± 5.85)	[0 ; 15.18]	**3.07**(± 1.74)	[0.62 ; 5.74]
CONV	**99.42** (± 121.14)	[16.25 ; 737.12]	**75.78** (± 81.94)	[0 ; 293.94]	**130.95** (± 265.33)	[0 ; 897.59]	0.53 (± 1.74)	[0 ; 8.63]	2.53 (± 3.6)	[0.01 ; 18.58]

**** p-value < 0.001; ** p-value < 0.01; * p-value < 0.05; NS not significant.*

Figure 2.4 Results comparing ORG and CONV systems in terms of indirect emissions.

Discussion

Overall GHG emissions. In this study, the overall mean value of corporate CF is 1443.63 kg CO_2-eq ha^{-1} y^{-1}. For ORG the mean value is 1568.77 kg CO_2-eq ha^{-1} y^{-1}, while for CONV the mean value is 1408.34 of kg CO_2-eq ha^{-1} y^{-1}. High variability was observed with corporate results ranging from 690.39 to 2937.03 kg CO_2-eq ha^{-1} y^{-1}. No statistically significant difference was found probably also due to the high heterogeneity of company CF estimated within each management system. In a winery in the North-East of Italy, Borsato et al. (2020) a study involving an organically-managed vineyard and a conventionally-managed one shows a greater emission of greenhouse gases for the conventional vineyard, about 2534 kg CO_2-eq ha^{-1} y^{-1} versus 1827 kg CO_2-eq ha^{-1} y^{-1} in organic vineyard. Different values were found by Volanti et al., 2022,(Volanti et al., 2022) who, in a study involving three Spanish wineries using different management systems, estimated a CF ranging 57.4 to 289.3 kg CO_2-eq ha^{-1} y^{-1} for ORG and 438.3 to 481.0 kg CO_2-eq ha^{-1} y^{-1} for CONV wineries. Average values similar to those presented here, have been found by Renaud-Gentié et al., 2020, (Renaud- Gentié et al., 2020) who, in a multi-year study conducted on 12 plots using different management systems, located in three different French wine-growing regions, found average CF values of about 1300 kg

CO_2-eq ha^{-1} y^{-1}. According to Tuomisto et al., 2012, (Tuomisto et al., 2012) ORG and CONV should be understood not as one viticulture system but rather as a set of different practices. Therefore, the level of greenhouse gas emissions depends more on the choice of winery management rather than the management system. Some ORG wineries may find low CF values as a result of minimal use of inputs, fertilizing based on the addition of organic soil improvers and the use of non-synthetic products with a low emission impact, as argued by Reganold and Wachter (2016). Similarly, some CONV wineries may find lower CF values to optimize energy inputs and fertilize not only synthetic products but also organic soil improvers.

Direct GHG emissions. The contribution of the category "Use of fuels for field operations", with an average value of 1199.48 kg CO_2-eq ha^{-1} y^{-1} accounts for 79.69% of the main emissions in the case of ORG systems, while it accounts for 61.99% in CONV systems, with an average value of 878.72 kg CO_2-eq ha^{-1} y^{-1}. (Figure 2.5). As noted by Gierling et al. (2021), due to fossil fuels, the impact is particularly relevant within the carbon footprint of grape production. This is infact a consequence of the mechanization. Also Rouault et al., (2016) in a study comparing the organic and conventional system in a Chenin Blanc vineyard in the Loire Valley, noted that the major carbon footprint impact in both management systems is due to fuel consumption, especially for plant protection treatments and soil management operations. The high contribution of “Fuels for field operations” to corporate CF is confirmed also by other studies. In a research involving 14 grape producers from four German administrative regions, Ponstein et al. (2019) observed the higher incidence of this category, with an average value of 565.59 kg CO_2-eq ha^{-1} y^{-1}, compared to the overall emissions. Litskas et al. (2020) analyzed three different vineyards in Cyprus, with high or low conventional input and organic management, and observed a higher incidence of emissions from fuel consumption in ORG systems than from other factors, which is in line with what has emerged in this paper. Increased fuel consumption in ORG systems vs CONV systems can be expected in relation to the high number of tractor transits in ORG systems (Litskas et al., 2020; Probst et al., 2008). In fact, non-synthetic copper-based fungicides are largely lost in foliar wash-off from vine leaves treated due to the action of rainfalls

(Pérez-Rodríguez et al., 2015), with the consequent need for numerous interventions in rainy periods and hence greater diesel consumption. Similarly, the non-use of herbicides entails the need for a greater number of tillage operations, such as hoeing and mowing, for mechanical weed control (Rouault et al., 2016). Direct emissions of nitrous oxide and carbon dioxide into the atmosphere during "Fertilizing" did not reveal any significant differences between the CONV and ORG systems. For both operations, some companies recorded zero emissions for lack of fertilizing in the study year. In accordance with the results of Venkat (2012), which compared 12 agricultural products, including wine grapes grown in California with ORG and CONV management systems, direct emissions for fertilizing are similar for both systems, where CONV wineries limit the use of synthetic fertilizers. As required by the legislation on organic farming, emissions related to synthetic fertilizing only concern CONV wineries when using synthetic fertilizers such as urea. For this reason, in ORG systems, the contribution of organic carbon is generally higher than that of CONV systems. Although the direct emissions from organic fertilizing are significant, it would be interesting to deepen the environmental benefits deriving from the use of these matrices, such as the improvement of the chemical-physical structure of the soil, the stimulation of the soil microbiota (Fregoni, 1999, p. 629), and the natural sequestration and maintenance of soil carbon stock (Brunori et al., 2016; Patinha et al., 2018). Furthermore, it is to be considered that unlike synthetic fertilizers produced specifically for agricultural fertilizing, organic fertilizers, which are often waste products from other activities, would still have an environmental impact.

Indirect GHG emissions. In CONV wineries the amount of indirect emissions due to "Fertilizers" and "Plant protection products and herbicides" is higher than that in ORG wineries (Figure 5). A total of 99.42 kg CO_2-eq ha^{-1} y^{-1} indirect emissions from "Pesticides and herbicides" were estimated on average in the CONV compared to 41.64 kg CO_2-eq ha^{-1} y^{-1} in the ORG; while the average estimated emissions due to "Fertilizers" in CONV is 75.78 kg CO_2-eq ha^{-1} y^{-1}, which more than 7 times the value measured in the ORG (10.46 kg CO_2-eq ha^{-1} y^{-1}). As observed by Cech et al. (2022), in the case of CONV systems, due to the production of pesticides (fungicides, herbicides and insecticides), the impact is overall greater than that of

fertilizers, also for use, in the case of some CONV systems, of organic fertilizers. Our estimates are consistent with the results measured by Chiriacò et al., 2019, (2019) The authors assessing the GHG balance in an organic winery in the Lazio administrative region (Central Italy) found that organic wineries can state emissions for the category "Plant protection products" lower than 10 kg CO_2-eq ha^{-1} y^{-1}, due to the non-use of synthetic products. In the Global Warming category, also Volanti et al., (2022) found a significant impact of conventional farming as the result of the use of fertilizers and synthetic products as herbicides. Synthetic fertilizers, pesticides and herbicides are key inputs in CONV systems; by contrast, ORG systems are based on the use of natural mineral or organic substances, generating less indirect emissions (Briar et al., 2007).

Regarding the differences highlighted in the "Fuels for contractors" category, where high values were found in CONV cellars, it is important to note that, although they are divided, these emissions are similar to fuel consumption for field operations. In fact, if the winery did not employ contractors, it would be required to directly manage the operations in the field. This category depends very much on the strategic choices and the winery's specific characteristics; indeed, equipment cost and size as well as the rapid pace of technological innovation all affect the choice of whether to use contractors, especially in small and medium-sized farms (Nye, 2020).

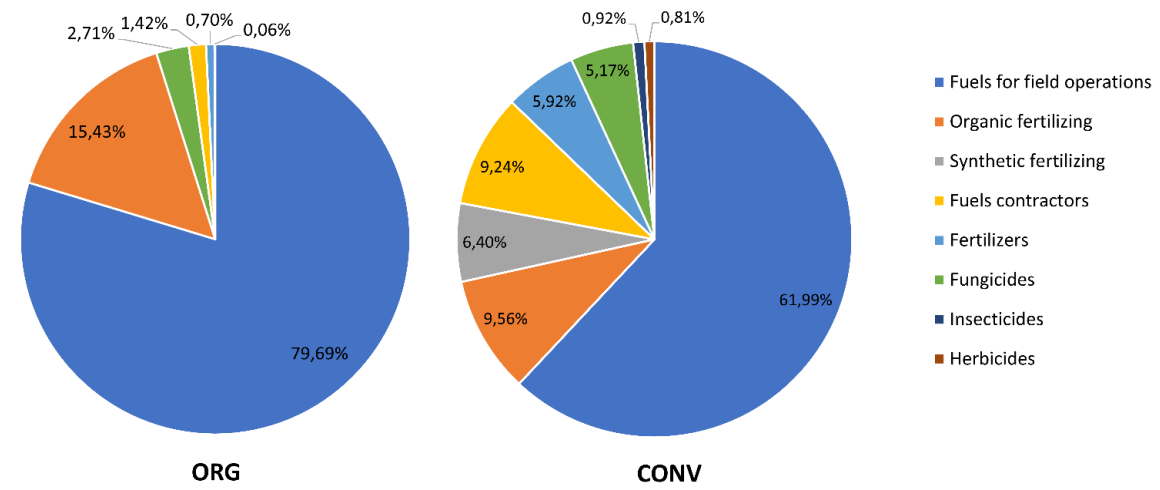


Figure 2.5 Contributions of the emission categories in ORG and CONV management.

Conclusions

In conclusion, the study of 25 wineries, including 19 CONV and 6 ORG, in several years of harvesting, did not reveal statistically significant differences between the overall CF of ORG and CONV wineries. The extent of the dataset made it possible to highlight the differences in impact of each category within the two systems. In relation to the total amount of GHG emissions, beyond the management system (ORG or CONV), a specific management approach is to be considered depending on each winery's characteristics and production strategies. A management approach encompassing the agricultural technical specifications according to the characteristics of the winery is more effective in mitigating corporate emissions. In both management systems, the greatest impact is due to fuel consumption for field operations, which suggests precise monitoring of fuel consumption in order to optimize management strategies. This is particularly relevant in ORG systems due to a high number of plant protection treatments and mechanical weed control. Nitrogen fertilizing has an important impact on CF, both in ORG and CONV systems, mainly in relation to the release of nitrous oxide into the atmosphere. Organic fertilizing, which is more common in ORG vineyards, should also be considered as a mitigation action contributing to the increase of naturally fixed carbon stock into the soil. The integration of organic carbon sequestration in the CF analysis can consequently lead to a more complete comparison of ORG and CONV systems. As already explore by Abad et al. (Abad et al., 2021), another aspect that can be explore in future study is the potential effect of the use of cover crops in the vineyard. Considering indirect emissions, synthetic products have a greater impact in terms of greenhouse gas emissions, although these emissions have a low share overall. From what has been observed with respect to the main GHG emissions, it is possible to adopt some mitigation strategies for both management systems: i) innovation in technology introducing agricultural machineries with a greater efficiency in fuel consumption, ii) reduce the number of interventions in the field, reducing the depth of soil tillage (Navarro et al., 2017b), iii) optimize the number of treatments based on weather conditions and previous fungal infections (Mian et al., 2021).

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3. Water

3.1. Integrated assessment of water footprint in nonirrigated vineyards

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Abstract

The topic of sustainable water management has become of paramount importance at a global level, especially when considering the high- amount of water used in agriculture, which is a threat to water resource balance. Focused on 38 inventories of nonirrigated vineyard management in the Franciacorta wine-growing region in Italy, this study aims to understand how agronomic practices impact water resources. The integrated statistical approach, based on generalized linear models, reveals how context variables influence different water footprint indicators, such as water scarcity, acidification and freshwater ecotoxicity. Plant density and the presence of hillside vineyards are the primary influencing factors, while others, such as variety susceptibility, vineyard age and soil type may influence the shortage of water. The outcomes help to better understand the impact of management, thereby raising awareness in the wine sector about aspects often overlooked in traditional investigations. These findings offer specific insights for viticulturists, emphasizing the importance of a tailored management approach to minimize water footprint in viticultural practices and contribute to environmental sustainability.

Introduction

The topic and critical issues related to sustainable water management have become central within the global debate across various areas: industry, economy, politics and society (OIV, 2021). Sustainable water management entails the responsible and efficient use, conservation and protection of water resources to meet present and future needs without jeopardizing water availability for future generations (FAO, 2015). In this context, multiple indicators have been developed over time to assess the impact of production on water resources, starting with the water footprint. The

concept of water footprint was first introduced in 2011 by Hoekstra and was realized through the Water Footprint Assessment (WFA) method. The water footprint of a product or a process encompasses the direct and indirect volume of water used throughout various stages of the production chain and the resulting pollution (Hoekstra, 2011). Subsequently, a new water footprint framework for was proposed by the Water Use in Life Cycle Assessment research group, leading to the development of a method for the midpoint of water scarcity for use in Life Cycle Assessment (LCA). This LCA-based water footprint incorporates the quantification of water impacts related to freshwater use in terms of water availability footprint, water scarcity footprint and water quality in terms of ecotoxicity, eutrophication and acidification (Borsato et al., 2019). In 2014, the ISO 14046 standard defined the specifications for calculating the water footprint, incorporating the use of the LCA methodology (ISO, 2014). Among the various sectors of application of the ISO 14046, the agro-industrial sector remains one of the most relevant as high water consumption in food production poses a threat to the balance of water resources in many basins (Taheri et al., 2019). As an example, the agricultural phase associated to food production contributes to eutrophication by releasing phosphorus into terrestrial runoff, which can account for between 25% and 75% of the total annual phosphorus loads in the waters of the European Union (Withers and Haygarth, 2007). Many sectors of agro-industry have been studied in terms of water footprint using the LCA-based approach (Roy et al., 2009). However, the wine industry, also due to its economic importance, is recognized as a relevant sector in relation to environmental sustainability issues (Bandinelli et al., 2020; Recchia et al., 2018). Wine ranks high among plant-based products in terms of its contribution to the environmental impact of EU food consumption, mainly concerning freshwater ecotoxicity, water use and water consumption (García-Herrero et al., 2023). Wine producers recognize the importance of preserving natural resources and minimizing the ecological footprint of their production (Corbo et al., 2014). Actually, the use of water during the winemaking process and vineyard management has a significant impact on water scarcity, especially in high water stress areas (Merli et al., 2018), even though grapevines may be considered drought-resistant plants that do not necessarily require irrigation[12]. Considering vineyard management, the

environmental impact on water resources remains relevant and is influenced by various factors that affect the entire vineyard management process. The decisions taken during the initial planting phase, including such choices as variety selection, as well as agronomic practices such as fertilization and pest control entail implications for water use and its potential environmental impact. Practices such as plant protection treatments and fertilization can lead to pollution of nearby water bodies and aquifers. Specifically, wastewater in vineyards primarily originates from these agricultural operations, generating runoff that is often laden with nutrients, chemicals, and organic residues, which can contaminate adjacent water resources. The use of chemicals for vineyard protection is the largest contributor to water contamination in the viticulture sector. (Borsato et al., 2019) Non-synthetic plant protection products can reduce risks related to ecotoxicity of active ingredients while potentially increasing plant protection treatments and thus fuel consumption, especially in rainy years due to their washable nature (Ghiglieno et al., 2023). The use of nitrogen and phosphorous fertilizers contributes to eutrophication and acidification impact categories (Ivanova, 2019). The use of nitrogen fertilizer can also result in water acidification due to ammonia emissions (Litskas et al., 2020) as nitrogen fertilizers are the major contributors to acidification in viticulture (Point et al., 2012). Fuel consumption from machinery use and pesticide production significantly contributes to freshwater acidification (Castellani and Sala, 2012). This issue is compounded by soil erosion from agricultural fields, which leads to sedimentation in streams, thereby reducing water quality and compromising aquatic habitats (Point et al., 2012). Furthermore, the conversion of natural landscapes into farmland exacerbates these problems by resulting in the loss of wetlands and biodiversity, which further negatively impacts aquatic ecosystems (Broome and Warner, 2008). In addition to management, context variables such as vineyard characteristics, structure, pathogen pressure and vine susceptibility also play a significant role. Soil moisture content and structural characteristics can influence field surface conditions and, consequently, fuel consumption (Abbaspour-Gilandeh et al., 2006). The planting density could also have a significant impact on pesticide use and soil tillage (Fouillet et al., 2022). Vineyard slope can impact spatial variability of disease incidence and levels of susceptibility to fungal pathogens,

thereby affecting necessary phytosanitary treatments (Vélez et al., 2023). Considering and managing these factors effectively is crucial for sustainable water management in viticulture, thereby minimizing potential negative environmental impacts on water resources. To the best of our knowledge, there are currently no studies that comprehensively address the impacts on water resources in the viticultural context, considering management and context variables. Therefore, it is essential to evaluate the effect of viticultural management on water resources by integrating the impact of these context variables into the assessment. This will enhance the awareness of viticulturists, guiding them towards the adoption of more flexible and context-adaptive strategies. This case study began by analyzing 38 vineyard management inventories from 12 nonirrigated wineries in Franciacorta, north-eastern Italy, using an integrated approach to explore the interactions between agronomic and context variables and their influence on water resources. The study employed the LCA approach to calculate the water footprint, involving nonirrigated vineyards, with the aim of exploring the impact of other management practices on water resources in greater detail.

Materials and Methods

Contextualization and years of the study

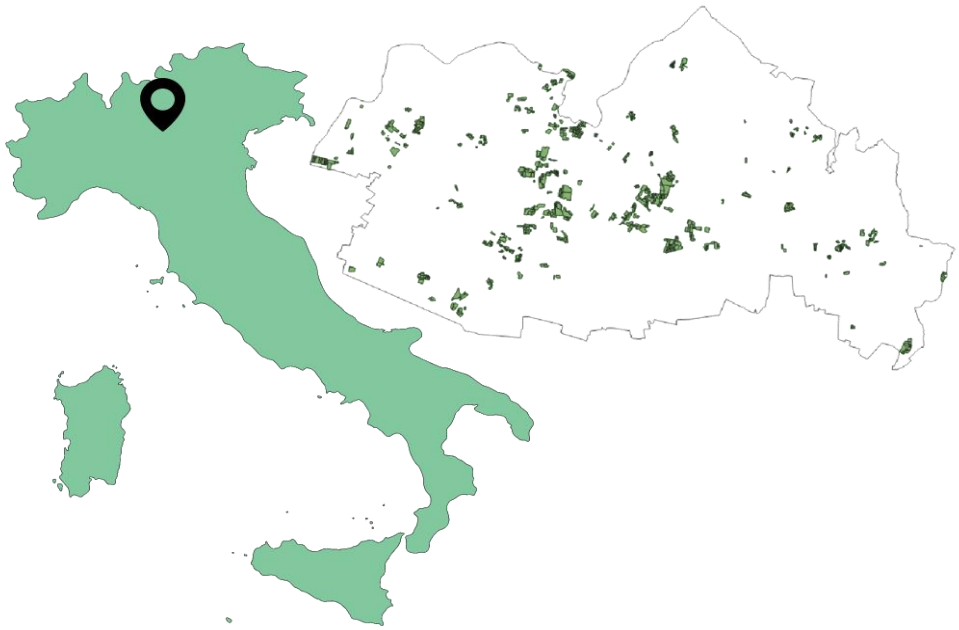


Figure 3.1 Winegrowing area of Franciacorta DOCG (Designation of Controlled and Guaranteed Origin) and georeferencing of the vineyards where inventory data were collected.

The case study encompasses 12 wineries located in Franciacorta, a prominent wine-producing region in northern Italy renowned for its sparkling wine production (Fig. 3.1). The collected data pertain to the timeframe spanning from 2009 to 2020.

Table 3.1 Number of case studies included in the study, years of data collection, grape production and vineyard surface area.

Years	Number of case studies	Grape production (kg)		Vineyard surface area (ha)	
		Mean	[min; max]	Mean	[min; max]
2009	3	613,571	[101,100; 1,353,731]	71.19	[23; 149.24]
2010	10	220,233	[44,150; 501,292]	43.29	[9.22; 149.24]
2011	6	661,205	[161,065; 1,528,257]	62.69	[15.58; 150.25]
2012	3	706,418	[245,900; 1,107,823]	86.96	[25.44; 150.78]
2013	3	767,849	[240,872; 1,194,264]	88.86	[25.44; 156.5]
2014	3	812,374	[247,357; 1,495,097]	90.36	[25.44; 160.98]
2015	2	1,167,957	[656,305; 1,679,610]	133.58	[84.65; 182.51]
2016	3	742,439	[161,111; 1,643,564]	96.44	[24.03; 180.63]
2017	1	229,814	[229,814; 229,814]	84.56	[84.56; 84.56]
2018	1	1,014,176	[1,014,176; 1,014,176]	84.56	[84.56; 84.56]
2019	2	445,736	[152,273; 739,200]	54.545	[24.53; 84.56]
2020	1	956,463	[956,463; 956,463]	84.57	[84.57; 84.57]

A case study includes all the data collected in one year from one winery. Table 3.1 displays the years, grape production and the overall vineyard area managed by each winery, as applicable to the number of case studies.

Climatic description and agrometeorological characterization

Franciacorta region falls under the Cfa classification according to the Köppen climate system (temperate climate, no dry season, hot summers). Referring to data from the Corte Franca weather station (45.633, 10.021, 220), the region recorded an average annual temperature of 14.7°C between 1997 and 2023. Annual precipitation amounts to 1140 mm, with 646 mm occurring during the vine growing season (GS), from April to September. Figure 3.2 shows a graph of cumulative precipitation during the GS (March-August) for the period under consideration. The graph also displays the average GS trend from 1997 to 2023, along with deviations of one and two times above and below the standard deviation for the period. The GS in 2010 and 2015 indicate, respectively, a high-rainfall year and a drought year compared to the average.

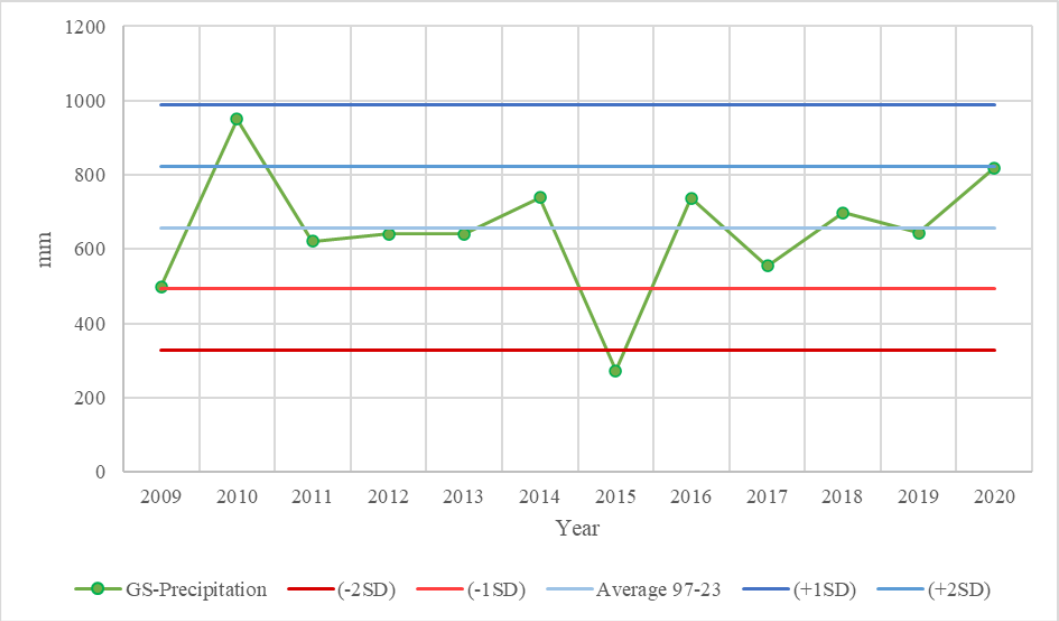


Figure 3.2 Graph of cumulative precipitation during the vine growing season (GS) for the period under consideration in the Franciacorta area, including the average GS trend from 1997 to 2023 and the standard deviation from the average.

Assessment framework and system boundaries

The assessment framework for the water footprint linked to grape production encompassed all viticultural activities within the system boundaries depicted in Fig. 3.3. By using a cradle-to-gate approach, this study included all major annual agronomic inputs that are essential for wine grape production. In agreement with other researches, the nursery stage and co-products related to grape production were not included within the system boundaries (Villanueva-Rey et al., 2018, 2014). As a result of data unavailability, information about machinery, infrastructure (including vineyard establishment) and vehicles was excluded. Information on

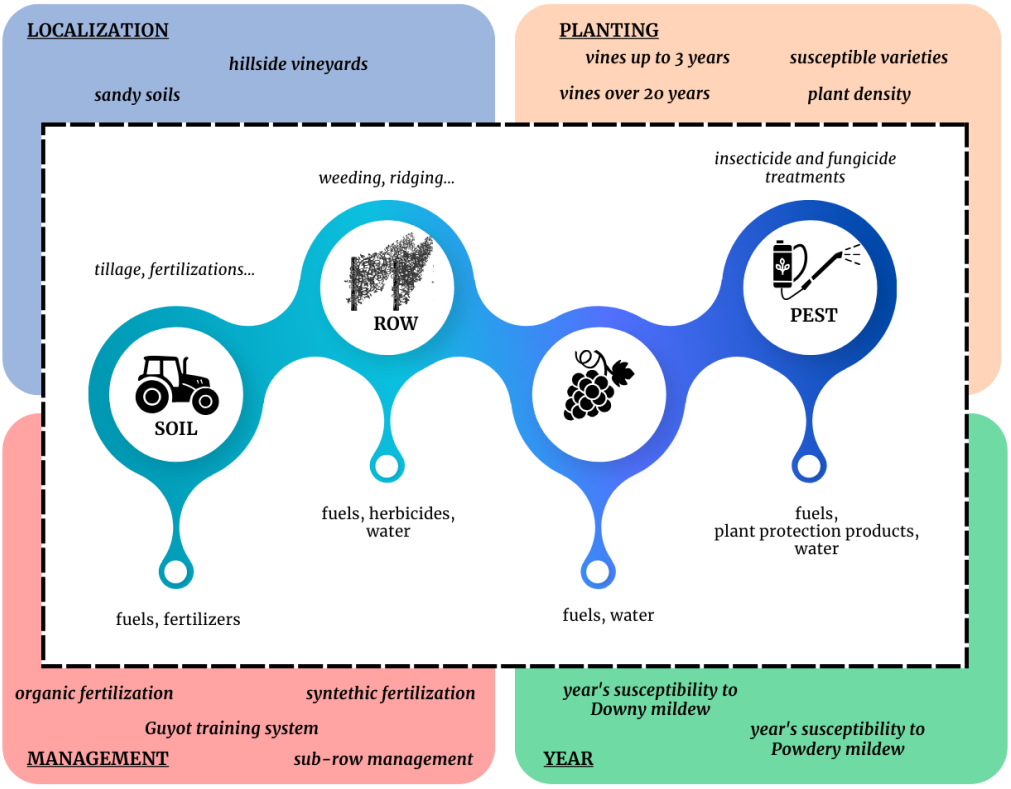


Figure 3.3 Assessment framework of the study on the impacts of viticulture on water resources. The centre shows grape production processes and the relevant inputs included within the system boundaries. The four colored boxes contain the context variables under consideration: Localization, Planting, Management and Year.

energy consumption was excluded, not being relevant in the context of the vineyard, given that, with no irrigation, there is no significant consumption from the system. The impact on waste management was excluded as it is deemed negligible in grape production (ANPA, 2001). The production area provides irrigation only in emergencies; therefore, the wineries in this study did not practice irrigation in their

vineyards. The direct use of water was limited to plant protection treatments, emergency irrigation operations, and young vineyards. Alongside the system boundaries, the assessment framework (Fig. 3.3) also includes such context variables as management, localization, planting and year, which were analyzed in relation to their influence on water resource impacts.

Data acquisition: inventories and context variables

For each case study, inventory data were collected to calculate the water footprint. These data included annual grape production (kg), the type and quantity of fertilizers, pesticides and herbicides used, the volume of water employed for phytosanitary treatments, the water supplied to young plants and the fuel consumption from vehicles owned by the winery or rented from agricultural subcontractors. Additionally, the data encompassed the total managed area (ha), planting years, cultivars, and vine pruning systems for each vineyard managed by the winery in the study year. All companies managed the inter-row space of the vineyard using permanent cover cropping. All primary inventory data are available in Supplementary File S1.

Table 3.2 Mean, standard deviation (SD), minimum and maximum values of vineyards. Active substance (AS).

Inventory data	Mean (±SD) [min; max]
Calcium ammonium nitrate (kg)	67.08 (±43.86) [36.00; 117.25]
Inorganic nitrogen fertilizer, AS N (kg)	1457.78 (±2622.52) [2.74; 8228.41]
Inorganic phosphorus fertilizer, AS P_2O5 (kg)	581.39 (±919.51) [4.10; 3162.00]
Inorganic potassium fertilizer, AS K_2O (kg)	929.80 (±1227.26) [8.20; 4556.00]
Manure (tons)	732.04 (±471.93) [569.00; 1573.00]
Single superphosphate (kg)	490.00 (±579.83) [80.00; 900.00]
Urea (kg)	1299.83 (±603.43) [690.00; 2116.00]
Benzimidazole-compound (kg AS)	13.09 (±5.33) [9.32; 16.86]
Copper (kg AS)	191.28 (±219.50) [2.3; 883.50]
Dithiocarbamate-compound (kg AS)	13.84 (±14.20) [2.10; 40.00]
Fosetyl-Al (kg AS)	297.55 (±295.43) [0.53; 960.45]
Fungicide unspecified (kg)	23.85 (±44.00) [0.03; 326.33]
Insecticide. unspecified (kg AS)	15.86 (±28.19) [0.16; 117.67]

Organophosphorus compound. unspecified (kg AS)	30.01 (±39.12) [0.45; 160.00]
Pyrethroid-compound (kg AS)	10.49 (±13.55) [0; 42.80]
Imidazole (kg AS)	24.38 (±9.37) [17.75; 31.00]
Mineral oil (kg)	65.25 (±92.70) [0; 330.40]
Sulfur (kg)	5136.07 (±5606.01) [246.25; 19079.51]
Sodium bicarbonate (kg)	478.18 (±51.29) [441.92; 514.45]
Fuels for field work (kg)	11860.81 (±20157.07) [0; 88316.28]
Fuel for other vehicles (km)	15497.24 (±40052.74) [0; 274080.00]
Glyphosate (kg)	60.99 (±63.26) [0.21; 189.95]
Herbicide unspecified (kg)	0.45 (±0.35) [0.08; 0.83]
Water for plant protection treatments (m3)	46.73 (±44.83) [5.93; 199.74]
Water for young vines or emergency irrigation (m3)	222.26 (±290.21) [56.00; 655.65]

The inventory structure also includes emissions to air and soil that impact water quality (ISO, 2014). Direct emissions to water, air and soil resulting from the use of plant protection products, fertilizers and fuels were determined as reported in Table 3.2.

Table 3.3 Direct emissions related to the input and the source generating them.

Input category	Emission	Sources
Synthetic and organic fertilizers in water, air and soil	Dinitrogen monoxide Ammonia Nitrate Phosphate	Nitrogen emissions to air and water, phosphate leachates and run-offs were computed using the emission factors proposed by Zampori and Pant, 2019. In the case of organic fertilizers, the content of nitrogen and phosphates was determined using data from organic matrices collected in the Franciacorta study area during the LIFE VITISOM Project (Valenti et al., 2019).
Fuel consumption	Carbon dioxide Carbon monoxide Hydrocarbon mixtures Nitrogen oxide Particulate	Emissions from fuel consumption were estimated using data from the Department for Environment Food & Rural Affairs (DEFRA, 2022).

Plant protection products in water, air, and soil	Active substance in water, air, and soil	In accordance with the studies conducted by Margni et al., 2002 and Audsley, 1997, it is assumed that leaching of the active substance from the soil into water is at most 10% of the applied dose. The 10% fraction of active substance is emitted into the air and the remaining fraction enters the soil.

The context variables for each case study were collected through three procedures: inventory data collection, the utilization of a georeferenced database of Lombardy (Northern Italy) at a scale of 1:250,000 (Brenna et al., 2002) and a survey conducted among the viticulturists. Context variables for each case study are shown in Table 3.4. These variables were collected both as continuous variables, representing the ratio over the entire surface of the vineyards managed by the winery for that study year and as dichotomous variables, by identifying two options for each variable. The variables of 'Planting' and 'Management' (Figure 3.2) were obtained through the inventory data collected for each case study. In detail, in the 'Planting' category, for the dichotomous variable 'plant density', the inventories with vineyard plantings exceeding 7,000 vines per hectare were classified as 'high' density, while others were categorized as 'regular' density. The continuous variables 'vines up to 3 years' and 'vines over 20 years' were determined based on the planting year and the year of the case study. For the continuous variable 'susceptible varieties', the ratio was calculated between the area planted with varieties considered more susceptible to fungal diseases (Borgo, 2022; CREA, 2020) and the total managed vineyard area. In the 'Management' category, for the dichotomous variable 'sub-row management', wineries were divided into those using chemical weed control, i.e. herbicides, and those employing only mechanical methods, i.e. tillage for sub-row management. Fertilizer data allowed the categorization of dichotomous variables for 'organic fertilization' and 'synthetic fertilization'. The continuous variable 'Guyot training system' was determined as the ratio of the area managed using the Guyot system to the total managed area. In the 'Localization' category (Figure 3.2), the georeferenced database of Lombardy was employed. More specifically, the continuous context variable 'sandy soil' was calculated as the ratio of the vineyard areas located on soils classified as sandy in

the soil map to the total area of vineyards managed by the winery for the year of the case study. Similarly, through level curves determination, the continuous context variable 'hillside vineyards' was determined as the ratio between the areas of terraced vineyards and the total managed area. Concerning the variable 'Years', a survey was conducted among viticulturists from the participating wineries, who were asked their opinion on the susceptibility to the main fungal pathogens in grapevines, namely Downy mildew (*Plasmopara viticola*), Powdery mildew (*Erysiphe necator*) and Bunch rot (*Botrytis cinerea*) based on years. As expected, 2010, characterized by higher rainfall was classified by the viticulturists from the participating wineries as susceptible to Downy mildew. In 2015, despite the drought year, none of the wineries in the study resorted to emergency irrigation.

Table 3.4 Context variables for each case study. Minimum and maximum values are provided for continuous variables, mean and standard deviation (SD). The counting of the two options is reported for dichotomous variables.

Context variables	**Mean (±SD) [min; max]**	**Dichotomous variables**
Localization		
Sandy soils	0.78 (±0.30) [0;1.00]	
Hillside vineyards	0.14 (±0.19) [0;0.80]	
Planting		
Vines up to 3 years	0.14 (±0.14) [0;0.48]	
Vines over 20 years	0.10 (±0.12) [0;0.34]	
Susceptible varieties	0.89 (±0.02) [0.85;0.95]	
Plant density		11 HIGH; 27 REGULAR
Management		
Sub-row management		15 HERBICIDES; 23 TILLAGE
Organic fertilization		17 NO; 21 YES
Synthetic fertilization		17 NO; 21 YES
Guyot training system	0.26 (±0.29) [0;1.00]	
Year		
Year's susceptibility to Downy mildew		19 NO; 19 YES
Year's susceptibility to Powdery mildew		32 NO; 6 YES

Year's susceptibility to Bunch rot	22 NO; 16 YES

Water Footprint Impact Assessment

The water footprint was assessed in accordance with the ISO 14046 standard for Water Footprint (WF) (ISO, 2014). Water scarcity was assessed using the Available WAter REmaining (AWARE) method, which is designed to gauge the impact of water extraction from natural systems in a specific area (Boulay et al., 2018). As to water quality, freshwater ecotoxicity was evaluated using the USEtox method (Rosenbaum et al., 2008). Freshwater eutrophication and freshwater acidification were assessed according to the Impact 2002 method (Jolliet et al., 2003). The functional unit (FU) chosen for this study is 1 kg of harvested grapes. For inventory structuring, background data were obtained through the Ecoinvent© database, version 3.8 (Wernet et al., 2016). SimaPro v9.4.0.2 LCA software was used to calculate water consumption and quality indicators.

Data analysis

The statistical analysis procedure consisted of three phases. In the first phase, the association or correlation between explanatory variables was assessed, considering their large number and the potential for significant multicollinearity. Explanatory variables were analyzed in terms of correlation or association, and multicollinearity was evaluated using the Variance Inflation Factor (VIF). Any regressor with a VIF value greater than 5 was excluded. Relationships between quantitative and dichotomous qualitative variables (see Table 4) were assessed through box-and-whisker plots and, when necessary, by calculating the point-biserial correlation coefficient (Spearman, 2010). Additional statistical tests, such as the Chi-square test (Pearson, 1900) and Cramér's V test (Rogers, 1950), were also applied.

In the second phase, the relationship between explanatory variables and the response variables was analyzed. The response variables included indicators of impact on water resources, such as water scarcity, acidification, freshwater eutrophication, and freshwater ecotoxicity. Given the nature of the variables in the model, which precluded the application of a standard multiple linear regression,

Generalized Linear Models (GLMs) were employed. A bidirectional stepwise selection process, based on minimizing the Akaike Information Criterion (AIC), was used to identify the subset of explanatory variables that best explained the variance in the response variables. The significance of the GLMs was assessed using McFadden's pseudo-R-squared (McFadden, 1974).

Finally, in the third phase, a 10-fold cross-validation was applied to enhance the robustness of the model results, with k set to 10. The statistical analysis was performed using R software (version 4.3.2) in the tidyverse and caret ecosystem packages (Kuhn, 2008; Wickham et al., 2019).

Results

Descriptive analysis

From the preliminary analysis, the regressors related to Bunch rot were excluded due to multicollinearity issues (it has a VIF value of 8.48). The other regressors have VIF values below five. Table 3.5 provides a summary of the inventory assessment for the calculation of water footprint indicators. Contextual variables and water footprint indicator results for each inventory are available in Supplementary File S2.

Table 3.5 Mean, standard deviation (SD) and minimum and maximum values of water footprint indicators for the case studies being analyzed.

Indicator	Mean (±SD) [min; max]	
Water Scarcity	3.94E-02 (±4.39E-02) [5.07E-03; 2.42E-01]	m3 freshwater/FU
Acidification	6.99E-04 (±5.55E-04) [1.15E-04; 3.08E-03]	kg SO_2/FU
Freshwater Eutrophication	2.18E-04 (±5.33E-04) [1.02E-05; 2.52E-03]	kg PO_4/FU
Freshwater Ecotoxicity	5.80E-00 (±4.85E-00) [1.57E-01; 2.37E+01]	CTUe/FU

GLMs analysis

Table 3.6 Results of the multiple stepwise linear regression model for the water scarcity indicator.

Coefficient	Estimate	Standard Error	p-Value
Vines of over 20 years	0.153	0.055	0.009 **
Susceptible varieties	0.978	0.309	0.004 **
Organic fertilization	0.023	0.012	0.069 .
Plant density: regular	-0.061	0.023	0.013 *
Sub-row management: tillage	-0.043	0.016	0.012 *
Sandy soils	-0.065	0.026	0.018 *
Hillside vineyards	0.081	0.036	0.029 *

*'***' p < 0.001; '**' p < 0.01; '*' p < 0.05; '.' p < 0.1.*

The GLM demonstrated a good fit to the data, explaining almost half of the variability in Water Scarcity values (adjusted pseudo-R-squared = 0.54). Table 3.6 lists the variables that proved to be significant in the model: Vines of over 20 years, Susceptible varieties, Organic fertilization, Plant density 'regular', Sub-row management 'tillage', Sandy soils, Hillside vineyards. The effects of each variable should be interpreted based on the consideration that all the other variables are equal.

Table 3.7 Results of the multiple stepwise linear regression model for the acidification indicator.

Coefficient	Estimate	Standard Error	p-Value
Plant density: regular	< -0.001	< 0.001	< 0.001 ***

*'***' p < 0.001; '**' p < 0.01; '*' p < 0.05; '.' p < 0.1.*

The GLM applied to acidification demonstrated an adaptation to the data that explains a lower amount of variability compared to water scarcity (pseudo-R-squared = 0.27). Table 3.7 shows the only significant variable is 'Plant density: regular', with a negative effect ($p < 0.001$).

Table 3.8 Results of the multiple stepwise linear regression model for the freshwater eutrophication indicator.

Coefficient	Estimate	Standard Error	p-Value
Guyot training system	< -0.001	< 0.001	< 0.001 ***
Plant density: regular	< 0.001	< 0.001	0.041 *

Sub-row management: tillage	< 0.001	< 0.001	0.016 *
Hillside vineyards	0.001	< 0.001	0.058 .

*'***' p < 0.001; '**' p < 0.01; '*' p < 0.05; '.' p < 0.1.*

Table 3.8 lists the variables that are found to significantly influence freshwater eutrophication: 'Guyot training system', 'Plant density: regular', 'Sub-row management: tillage', and 'Hillside vineyards'. As with water acidification, the GLM showed an even lower fit for the water scarcity data (pseudo-R-squared = 0.26).

Table 3.9 Results of the multiple stepwise linear regression model for the freshwater ecotoxicity indicator.

Coefficient	Estimate	Standard Error	p-Value
Plant density: regular	-6.754	1.612	<0.001 ***
Hillside vineyards	7.248	3.981	0.077 .

*'***' p < 0.001; '**' p < 0.01; '*' p < 0.05; '.' p < 0.1.*

The GLM for freshwater ecotoxicity showed a better fit to the data compared to acidification and eutrophication, explaining the variability reasonably well (pseudo-R-squared = 0.33). The variables 'Plant density: regular' and 'Hillside vineyards' proved to be significant and are shown in Table 3.9.

Discussion

Water footprint indicators values

In Life Cycle Assessments (LCA), such factors as the data reference period, geographical context and the level of development and technological innovation can influence the results (Ciroth et al., 2020). The variability of values obtained for different impacts, considering the diversity of study contexts, results in a wide range of values. From the calculation of water footprint indicators, an average value of 3.94E-02 m3 freshwater/FU was obtained for water scarcity, with a minimum of 5.07E-03 and a maximum of 2.42E-01. This average value is in agreement with that resulting from previous studies which,, for the same functional unit, include a 2021 study on table grape production in integrated management vineyards in the Mediterranean area (Canaj et al., 2021), which reported an average of 3.93E-02 for water scarcity, against an average of 7.48E-01 m3/kg as resulting from a 2017 study

on Peruvian grape production conducted by Ian Vázquez-Rowe et al.(Vazquez-Rowe et al., 2017). As far as acidification is concerned, an average value of 6.99E-04 kg SO_2/FU was obtained, with a minimum of 1.15E-04 and a maximum of 3.08E-03. Highly variable values are observed in the studies available in literature with regard to this indicator. For example, Canaj et al. (2021) reported an average of 5.56E-02. A more similar value was obtained in a study on the water footprint in a winery in northeastern Italy, where Borsato et al. ((Borsato et al., 2019) observed a value of 8.45E−04 for acidification, considering only the impact fraction associated with the vineyard phase. Regarding freshwater eutrophication, an average value of 2.18E-04 kg PO4/FU was obtained, with a minimum of 1.02E-05 and a maximum of 2.52E-03. Similarly, a study by Ferrari et al. (2018) analyzed the impacts of Lambrusco grape production, observing 3.23E-04 for freshwater eutrophication. Other studies, however, have observed highly variable values. Ian Vázquez-Rowe et al. (2017) reported 4.23E-02, while Canaj et al. (2021) reported an average of 1.61E-03. A previous Life Cycle Assessment (LCA) on red wine production in Spain highlighted that freshwater eutrophication resulting from the grape production phase could amount to 1.47E – 03(Meneses et al., 2016). Finally, for freshwater ecotoxicity, an average value of 5.80E-00 CTUe/FU was obtained, with a minimum of 1.57E-01 and a maximum of 2.37E+01. Variable results have also been observed in the literature for this value; Ferrari et al. (2018) calculated a value of 3.23E-04, while Ian Vázquez-Rowe (2017) reported 1.27E+00 while Canaj et al. (2021) reported an average of 4.27E+01. Compared to what has already been explored in various studies, the results of this work investigate the impacts of water footprint management in a nonirrigated context, a relatively underexplored area.

Influence of contextual variables on water impacts

In the detailed analysis of significant variables, a positive effect ($p < 0.01$) is noted for Water scarcity in vineyards with a higher presence of plants over twenty years old. This could be associated with a greater need for maintenance and replacement of new vines to sustain vineyard productivity. As the vineyard ages, there is a need to replace diseased or dead vines, often more frequently than replanting the entire vineyard. In fact, in the study area, there is a tendency to carry out replacements rather than complete replanting. The higher presence of ‘Susceptible varieties’

shows a positive correlation with Water scarcity ($p < 0.01$). This can be associated with an increase in water consumption, most likely linked to a greater use of phytosanitary treatments in areas where high susceptible variables were cultivated (Bunea et al., 2013). Organic fertilization has a positive effect on water scarcity, although with low significance ($p < 0.1$). A negative influence emerges for 'Plant density: regular', indicating that low plant density (< 7000 vine/ha) is associated with low water consumption. Low vineyard density of vineyards and low canopy volume per hectare can actually lead to reduced water consumption in nonirrigated settings due to less requirements associated with other practices, such as plant protection treatments (Yuste et al., 2004). Vineyards managed using sub-row tillage ('Sub-row management: tillage') also showed negative significance, indicating lower water consumption than in vineyards treated with herbicides. Furthermore, a negative effect is observed in 'sandy soils,' probably due to improved drainage and, consequently, less soil moisture, requiring increased inputs and treatments. In better drained vineyards, not too much water available prevents excessive vigor, which can lead to an increased incidence of pressure from fungal infections (Leeuwen et al., 2009; Wolf, 2008). The variable Hillside vineyards showed a positive effect ($p <0.05$). This could be attributed to the fact that in terraced settings, inefficiency in surface management is greater than in flat settings. This can lead to wastage of products and water in the distribution of plant protection products. Regarding Acidification, the relevance of fossil fuel combustion in relation to this phenomenon has already been reported in the literature.(Rice and Herman, 2012). Low or regular planting density (< 7000 plants/ha) could result in reduced fuel consumption for field operations; however, this is closely related to the size of the machinery used and the time required to carry out operations in the field (De Gennaro et al., 2012). Freshwater eutrophication, as previously mentioned, primarily depends on the use of fertilizers. Although, similar to acidification, the GLM showed a poorer fit to the data, several significant relationships with contextual variables were observed in this case. It is interesting to note that no significant differences were found between management practices using organic or synthetic fertilizers, suggesting that the impact may be influenced more by the timing and quantities of application rather than the type of fertilizer used. For Freshwater ecotoxicity, like Water scarcity, a

negative effect is observed on the variable ‘Plant density: regular’, probably in relation to the reduced consumption of plant protection products in low-density vineyards. A wide in-row spacing results in a reduced tree row volume (TRV), taken as plant canopy volume per hectare of vineyard (Byers et al., 1971). Canopy volume and plant density, along with the growth stage and the application method, can actually influence the metering of plant protection products (EPPO, 2021). This results in less product being applied in reduced density or regularity for the same surface area. A slight significance also exists for ‘Hillside vineyards’, which may still be attributable to difficulties in working in terraced vineyards. The use of sprayers equipped with product recovery systems can significantly reduce wastewater, particularly by minimizing the runoff of active ingredients into water bodies and their leaching into aquifers. These advanced spraying systems are designed to capture and recycle excess pesticides that do not adhere to the target vegetation, thereby minimizing environmental contamination. In vineyards, sprayers with air-droplet separators for mist recovery have shown promise by improving spray recovery and target coverage while reducing pesticide dispersion into the environment (Panneton and Lacasse, 2004). The inclusion of more specific information on viticultural practices, such as soil management or the type of machinery used for phytosanitary treatments, could have further enhanced the understanding of how context variables influence different water footprint indicators.

Water footprint: implications of management strategies

Other studies have examined the water footprint in viticulture, focusing on the effects of management practices. Among these, a study conducted by Tomaz et al. (2024) in Portugal evaluated the water footprint in irrigated vineyards, analyzing the environmental impact of irrigation practices and proposing sustainable management strategies to mitigate these effects. While this study focuses on a nonirrigated context, the impacts of viticultural practices on water resources remain closely linked to management decisions. These impacts extend beyond emergency irrigation to include water usage in plant protection treatments. Furthermore, the application of fertilizers and plant protection products can contribute to the eutrophication, acidification, and ecotoxicity of water bodies. Given the limited

availability of water resources, it is critical to evaluate the effects of management not only in terms of withdrawals but also regarding their broader environmental impacts. The results highlight the significant influence of vineyard structural factors, such as planting density and varietal composition, can significantly influence the effects on water resources. From a sustainability perspective, these elements should be carefully considered in vineyard design and in adapting practices to an integrated resource management framework.

Conclusions

The result of this study emphasizes the importance of calculating the water footprint even in nonirrigated vineyard contexts, thereby providing a better understanding of how agronomic practices beyond vineyard irrigation can have an impact on water resources. An integrated statistical approach involving data collected from various companies over several years was applied, the aim being to understand how the contextual variable leads to different impacts assessed through the water footprint calculation. As a result, this methodology highlighted how water scarcity is associated with contextual variables. It also explained, though to a lesser extent, the association of some variables with indicators of freshwater acidification and ecotoxicity. Among the most relevant contextual variables, vine density and the presence of hillside vineyards emerge as major factors influencing water consumption and associated water footprint impacts. In addition, there is clear evidence that such variables as variety susceptibility, vineyard age, vineyards on sandy soils and the sub-row management with cultivation can influence water scarcity rather than herbicides. Results obtained allow to increase knowledge about the influence of management, excluding irrigation, on reported water footprint, providing useful information for viticulturists. Furthermore, the study can contribute to raising awareness in the sector about issues related to the impacts of management on water footprint, an aspect often overlooked in traditional investigations. Future research could benefit from including more detailed data on viticultural practices, such as specific soil management strategies or the types of machinery used for phytosanitary treatments. These additions could provide deeper insights into how context variables influence water footprint indicators, ultimately enhancing the precision and applicability of the findings. Expanding the analysis to

incorporate alternative methodological approaches or broader datasets could also contribute to a more comprehensive understanding of the environmental impacts of viticulture. Such advancements would support the development of more specific and sustainable management strategies, addressing the challenges posed by climate change and increasing resource pressures.

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Supplementary materials

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4. Soil

4.1. Development of an integrated indicator for assessing management impacts on soil quality: A case study in organic viticulture

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Abstract

Given that soil is an invaluable resource for viticulture, it is important to maintain its properties in order to keep it healthy and optimize ecosystem processes underpinning productivity. Although measuring sustainability poses challenges, it remains crucial for developing specific management strategies designed for a given geographic area. This study introduces the Management Impact on Soil Quality (MISQ), an integrated indicator designed to assess how common management practices influence the attributes of soil health in organic vineyards. The MISQ evaluates five key management components: soil, carbon, copper, nutrients and biodiversity. This indicator was applied using data collected from an organically-managed vineyard in Franciacorta, a grape-producing area in Northern Italy over the years 2014, 2015, 2019 and 2021. The results indicate how enhanced soil function depends on increased supply of organic matter and diversified cover cropping with legumes, thereby improving soil biodiversity. However, managing potential nutrient surplus and recognizing the risks associated with tillage for row spacing management are also crucial factors. These results provide viticulturists with a valuable tool for assessing the effects of agronomic techniques on soil quality, thereby facilitating sustainable management practices. This study highlights the need to preserve the soil multifunctionality, which is critical for nutrient cycling, soil structural stability and biological population control. The straightforward approach of the MISQ makes it suitable for use in different environments, thereby promoting effective management strategies that mitigate a negative impact on soil functionality.

Keywords: Soil quality, Viticulture, Soil management, Integrated Indicator, Sustainability

Introduction

Soil security is a fundamental concept that ensures the long-term availability and functionality of soils to support human and environmental needs. It encompasses not only soil health but also factors such as governance, economics, and sustainable management to maintain soil resources for future generations (McBratney et al., 2014). As a key component of soil security, soil health considers soil as a living ecosystem, emphasizing its biological activity, resilience, and capacity for self-regeneration and adaptation to changing conditions (Lal, 2016; Weil and Brady, 2017). Healthy soils support biodiversity, sustain plant and microbial life, resist degradation, and maintain their functions over time (Lehmann et al., 2020). Preserving soil health is essential for agricultural productivity, carbon sequestration, and climate resilience, making it a cornerstone for achieving the Sustainable Development Goals (Hou et al., 2020). However, soil degradation caused by intensive agriculture, deforestation, and climate change threatens both soil health and overall soil security by reducing fertility, increasing erosion, and depleting organic matter. Addressing these challenges requires sustainable land management strategies that restore and protect soil functions. In this context, soil quality plays a crucial role by providing the measurable foundation upon which soil health is built. While soil health focuses on biological and ecological dynamics, soil quality reflects the soil's capacity to perform essential functions such as nutrient cycling, water retention, and pollutant filtration. Assessing soil quality involves integrating physical, chemical, and biological properties to evaluate the soil's ability to support ecosystem functions and agricultural sustainability (Karlen et al., 2001; Seifu and Elias, 2018; Sepehya et al., 2024). Recognized as a key indicator of sustainable management, soil quality directly influences biological productivity, environmental quality, and ecosystem health (Herrick, 2000). Growing awareness of soil security has led to the introduction of new policies aimed at its protection. In particular, the European Union has developed regulatory frameworks, such as the European Soil Monitoring Law, to ensure sustainable management and promote the restoration of degraded soils (Kotschik et al., 2024). Assessing soil quality

comprehensively and accurately is often complex and costly, as it requires integrating multiple multifunctional requirements and considering the impacts related to its use. Consequently, adopting an approach based on cross-functional indicators, which can simultaneously account for multiple soil functions, enables more efficient and sustainable assessment (Bone et al., 2010). Various approaches have been proposed for developing indicators to assess soil quality in agricultural contexts, including indices derived from the averaging of specific soil properties (Luo et al., 2017), composite indices based on expert scoring (Drobnik et al., 2018), and the use of Principal Component Analysis (PCA) to identify the principal components that explain most of the variability as synthetic indicators of soil quality (Bedolla-Rivera et al., 2020; Chandran et al., 2023; Sofi et al., 2016). Given the growing interest in sustainable agricultural practices, soil quality assessment is particularly relevant in viticulture, where soil conditions directly influence both environmental sustainability and crop productivity (Baiano, 2021; García-Navarro et al., 2023). Vineyard management can lead to high rates of soil loss, influenced by factors such as topography, soil properties, and precipitation. In particular, vineyards, especially those without inter-row vegetation cover, are among the most erosion-prone crops due to management practices and soil characteristics (Prosdocimi et al., 2016; Raclot et al., 2009). In viticulture, as in other perennial crops, mechanization poses a high risk of soil degradation, particularly due to compaction. This process can be influenced by both the soil's intrinsic vulnerability and the agricultural practices adopted. Factors such as high traffic intensity, the use of high-pressure tires, and the absence of cover crops, which reduce soil bearing capacity, can exacerbate the problem in vineyards (Polge de Combret - Champart et al., 2013). Additionally, tillage can contribute to the depletion of organic matter and impact long-term soil fertility (Chopin et al., 2008). Improper use of pesticides can lead to groundwater contamination (Zambito Marsala et al., 2020), while intensive use of fungicides in vineyards may cause soil contamination, affecting biodiversity and altering soil ecosystems (Komárek et al., 2010). In response to these environmental concerns, organic viticulture has gained popularity as a valuable solution for advancing sustainable agriculture (Ostandie et al., 2021). However, despite its benefits, organic viticulture also faces challenges related to

soil quality. Among the pesticides authorized in organic viticulture, copper is the primary fungicide to combat downy mildew, but its progressive accumulation in soils poses a threat to soil fertility (Cesco et al., 2021). Copper accumulation in organic vineyards is often excessive (Jez et al., 2023), and some European vineyards have already exceeded the ecotoxicological threshold (Imfeld et al., 2021). Copper is highly toxic to soil ecosystems, with significant environmental impacts. Its ecotoxicity varies spatially, with higher toxicity observed in acidic and sandy non-calcareous soils due to lower buffering capacity, and in low-alkalinity waters where copper remains more bioavailable (Peña et al., 2018; Viveros Santos et al., 2018). Viticultural practices, if not done properly, can also result in water deficiency and nutrient loss, low nitrogen availability, low organic matter content, and poor drainage capacity, making it difficult to restore soil fertility (Costantini, 2018). An excess of some nutrients, particularly N and P, poses a threat to the environment and potentially to our health. Strategies for sustainable vineyard management should also prioritize enhancing soil biodiversity. For example, cover cropping with different species and combinations can impact plant nutrient and water uptake, soil health and grape quality (Lazcano et al., 2020). However, assessing how vineyard management has an impact on soil quality becomes a challenge when considering the multidimensional heterogeneity of these impacts. In this context, indicators serve as a fundamental tool, as they are variables based on qualitative or quantitative data - observed, measured or calculated from other data - that provide information on more complex or less accessible variables (Latruffe et al., 2016). The choice of how to aggregate and weigh indicators depends on their degree of compensability and the purpose. Equal weighting is a pragmatic solution in the absence of a clear consensus on their relative importance, while more advanced methods can offer greater accuracy, albeit with potential limitations related to subjectivity and data sensitivity. Aggregation is also crucial: a linear method allows full compensability between indicators, potentially masking critical issues, whereas a geometric aggregation reduces compensability, giving more weight to weaker indicators and promoting targeted interventions (Nardo et al., 2008). Although various indicators have been proposed for assessing soil quality in viticulture, no specific tools have been developed to comprehensively analyze the

integrated effects of viticultural practices on soil quality. In this study, an integrated indicator is proposed to measure the impact of management on soil quality in organic vineyards, with the aim of providing a comprehensive assessment and supporting viticulturists in adopting sustainable practices. Specifically, the Management Impact on Soil Quality (MISQ) indicator is introduced as a tool to comprehensively evaluate the effects of management practices on soil quality. Unlike existing indices, the MISQ considers a broad range of soil functions, including nutrient cycling, biodiversity, and resilience to degradation. Designed for operational use in vineyard management, it provides viticulturists with an effective tool to monitor and improve sustainability. This approach ensures a more comprehensive and reliable evaluation of the impact of viticultural practices on soil functionality and, consequently, soil quality. The aim is to offer a thorough assessment of soil quality and support viticulturists in achieving sustainable vineyard management. After identifying and normalizing the evaluation indicators, a case study is presented in an organically managed vineyard located in the Franciacorta grapevine-producing-growing area over a four-year assessment period.

Table 4.1 Potential negative and positive impacts assessed by each of the five MISQ indicators for each management component.

Management components	**Potential impact**		**Indicator**
	Negative	**Positive**	
Soil management	Soil degradation and erosion	Reduction of erosion risk	Soil disturbance (S_{dis})
	Compaction, alteration of the structure and	Maintenance of soil porosity	
	Reduction of water retention capacity	Maintenance of water retention capacity	
Carbon management	Loss of organic matter	Increase in soil carbon stock	Regeneration of the SOM (R_{som})
	Reduction of water retention capacity	Maintenance of water retention capacity	
Copper management	Terrestrial eco-toxicity due to copper contamination	Reduction of copper contamination risk	Protection from copper eco-toxicity (C_{tox})
Nutrients management	Deficiency or excess of nitrogen	Optimal nitrogen balance	Nutrient Use Efficiency (N_{eff})
	Deficiency or excess of phosphorus	Optimal phosphorus balance	

	Deficiency or excess of potassium		
		Optimal potassium balance	
Biodiversity management	Loss of arthropods and biological quality	Maintenance or increase of arthropod diversity	Protection of biodiversity (P_{bio})
	Loss of the bacterial microbiota	Maintenance or increase of bacterial diversity	
	Loss of fungal communities	Maintenance or increase of fungal diversity	

Material and methods

Conceptual model of the management soil indicator

In order to evaluate the impact of management practices on soil quality, we developed the Management Impact on Soil Quality (MISQ) integrated indicator, based on an integrated assessment of five main management components: soil, carbon, copper, nutrients and biodiversity (Figure 4.1), as indicated by the equation below:

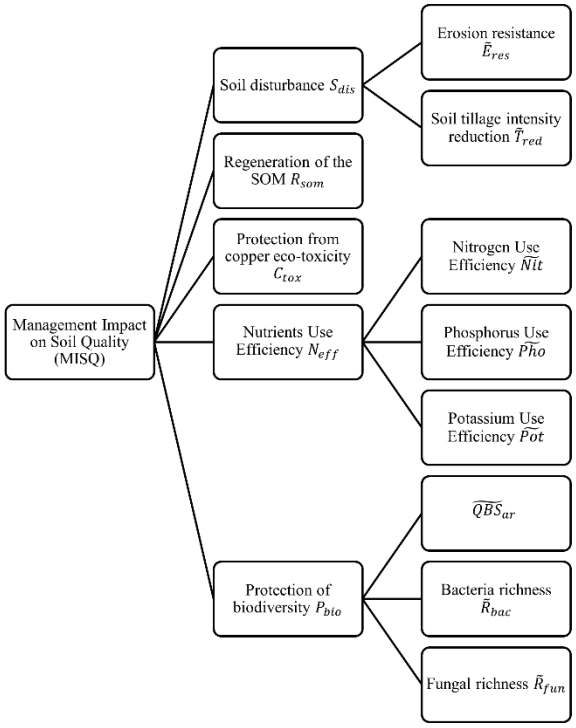
$$\text{MISQ} = \sqrt[5]{S_{dis} \cdot R_{som} \cdot C_{tox} \cdot N_{eff} \cdot P_{bio}} \quad (1)$$

where $S_{dis}, R_{som}, C_{tox}, N_{eff},$ and P_{bio} are the indicators related to the five components of MISQ (

The proposed integrated indicator aims to assess the effects of agricultural practices on soil quality. Since soil quality is also strongly influenced by site-specific soil properties (Sepehya et al., 2024), analyzing its changes over time requires an assessment that considers a temporal horizon, starting from a reference baseline. In this context, the MISQ proves particularly suitable for intra-site and interannual evaluations, allowing for an accurate analysis of the effects of viticultural management practices on soil quality.

). Details on these indicators are presented in the following section. In this study, the assessment components refer to an organic viticulture scenario; therefore, the selected indicators are based on practices and products permitted under the EU organic production regulation (EP, EC, 2018).

Figure 4.1 Conceptual model of the Management Impact on Soil Quality (MISQ) indicator.



The MISQ is based on a geometric mean that reflects the specific nature of each indicator. This method is particularly useful when positive indicators are expressed in ratio scales as it involves partial compensability, which means that poor performance in some indicators can be offset by sufficiently high values in other indicators. Moreover, partial compensability is lower when using the geometric mean method compared to linear aggregation, especially with indicators presenting low values (Nardo et al., 2008). Both the arithmetic and geometric mean are stable when the positive and negative trends and their magnitude are balanced (van Strien et al., 2012). However, when just one indicator reaches zero, the geometric mean, and hence the integrated indicator, goes to 0. This characteristic is significant when a score of 0 for one of the elements making up the indicator becomes a crucial factor, thereby nullifying the assessment of the entire phenomenon represented by the integrated indicator. For these reasons, the geometric mean has been widely

used as an aggregation method (Bacchini et al., 2020), particularly in the case of biodiversity indicators (Korner-Nievergelt et al., 2022).

The proposed integrated indicator aims to assess the effects of agricultural practices on soil quality. Since soil quality is also strongly influenced by site-specific soil properties (Sepehya et al., 2024), analyzing its changes over time requires an assessment that considers a temporal horizon, starting from a reference baseline. In this context, the MISQ proves particularly suitable for intra-site and interannual evaluations, allowing for an accurate analysis of the effects of viticultural management practices on soil quality.

Quantification of individual components of the MISQ integrated indicator

Each component is characterized by an indicator, which considers two or more aspects relating to a specific theme. When performing an integrated analysis, the variables representing aspects under examination, which may be expressed in different units, must be converted into a common unit of measurement. The normalization step is essential when preparing data to be included into an aggregated score (Pollesch and Dale, 2016), which in this case is the MISQ. In defining the normalization threshold, we used two different approaches, depending on the nature of each variable: one based on the maximum or minimum values of the variable and the other on the optimal value relating to the MISQ (Castoldi and Bechini, 2010). The proposed indicators have been adapted to the larger-the-better normalization scheme developed by Krajnc and Glavič (Krajnc and Glavič, 2005), where, in a range of 0 to 1, values closer to 1 are considered optimal. Details of normalizations are given in Table 3.

Soil disturbance indicator. The indicator of Soil disturbance (S_{dis}) considers the erosion resistance ($\tilde{E}_{res}$) and soil tillage intensity reduction ($\tilde{T}_{red}$) as sub-indicators:

$$S_{dis} = \frac{\tilde{E}_{res} + \tilde{T}_{red}}{2} \quad (2)$$

In order to assess the soil disturbance, the impact was evaluated in terms of erosion resistance and reduction of tillage intensity, including the consideration of the effects of tillage frequency and the potential consequences of soil compaction on its structure. The cover and management factor (C_m) from the RUSLE equation was

used (Renard, 1997) to determine erosion resistance. As noted by other authors (Lamastra et al., 2016), the C_m factor can be easily employed to reflect the effect of cropping and management practices on erosion rates, while the other factors of the RUSLE equation are more closely related to specific soil characteristics rather than management options.

Here, factor C_m is determined according to equation (3).

$$C_{management} = C_{tillage} \times C_{residues} \times C_{cover} \quad (3)$$

The sub-factor $C_{tillage}$ was calculated according to equation (4). Here, $F_{inter\text{-}row}$ and F_{row} represent the surface fractions of inter-row and row areas, while $\mu\ TI_{inter\text{-}row}$ and $\mu\ TI_{row}$ are the arithmetic means of tillage intensity for inter-row and row areas, based on values proposed by the ORUSCAL (Orchard RUSle CALibration) model, which is derived from a calibration of RUSLE2 developed for tree crops like vineyards (Biddoccu et al., 2020).

$$C_{tillage} = F_{inter\text{-}row} \times \mu\ TI_{inter\text{-}row} + F_{row} \times \mu\ TI_{row}. \quad (4)$$

As proposed by the study conducted by Panagos et al., (2015), which obtained C-factors for tree crops such as vineyards based on the calibration of soil cover fractions deriving from satellite images, the sub-factor $C_{residues}$ was calculated according to equation (5), where $F_{residues}$ represents the fraction of the inter-row area subjected to organic residue redistribution (such as vine prunings and dead vegetation).

$$C_{residues} = (0.88 \times F_{residues}) + (1 - F_{residues}) \quad (5)$$

Finally, the cover crop sub-factor was calculated according to equation (6), where $F_{crop\text{-}cover}$ is the fraction of the inter-row area managed with cover crops.

$$C_{cover} = (0.80 \times F_{crop\text{-}cover}) + (1 - F_{crop\text{-}cover}) \quad (6)$$

The reduction in soil tillage intensity was calculated for each year using the Soil Tillage Intensity Rating (STIR) method developed by the USDA. STIR is a numerical index that represents the type and severity of disturbance caused by tillage operations. The STIR value incorporates the type, speed, depth and degree of disturbance caused by tillage management decisions. The STIR is the sum of the

STIR values of individual field operations (Claassen et al., 2018). Both "erosion resistance" and "reduction in soil tillage intensity" values take into account tillage intensities; however, they consider somewhat different aspects. In the former case, soil cover is also considered, while in the latter case, both intensity and frequency of passes are taken into consideration. As other assessments suggest (Triviño-Tarradas et al., 2020), both indicators are considered in this study. The maximum thresholds of the C-factor observed in European vineyards (Panagos et al., 2015) were used to normalize the erosion resistance indicator. For the soil tillage intensity reduction indicator, the USDA maximum value of 80 for conservation tillage management was considered (NRCS, 2022).

Organic matter indicator. The indicator relating to the ability to regenerate soil organic matter (SOM) is equal to the normalization of the Organic Matter Indicator (OMI) proposed by Bockstaller (1997). The OMI assesses the effect of farming systems on the evolution of the SOM. The calculation of the indicator is based on the comparison of organic matter inputs through manure and crop residues with the recommended input levels, which are designed to maintain a satisfactory level of SOM in the long term. These levels were obtained using the Hénin-Dupuis model (Mary and Guérif, 1994) for various classes of clay and limestone soil content. The OMI indicator ranges from 0 to 10, where 7 is an optimal value (Bockstaller et al., 1997). However, the potential excess of nutrient inputs is considered in the Nutrients Use Efficiency indicator. A normalization with an optimal value of 10 was used in this study, where only the organic matter input was considered in this indicator.

$$R_{som} = OMI \quad (7)$$

Terrestrial eco-toxicity impact indicator. Among the active ingredients permitted in organic farming, copper is one of the most closely monitored due to its high eco-toxicity for soil fauna communities (Beaumelle et al., 2023; Goritschnig et al., 2024). Its persistence in the soil and widespread use in organic agriculture raise concerns about potential effects on soil health. Copper toxicity is particularly high in acidic soils with low organic matter content, where its bioavailability is greater (Karimi et al., 2021). The terrestrial eco-toxicity impact score (PAF·m^3·day·kg of

grapes^{-1}) was used to assess protection from copper eco-toxicity (C_{tox}), considering the characterization factors (CFs) proposed by Viveros Santos et al., (2018). These factors account for both farming systems and the distribution of copper in the soil within the reference vine-growing area. The CFs for copper terrestrial eco-toxicity were obtained using the spatial resolution of the soil mapping units from the HWSD. The distribution was geochemically modelled using WHAM 6.0 (Windermere Humic Aqueous Model), a model that enables geochemical speciation. WHAM 6.0 is utilized by USEtox to calculate CFs that consider metal speciation based on freshwater chemistry for aquatic eco-toxicity (Gandhi et al., 2010). The terrestrial eco-toxicity impact score I_w (PAF·m^3·day·kggrapes^{-1}) was therefore calculated according to Equation 5, where m_w represents the amount of copper released into the soil per kilogram of grapes (kg Cu·kggrapes^{-1}), and CF_w is the characterization factor for copper terrestrial eco-toxicity (PAF·m^3·day·kgCu^{-1}) in the reference vine-growing area.

$$I_w = m_w \cdot CF_w \quad (8)$$

In order to calculate m_w, the amount of copper released into the soil from the active ingredients of phytosanitary products used was considered according to the Product Category Rules (PCR) manual for arable and vegetable crops (EPD International, 2023). For the C_{tox},the maximum value, representing the worst-case scenario, was determined based on an applied copper content of 6 kg/ha, which is considered the threshold necessary to prevent the disruption of soil biological functions (Karimi et al., 2021). The corresponding territorial characterization factor was based on the highest value calculated for vineyards in the vine-growing area of "Lombardy" as calculated by Viveros Santos et al., (2018).

$$C_{tox} = \widetilde{I_w} \quad (9)$$

Nutrient Use Efficiency Indicator. The indicator for nutrient use efficiency (N_{eff}) was determined as the arithmetic mean of three normalized nitrogen-related sub-indicators: nitrogen ($\widetilde{Nit}$), phosphorus ($\widetilde{Pho}$) and potassium ($\widetilde{K}$). For each nutrient, the non-normalized variable refers to the ratio between the nutrient input and output, based on the principle of nutrients mass balance (Oenema et al. (2015). This

involves considering nutrient input and nutrient output for the calculation: nutrient output / nutrient input. Based on the proposal by Oenema et al. (2015) concerning Nitrogen Use Efficiency (NUE), the normalization of N_{eff} was carried out considering 0.7 as the optimal value. This ideal value falls between the risky limits of 0.9, which poses risks due to soil mining effects, and 0.5, which poses risks due to excess nitrogen. The same criterion was applied to phosphorus and potassium.

$$N_{eff} = \frac{\widetilde{Nit}+\widetilde{Pho}+\widetilde{Pot}}{3} \quad (10)$$

Biodiversity indicator. As highlighted by several authors, soil arthropod communities serve as valuable bioindicators of changes in soil properties and the impact of human activities (Ghiglieno et al., 2021; van Straalen, 1998). Bacteria and fungi play a crucial role in various ecological processes within the soil, contributing to its fertility and the maintenance of its characteristics (Belda et al., 2025; de Menezes et al., 2017). Given their ecological importance, this study considers biodiversity protection (P_{bio}) in terms of soil arthropods and microorganisms (fungi and bacteria). The indicators is the arithmetic mean of the normalized versions of the biological soil quality index (QBS_{ar}) (Parisi et al. (2005), the Fungal richness (R_{fun}) and Bacteria richness (R_{bac}). For assessing arthropod biodiversity, QBS-ar index values were normalized using the Soil Quality Classes proposed by Parisi for Northern Italy (Parisi et al., 2003). These classes increase in score from 0 to 6, where a score of 6 indicates higher QBS-ar values associated with the presence of Proturans and eu-edaphic groups (eco-morphological index greater than 20). In order to assess bacterial and fungal biodiversity, microbial diversity values, defined as the richness of Operational Taxonomic Units (OTUs), were normalized by identifying a maximum achievable limit for their respective microbial groups. The maximum values of OTUs were determined for the reference area, based on over 200 samplings carried out in managed vineyards in Franciacorta, a viticultural area in northern Italy, which was chosen as the case study. In the absence of a measured data set for the reference study area, it would have been possible to use reference OTU values obtained from studies on soil microbial communities in vineyards.

$$P_{bio} = \frac{\widetilde{QBS_{ar}} + \tilde{R}_{fun} + \tilde{R}_{bac}}{3} \quad (11)$$

Table 4.2 Normalization phase of the variables included in the indicators, encompassing the minimum (Min), maximum (Max), and optimum (Opt) levels of each indicator.

Indicator	Normalized variable	Original indicator	Min value	Max value	Opt value	Normalization
S_{dis}	$\tilde{E}_{res}$: Erosion resistance	Cover and management factor (Panagos et al., 2015)	0.00	3.45	0.00	$1 - \frac{C_{m_i}}{3.45}$
	$\tilde{T}_{red}$: Soil tillage intensity reduction	Soil Tillage Intensity Rate (Claassen et al., 2018)	0.00	80	0	$1 - \frac{T_{red_i}}{80}$
R_{som}	$\widetilde{IMO}$	IMO Organic Matter Indicator (Bockstaller 1997)	0.00	10	10	$\frac{IMO_i}{10}$
C_{tox}	$\widetilde{I_w}$	Copper terrestrial ecotoxicity (Viveros Santos et al., 2018)	0.00	53.69	0.00	$1 - \frac{I_{w_i}}{53.69}$
N_{eff}	$\widetilde{Nit}$	Nitrogen Use Efficiency (Oenema et al. 2015)	0.00	1.00	0.70	$1 - \frac{\lvert Nit_i - 0.70\rvert}{0.70}$
	$\widetilde{Pho}$	Phosphorus Use Efficiency	0.00	1.00	0.70	$1 - \frac{\lvert \mathrm{Pho}_i - 0.70\rvert}{0.70}$
	$\widetilde{Pot}$	Potassium Use Efficiency	0.00	1.00	0.70	$1 - \frac{\lvert \mathrm{Pot}_i - 0.70\rvert}{opt}$
P_{bio}	$\widetilde{QBS_{ar}}$	QBS-ar (Parisi et al. 2005)	0.00	6.00	6.00	$\frac{QBS_{ar_i}}{6.00}$
	$\tilde{R}_{bac}$	Bacteria richness	0.00	2353	2353	$\frac{OTUs_{bac_i}}{2077}$
	$\tilde{R}_{fun}$	Fungal richness	0.00	293	293	$\frac{OTUs_{fun_i}}{293}$

Table 4.3 Descriptive statistics of data useful for calculating the indicator for soil management (S_{dis}).

Viticultural practice	Working hours (h)				Intensity coeff.[1]	Modifier coeff. [2]	% of surface disturbed
	2014 baseline	2015	2019	2021			
Harrow	50	41	56	107	0.65	0.7	83%
Row chisel	200	34	91	100	0.8	0.8	17%
Subsoiling	0	18	22	18	0.8	0.7	83%
Mowed cover crop	53	40	0	64	0.7	0.4	83%
Cultivated manually	7	0	144	98	0.65	0.7	17%
Other	284	228	273	183	0.65	0.15	83%

[1]Intensity coefficient (erosion) obtained from Biddoccu et al., (2020)

[2]Modifier coefficient (tillage intensity rate) obtained from

Table 4.4 Description of the inter-row management practised during the study years.

Year	Inter-row management
2014 (base line)	Spontaneous grassing year-round, periodic mowing
2015	Spontaneous grassing year-round, periodic mowing, autumn subsoiling
2019	Sowing functional grassing mixture*, termination of cover cropping with rolling, autumn subsoiling. Composition of the cover crop mixture: fava bean (*Vicia faba L.*), common vetch (*Vicia sativa L.*), pea (*Pisum sativum L.*), Egyptian clover (*Trifolium alexandrinum L.*) and red clover (*Trifolium pretense L.*)
2021	Spontaneous grassing year-round, periodic mowing, autumn subsoiling

Contextualization of the case study and data collection

The case study was conducted in a 2.98-ha Pinot Noir vineyard at Guido Berlucchi, a farm located in Franciacorta, a grape-growing area in northern Italy. The vineyard planting density is spaced 2 meters inter-row and 0.8 meters between vines, with 0.2 meters on each side considered for the tilled surface area along the row. The indicators were applied using data collected by the farm for the years 2014 (baseline), 2015, 2019, and 2021. Table 3 shows the types of viticultural practices, their intensity coefficient (erosion) and modifier coefficient (tillage intensity rate), as defined by Biddoccu et al., (2020) and Claassen et al., (2018) respectively, and used to calculate the S_{dis} indicator. All indicators were calculated for each year,

except for the S_{fun} and S_{bac}indicators, which cover 2019 and 2021 only. For 2014 and 2015, the biodiversity protection indicator was determined only with the QBS_{ar}, as data relating to the OTUs richness for fungi and bacteria were not available. Management of the inter-row area was carried out over various years, as reported in Table 4.4.

Table 4.5 Description of nutrient inputs and the quantity of copper applied during the study years.

Vineyard inputs	**2014**	**2015**	**2019**	**2021**
Nitrogen* from organic fertilizers (kg ha^{-1})	198.07	177.24	332.28	250.47
Phosphorus* from organic fertilizers (kg ha^{-1})	44.74	40.04	75.06	56.58
Potassium* from organic fertilizers (kg ha^{-1})	142.27	127.31	238.67	179.91
Metallic copper from copper-based fungicides (kg ha^{-1})	5.15	3.47	4.18	3.60

*Content of N, P, K derived from the analysis of the organic fertilizer used.

The grape yield considered for all years covered by the study was 12 tons per hectare, which is the actual production of the vineyard in the years covered by the study and corresponds to the maximum limit set by the Franciacorta Controlled and Guaranteed Denomination of Origin (CGDO) production regulation. The average consumption of nutrients has been considered based on the production level, as proposed by Fregoni, (1981). In order to include biological nitrogen fixation (BNF) in assessing the $\widetilde{Nit}$ indicator, the BNF values (kg ha^{-1}) proposed by Vasconcelos et al., (2020) for the legumes in the functional mix used as green manure were utilized. More specifically, the proposed mix had a total contribution of 134.73 kg ha^{-1}. A gradual release and nitrogen mineralization was considered in order to account for the controlled input over 4 years (Kebede, 2021). As required for the R_{som} indicator (Bockstaller et al., 1997)., the calculation of nutrient efficiency also considered the mean organic fertilizer input from the 4 preceding cropping years, given that organic fertilizers release nutrients slowly (Niedziński et al., 2021) and fertilizations are not carried out every year. Regarding copper for calculating the indicator C_{tox}, the metal copper applied per year has been considered, taking into account the fraction applied to the soil (EPD International, 2023). The active

ingredients and quantities of products applied in the different years are reported in Table 6. In order to assess the $\widetilde{QBS}_{ar}$ indicator, a cubic soil sample (10 × 10 × 10 cm) was placed in a Berlese–Tüllgren funnel under a 60W incandescent bulb. This setup prompted the soil arthropods to migrate towards the moist part of the sample, away from the light, and fall through the funnel into a preserving solution (alcohol and glycerol). The extracted arthropods were then classified to determine the QBS-ar index. In order to determine the OTUs, the amplicon sequencing of the bacterial 16S rRNA gene and fungal ITS, total DNA was extracted from 1 g of soil and amplicon sequencing was performed using Illumina MiSeq as described in Marasco et al., (2022).

Results and discussion

Trend of individual indicators over the study years

The Soil disturbance S_{dis} indicator obtained as the arithmetic mean of erosion resistance $\tilde{E}_{res}$ and soil tillage intensity reduction $\tilde{T}_{red}$. Throughout the study, $\tilde{E}_{res}$ remained consistently high, though a slight decline was noted after 2014, likely due to shifts in soil management. That year marked the only instance in which subsoiling was not performed in the inter-row - a high-intensity tillage practice - suggesting its role in maintaining earlier values. This trend was even more pronounced in $\tilde{T}_{red}$, which exhibited a sharp decrease as tillage operations and tractor traffic intensified in subsequent years. The impact was particularly evident in 2019 when, despite maintaining functional cover cropping throughout the season without mowing, frequent tillage for seeding preparation and manual cultivation for weed control and row management contributed to further reductions. As some authors have already underlined, the intensity and frequency of tillage have a significant impact on soil organic carbon (Haddaway et al., 2016) and contribute to soil compaction, which negatively affects hydrological processes (Capello et al., 2019). Despite very low $\tilde{T}_{red}$ values, particularly in 2021 and 2019, the cover cropping accounted for in the $\tilde{E}_{res}$ calculation helps offset the S_{dis} indicator. As observed by various authors (Morvan et al., 2014; Stanchi et al., 2021), grass cover, especially permanent cover cropping, significantly reduces soil erosion, while tractor passes accelerate it. Some authors have found that conventional tillage in

vineyards increases runoff and soil erosion, while grass cover can reduce these effects by over 60% (Biddoccu et al., 2017). The S_{dis} indicator, therefore, reflects an overall positive management approach, even in years with higher tillage intensity, thanks to the adoption of cover crops in the vineyard. As to the regeneration of the SOM R_{som} indicator, the years in which organic matter input was deemed insufficient or excessive are penalized. Higher values were observed in 2019 and 2021, indicating an improvement, despite organic fertilization being consistent in previous years. Like the original organic matter indicator (Bockstaller et al., 1997), the R_{som} indicator assesses the effect of agricultural practices on the evolution of soil organic matter (SOM), taking into account multi-year organic fertilization. In addition to having a positive impact on vine health and grape quality (Mulotto et al., 2022), organic fertilization improves soil health and boosts soil fauna and microbial activity in particular (Wang et al., 2022; Zhou et al., 2022). The protection from copper eco-toxicity C_{tox} indicator considers the potential impacts due to the application of copper. In organic farming, the use of non-synthetic products such as mineral-based fungicides like copper or sulfur is allowed. Unlike sulfur, whose environmental impact is considered very low (Spruijt-Verkerke et al., 2004), residues from copper-based fungicides can alter soil pH, lead to nutrient deficiencies and, most importantly, cause toxicity to soil biota (Akinnifesi et al., 2006; Wightwick et al., 2013). The C_{tox} indicator shows slightly lower values in 2014 and relatively stable values in the following study years. This is to be expected, as the pressure from *Plasmopara viticola* was particularly high in 2014 in the area covered by the study. Nevertheless, the indicator reveals high performance across all the study years, highlighting how copper-based disease management in the study context was not penalized according to the indicator. By including the characterization factors derived from Viveros Santos et al., (2018), the area-specific factors, such as copper complexation with soil organic matter (SOM), are taken into account. Copper has a high affinity for organic matter (Matar et al., 2015), which affects its bioavailability and, consequently, its potential toxicity to soil fauna and microorganisms. The nutrient use efficiency N_{eff} indicator shows relatively consistent trends over the years covered by the study, although there are differences in individual nutrients, such as nitrogen, where

lower values can be observed in 2019 and 2021. Fluctuations can be attributed to several factors, primarily differences in fertilization inputs and dosages, as well as the influence of legume cover cropping in 2019, which contributed to biological nitrogen fixation. To optimize nutrient efficiency, particularly for nitrogen, fertilization doses should also be adjusted based on nutrient inputs from legume cover cropping. In general, inputs exceeded outputs, except for potassium in 2014 and 2015, where inputs were lower. It should be noted that the yield limit set by production regulations does not account for any excess production per plant, which may be removed through green harvesting. Therefore, the years in which inputs exceeded outputs relative to the set limit are considered years with excess nutrients. Improving nutrient use efficiency is crucial for enhancing both productivity and sustainability. Strategies adopted to achieve this result include appropriate dosing, the use of effective sources, as well as optimal timing and application methods (Baligar and Fageria, 2015). It is also important to consider the mineralization rates of nutrients, particularly nitrogen, in organic amendments. The release of mineral nitrogen from organic fertilizers greatly depends on the cultivation substrate, temperature, humidity and the nature of the fertilizer, ranging from 10.7% to 71.3% of the applied fertilizer nitrogen (Cannavo et al., 2022). Regarding excesses, proper management of phosphorus and nitrogen is required to limit the risks of eutrophication (Haque, 2021). Although the potential role of potassium in eutrophication is considered minimal (Leentvaar, 1980), an excess or deficiency of potassium in agricultural systems can lead to long-term sustainability issues with soil resources, thereby compromising agricultural production (Öborn et al., 2005). Adequate potassium input is essential to maintaining soil health (Das et al., 2019). In this case, the indicator aggregation was based on an equally weighted average of the three nutrients. A potential further development could involve weighting the nutrients based on their importance for production or the risk associated with potential environmental impacts. Additionally, a more detailed monitoring of nutrient release over time should be considered. The Protection of biodiversity P_{bio} indicator shows variability, with lower values in 2014 and 2015. In these years, the indicator only considered the $\widetilde{QBS}_{ar}$. Even when analyzing the $\widetilde{QBS}_{ar}$ values exclusively, 2014 and 2015 still show lower values. With a higher H' index value

for bacteria and a lower H' index value for fungi, there is a slight contribution to the reduction of the averaged indicator in 2019 and 2021 compared to the assessment based solely on $\widetilde{QBS}_{ar}$ for the same years. The years with lower $\widetilde{QBS}_{ar}$ values also show lower scores, partly due to the absence of some groups (deep soil-living organisms), such as Protura, which are more sensitive to variations in soil environment and better adapted to life in the soil (Parisi et al., 2003; Wahsha et al., 2012). Although, in this case, as a "measured indicator", it is not possible to assess direct associations between the effects of individual practices on biodiversity, various authors (Karimi et al., 2020; Winter et al., 2018) have highlighted that organic viticulture practices, such as cover cropping, organic fertilization and the addition of pruning wood, can improve diversity and activity of soil microorganisms. In contrast, soil tillage, lack of cover and mineral fertilization can harm them. The reduced use of copper-based products in organic viticulture enhances yield and environmental sustainability without compromising grape quality, while simultaneously improving soil biodiversity (Storchi et al., 2022). This aspect has already been accounted for by the C_{tox} indicator.

Table 4.6. Results of individual indicators and their respective sub-indicators across the different study years.

Indicator	2014	2015	2019	2021
$\tilde{E}_{res}$	0.852	0.841	0.843	0.844
$\tilde{T}_{red}$	0.842	0.759	0.561	0.671
S_{dis}	0.847	0.800	0.702	0.758
R_{som}	0.900	0.806	1.000	1.000
C_{tox}	0.968	0.978	0.977	0.980
$\widetilde{Nit}$	0.967	0.919	0.436	0.546
$\widetilde{Pho}$	0.666	0.744	0.397	0.527
$\widetilde{Pot}$	0.354	0.161	0.981	0.699
N_{eff}	0.662	0.608	0.605	0.590
$\widetilde{QBS}_{ar}$	0.500	0.500	0.833	0.833
$\tilde{R}_{bac}$	*NA*	*NA*	0.631	0.801
$\tilde{R}_{fun}$	*NA*	*NA*	0.631	0.751
P_{bio}	0.500	0.500	0.699	0.795

Integrated assessment of individual indicators and MISQ

A synthesis of the variations in the contributions of individual indicators are shown in the multi-year doughnut chart on the left in Figure 4.2. Higher values are recorded in the last two years of management for the P_{bio} and R_{som} indicators. A slight improvement was also observed in C_{tox}, although it was limited. While the values of N_{eff} are variable, higher values of S_{dis} are observed in the earlier years of the study, where fewer operations were conducted. As observed, the addition of organic matter in vineyards and long-term use of manure increase soil microarthropod biodiversity and abundance (Ghiglieno et al., 2020; Kautza et al., 2002). Organic fertilization can also enhance the complexity of microbe-microfauna ecological associations (Suleiman et al., 2019). Some authors have observed greater diversity and stability in arthropod communities in vineyards managed with spontaneous vegetation compared to those managed with tillage or sown vegetation (Gonçalves et al., 2020). However, other studies suggest that soil properties and climatic conditions often have a greater influence on the movement and presence of soil arthropods (Xin et al., 2018). Cover crops in vineyards can generally increase beneficial arthropod populations and reduce harmful ones, potentially benefiting integrated pest management programs (Vogelweith and Thiéry, 2017). Sowing legume-rich mixtures can improve the structure of the soil microbial community (Moreno et al., 2021). Additionally, organic carbon and nitrogen deposits in the soil increase through mixed cover crops of grasses and legumes in vineyard agroecosystems, thereby improving nitrogen availability and reducing soil erosion (Ball et al., 2020). Selecting functional aspects in artificial cover cropping can positively impact biotic activity and lead to a more significant overall improvement compared to the use of spontaneous vegetation (Tang et al., 2022). As observed by some authors (Messiga et al., 2015), the combination of legume-based cover crops and soil amendments can, depending on the conditions, provide a supply of soil mineral nitrogen and available phosphorus comparable with that of fertilized treatments, while also improving the chemical and biological properties of the soil and overall soil quality under the pedoclimatic conditions of the vineyards. The right side of Figure 4.2 shows the trend of the MISQ integrated indicator, obtained from the geometric mean. A rising trend can be observed in the surveyed scenario, with values higher in 2019 and 2021. The MISQ provides a synthetic overview of

the individual indicators' trends, but it remains essential to monitor their evolution over time. Comparing different years allows for a better refinement of management strategies and an assessment of long-term effects. In addition to the integrated indicator value, a comprehensive analysis of individual parameters helps identify the most effective combinations of practices to maintain and enhance soil fertility, functionality, and biodiversity, and thus its overall quality.



Figure 4.2. a. A multi-year doughnut chart illustrates the trends of the MISQ indicators for each year. 4.2 b. A bar chart shows the different values of the integrated indicator over the study years.

Conclusions

Soil is a fundamental resource for viticulture and maintaining its functionality is essential to preserve soil health and optimize the ecosystem services it provides for production. This study introduces an integrated indicator, the Management Impact on Soil Quality (MISQ) indicator, which provides a comprehensive assessment of the effects of organic viticulture practices on soil functions. Enhanced functionality has been observed in years when the biological community was supported through the optimized distribution of organic matter and the use of functional cover crops. Measuring the sustainability of agricultural practices is a challenging task but is vital for developing localized strategies. The simplicity of the indicators used makes this tool applicable in various scenarios, thereby facilitating the development of effective management strategies that minimize a negative impact on soil functions. Furthermore, the indicator is expected to be adaptable for use in other studies, with its composition customized to fit specific research settings. As previously

mentioned, the MISQ proves particularly effective for intra-site and interannual evaluations, allowing for a precise analysis of the effects of viticultural management practices on soil quality. Given its structured approach, it would be valuable to explore its application in different contexts. However, caution is needed when considering initial conditions and, in order to ensure comparability across different scenarios, assessing the relative increase from a baseline may be a more suitable approach. Expanding the applicability of the MISQ requires a deeper understanding of the relationships between soil types and their specific characteristics. While the indicator was developed for organic viticulture, adapting it to systems with different management practices would necessitate considering additional factors, such as incorporating other active ingredients beyond copper in the toxicity indicator. The MISQ can serve as a functional tool for grape growers, contributing to the reduction of the environmental impact of viticultural practices on soil quality. Future research should focus on refining the indicator's adaptability to diverse agricultural contexts, ensuring it remains a reliable tool for assessing and improving soil quality under various management strategies.

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5. Biodiversity

5.1. Deep-Learning-Based Land Cover Mapping in Franciacorta Wine Growing Area

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Abstract

Land cover mapping is essential to understanding global land-use patterns and studying biodiversity composition and the functioning of eco-systems. The introduction of remote sensing technologies and artificial intelligence models made it possible to base land cover mapping on satellite imagery in order to monitor changes, assess ecosystem health, support conservation efforts, and reduce monitoring time. However, significant challenges remain in managing large, complex satellite imagery datasets, acquiring specialized datasets due to high costs and labor intensity, including a lack of comparative studies for the selection of optimal deep learning models. No less important is the scarcity of aerial datasets specifically tailored for agricultural areas. This study addresses these gaps by presenting a methodology for semantic segmentation of land covers in agricultural areas using satellite images and deep learning models with pre-trained backbones. We introduce an efficient methodology for preparing semantic segmentation datasets and contribute the "Land Cover Aerial Imagery" (LICAI) dataset for semantic segmentation. The study focuses on the Franciacorta area, Lombardy Region, leveraging the rich diversity of the dataset to effectively train and evaluate the models. We conducted a comparative study, using cutting-edge deep-learning-based segmentation models (U-Net, SegNet, DeepLabV3) with various pre-trained backbones (ResNet, Inception, DenseNet, EfficientNet) on our dataset acquired from Google Earth Pro. Through meticulous data acquisition, preprocessing, model selection, and evaluation, we demonstrate the effectiveness of these techniques in accurately identifying land cover classes. Integrating pre-trained feature extraction net- works significantly improve performance across various metrics. Additionally, addressing challenges such as data availability, computational resources, and model

interpretability is essential for advancing the field of remote sensing, in support of biodiversity conservation and the provision of ecosystem services and sustainable agriculture.

Keywords: land cover mapping; semantic segmentation; deep learning; satellite imagery; pre-trained backbone

Introduction

Background

Land cover mapping is a fundamental tool for understanding complex land-use patterns across the globe. It provides key information for such critical issues as ecosystem health and biodiversity conservation, and it monitors changes over time. By accurately classifying various types of land covers, like forests, agricultural lands, wetlands, and urban areas, land cover maps offer valuable insights. Advancements in remote sensing technology have increased the availability of satellite imagery with diverse characteristics, making it a cornerstone in land cover mapping (Olofsson et al., 2013). Vineyards contribute significantly to biodiversity by supporting habitats that provide critical ecosystem services (Williams et al., 2020). Grasslands, herbaceous zones, and forested areas surrounding vineyards act as ecological corridors, promoting species richness and fostering pollinators and natural predators essential for pest regulation and crop production ("Advancing Regenerative Viticulture Worldwide | RVF," n.d.; Giffard et al., 2022). These habitats also improve soil health, reduce erosion, and support water retention, thereby enhancing overall ecosystem resilience (Abad et al., 2021). By maintaining a diverse landscape, vineyards can help preserve local flora and fauna, thereby supporting ecological stability and productivity (Hurajová et al., 2024). Mapping surrounding land cover types is indispensable for biodiversity conservation in vineyard ecosystems. High-resolution maps generated through advanced technologies, such as satellite imagery and UAVs, allow the precise identification and monitoring of diverse habitats. These maps facilitate the understanding of spatial patterns, enabling informed decisions to optimize agricultural practices while conserving biodiversity (Paiola et al., 2020). For instance, detailed land cover maps guide the management of cover crops, monitor pest-prone zones, and assess

the ecological benefits of natural habitats within and around vineyards (Candiago et al., 2023). Traditionally, classical machine learning techniques, such as SVM (Pal and Mather, 2005), decision trees (Pal and Mather, 2003), and random forest (Cutler et al., 2007) have been used for land cover mapping from satellite images. However, these methods have limitations, such as the need for expert analysis (Laban et al., 2019) and challenges with high-resolution imagery (Phiri et al., 2020). An example is maximum likelihood classification (MLC), which is based on pixel probabilities but struggles with resolution limitations and expert input (Gauci et al., 2018).

Problem Statement

The emphasis on using high-resolution satellite imagery for land cover mapping highlights the limitations of traditional classification methods (Candiago et al., 2023). While studies showcase the effectiveness of random forests and support vector machines with high-resolution data, such challenges as sensitivity to parameters and class imbalance persist, which requires careful optimization (Mardani et al., 2019; Pelletier et al., 2016). Land cover data is crucial in urban planning to address global challenges, but limitations in satellite image analysis, such as managing large data volumes and complex classifications, remain (Ouchra et al., 2023). To address these challenges using very high- resolution (VHR) imagery, integrated approaches combining object-based image analysis (OBIA) and random forests have been proposed (Han et al., 2020). However, even these approaches face issues like spectral redundancy and the computational demands of incorporating temporal features (Han et al., 2020).

Recent Advancements and Challenges in Deep Learning

Recent technological advancements have driven the evolution of image analysis, particularly with the introduction of deep learning algorithms (Ma et al., 2019). Deep learning offers the advantage of automatic feature extraction, exemplified by the TASSEL framework, which combines CNN-based feature extraction with OBIA classification (Zaabar et al., 2022). Recent advancements in deep learning, particularly convolutional neural networks (CNNs), hold significant potential for land cover classification and object detection using high-resolution imagery (Zhang

et al., 2020). However, challenges remain in enhancing the generalization and robustness of these models, necessitating the use of diverse training datasets (Chi et al., 2016). Additionally, studies have presented techniques using pre-trained neural networks for land cover mapping on Landsat 5/7 images, potentially accelerating map production but limiting generalizability (Ienco et al., 2020). In land cover mapping with deep learning, semantic segmentation excels by dividing images into meaningful segments, offering superior accuracy, especially in vegetation mapping (Marmanis et al., 2016; Yang and Tang, 2021). To address the limitations of single-scale convolution kernels, advancements like multi-scale fully convolutional networks (MSFCNs) have been introduced (Li et al., 2022). Similarly, the U-Net temporal attention encoder (U-TAE) and the remote sensing segmentation transformer (RSSFormer) approaches enhance semantic segmentation with temporal attention or are specifically tailored for high-resolution remote sensing applications, respectively (Tzepkenlis et al., 2023; Xu et al., 2023). While CNNs are explored for per-pixel classification in high-resolution remote sensing, leveraging detailed data for precise object classification (Längkvist et al., 2016), challenges persist in acquiring specialized datasets due to high costs associated with data collection, demanding significant time, labor, and financial resources for activities such as field surveys and manual annotation of vegetation classes (Längkvist et al., 2016; Tzepkenlis et al., 2023).

Study Objective and Research Gap

While significant progress has been made in developing deep-learning-based methods for land cover classification (Marmanis et al., 2016; Yang and Tang, 2021), a notable gap remains in the availability of remote sensing datasets tailored to agricultural regions (Digra et al., 2022; Vali et al., 2020). To address this gap, this study presents a cost-effective methodology for preparing semantic segmentation datasets, focusing on reducing the time and costs traditionally required for data collection. This methodology enhances reproducibility and provides an effective approach to generating datasets for land cover mapping in vineyard ecosystems. Our study focuses on mapping different land cover classes, including grasslands, herb-dominated habitats, and tree-dominated areas in the Franciacorta region of Lombardy, Italy. By using remote sensing and artificial

intelligence, we introduce a methodology for mapping large areas, laying the groundwork for future studies on how surrounding land cover can contribute to the ecological balance and sustainability of vineyard ecosystems. While significant progress has been made in developing land cover classification using semantic segmentation, a notable gap persists in creating comprehensive remote sensing datasets tailored to agricultural regions. To bridge this gap, this study presents a cost-effective methodology for preparing a semantic segmentation dataset to ensure reproducibility for other researchers. We introduce a novel land cover dataset comprising seven manually annotated classes, specifically designed for large-scale semantic segmentation, with a particular focus on the wine cultivation area. These essential classes include grasslands, arable land, herb-dominated areas, hedgerows, vineyards, tree-dominated man-made habitats, and olive groves. The dataset was created through the analysis of a large agricultural area, specifically the Franciacorta region of Lombardy, Italy. Landsat satellite RGB images with a 30 m resolution, obtained using Google Earth Pro 7.3.6 software, served as the image source for in-depth analysis. In this paper, we conducted a rigorous comparative analysis of state-of-the-art deep- learning-based segmentation models to determine the optimal approach. We employed a variety of models, including UNet, SegNet, and DeepLabV3, combined with different backbone convolutional neural networks.

Materials and Methods

The research methodology consisted of four sequential steps, as illustrated in Figure 5.1.1. Firstly, the study focused on the Franciacorta area in Lombardy, Northern Italy, defining the geographical context. Secondly, satellite imagery was acquired from Google Earth Pro, georeferenced with ArcGIS, and segmented using eCognition to create homogeneous image regions. In the third step, these segmented images were validated and classified by a plant expert using QGISto ensure accurate identification of land cover types such as grasslands and vineyards. Lastly, the fourth step involved training semantic segmentation models U-Net, SegNet, and DeepLabV3—on smaller image patches derived from the large original images, with and without pre-trained backbones. Models were assessed based on performance metrics such as accuracy and the Jaccard Index, thereby completing a thorough approach to land cover analysis and classification.

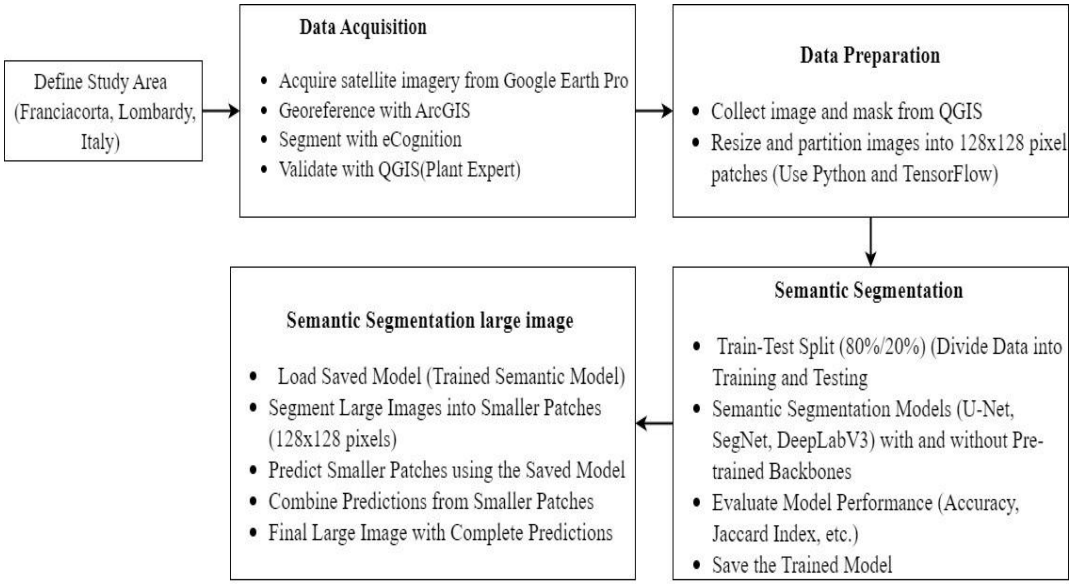


Figure 5.1.1 General workflow of semantic segmentation.

Study Site

This study focuses on the Franciacorta area, a famous Italian wine growing region located in Lombardy, Northern Italy (as shown in Figure 5.1.2). Nestled in the picturesque province of Brescia, Franciacorta is renowned for its exquisite landscape, rich history, and world-class wine production. This area encompasses approximately 195 square kilometers (77 square miles), and the study area is located at approximately 45◦37′31.05″ N and 9◦55′52.33″ E.

Data Acquisition

The total study area covers 2981.4 hectares. We divided this area into 18 image tiles. Among these tiles, the smallest covers 14 hectares with a 1192 × 700-pixel picture, and the largest 172 hectares with a 2392 × 1402-pixel picture. The following steps were taken to prepare the picture and the corresponding mask image:

Step 1: The process initiated with the acquisition of satellite imagery from Google Earth Pro by capturing both the visual image and its accompanying shape file in .kmz format as shown in Figure 5.1.3. This imagery encompasses a broad spatial scope and pro- vides a comprehensive view of the target area. Subsequently, the acquired images were georeferenced using ArcGIS 10.3 software, a crucial step in

aligning the satellite image with geographic coordinates for accurate spatial analysis.



Figure 5.1.2 Geographic coverage of the study area in Franciacorta, Lombardy, Northern Italy. Here Italy is outlined in red, Lombardy in yellow, and the study area in blue.



Figure 5.1.3 Satellite imagery acquisition and georeferencing process.

Step 2: After georeferencing, multiresolution segmentation (MRS) in eCognition parti- tioned the imagery into homogeneous regions based on spectral and spatial characteristics. The scale parameter was set to 100, compactness to 0.5, and shape to 0.4; these values optimized the balance between spatial coherence and object

delineation. A georeferenced shapefile was then generated. This facilitated expert masking in QGIS to remove unnecessary fragmented objects.

Step 3: Following segmentation, the resulting segmented shape file and image were subject to meticulous examination and validation by a knowledgeable plant expert as shown

in Figure 5.1.4. Leveraging the capabilities of QGIS software 3.24.0, the expert meticulously inspected each segmented polygon and assigned appropriate plant names based on their botanical characteristics and distribution within the landscape.



Figure 5.1.4 Validation process of segmented shape file in QGIS: original image (left); segmented classes (right). Grasslands are shown in green, arable lands in yellow, herb-dominated habitats in medium-dark green, vineyards in purple, tree-dominated man-made habitats in black. Additionally, Olea europaea groves are shown in brown.

Classes:

1. Grassland: grasslands are crucial for maintaining biodiversity in vineyard ecosystems in that they support various pollinators, herbivores, and predators (Giffard et al., 2022). These areas provide habitat for beneficial insects, such as bees and butterflies, which aid in pollination, a key service for vineyards.

Additionally, grasslands can foster natural pest control by harboring insectivorous species that help keep pest populations in check (Williams et al., 2020).

2. Arboreal land: tree-dominated habitats, such as forests or woodlands, are vital for fostering biodiversity as they offer shelter and food resources for a variety of species, including birds, mammals, and insects. These areas also play a critical role in climate regulation and contribute to ecosystem connectivity. In vineyard landscapes, arboreal land acts as a buffer zone that protects against wind erosion, provides shade, and enhances the resilience of the ecosystem as a whole.

3. Herbaceous habitats: herbs and grasses are important to foster biodiversity in that they support herbivores, pollinators, and decomposers. These areas typically host plant species that help improve soil health and nutrient cycling, and hence the sustainability of surrounding agricultural areas. In vineyards, herb-dominated habitats can play a role in reducing soil erosion, supporting beneficial micro fauna, and providing a diverse range of species that contribute to the overall ecosystem.

4. Hedgerows: these are critical for maintaining ecosystem connectivity in agricultural landscapes. These linear strips of vegetation provide a corridor for wildlife movement, as they offer shelter, food, and protection for pollinators, birds, and small mammals. In vineyards, hedgerows can also act as natural pest control systems by supporting predatory species that reduce the abundance of vineyard pests, such as aphids or grapevine moths.

5. Vineyards: as the primary agricultural feature in this study, vineyards play a dual role in biodiversity. While they are managed for grape production, vineyards can still contribute to biodiversity by supporting specialized plants and animals, such as birds and insects that thrive in cultivated areas. Effective vineyard management practices, such as cover crops and organic farming methods, can enhance biodiversity by providing pollinator habitats, improving soil health, and promoting sustainable farming practices.

6. Tree-dominated man-made habitats: these areas, including urban parks, orchards, and landscaped gardens, offer refuges for a range of fauna and flora, thereby promoting biodiversity within human-modified environments. While these habitats may not be as diverse as natural forests, they support species that are adapted to urbanized landscapes. In relation to vineyards, tree-dominated habitats can provide important wildlife corridors that help maintain genetic diversity among species and support beneficial pollinators and pest controllers.

7. *Olea europaea* groves: olive groves, primarily found in Mediterranean regions, offer

a specialized habitat for certain plant and animal species. These groves support a range of native vegetation and provide food and shelter for various wildlife species, including birds, insects, and small mammals. In vineyards, the presence of olive groves can enhance biodiversity by fostering species interactions across adjacent agricultural landscapes, thereby contributing to sustainability and ecosystem services like pollination and pest control.

Experiment

In this work, the original images were large in pixel size. This posed a challenge for deep learning models, in that large image sizes require significant memory and can slow down the training process. This challenge was addressed by setting up a Python code to efficiently process large images. The code started by iterating through the directories and subdirectories within a specified root directory, which contained both image and mask files. For each image and mask file found, the code resized them to the nearest size divisible by a predefined 128 × 128-pixel patch size. The resized images and masks were then divided into non-overlapping patches using the patchify library from the TensorFlow function, making sure each patch matches the specified dimensions. These patches were saved as individual image files, preserving their association with their corresponding masks as shown in Figure 5.1.5. Additionally, the code utilized the split folders library from TensorFlow to split the patched images and masks into training, validation, and testing datasets at 70%, 15%, and 15% ratios, respectively. After splitting, the training dataset was comprised of 536 images, the validation dataset contained 115

images, and the testing dataset included 115 images. This streamlined process facilitated efficient model training, validation, and evaluation.

Backbones

In our study, we performed two semantic segmentation approaches: with and without leveraging a backbone. Semantic segmentation without a backbone involves training models from scratch, without the use of pre-trained networks. This method relies solely on the model's architecture to extract features directly from input data. While this approach offers independence from pre-existing biases and data patterns embedded in pre-trained networks, it typically requires more extensive training and larger datasets to achieve performance comparable with pre-trained backbone models.

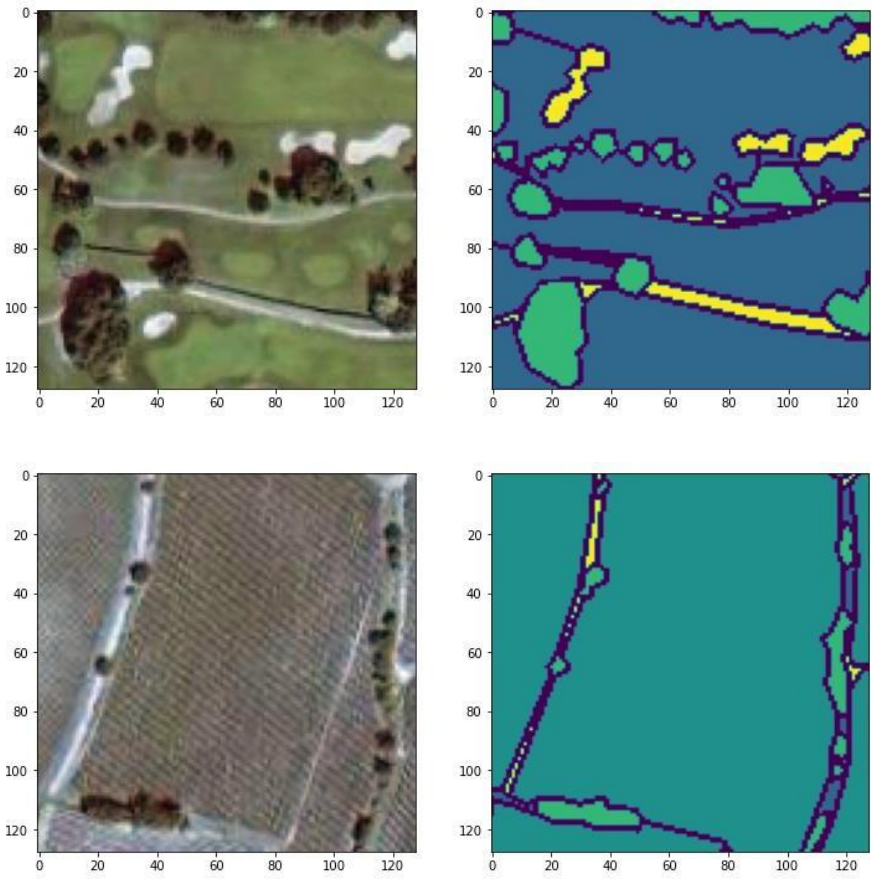


Figure 5.1.5 Illustration of two randomly selected 128 × 128-pixel image patches, extracted from the original images along with their corresponding ground truth masks. These patches are used to train and evaluate a deep learning model.

Conversely, leveraging a pre-trained backbone is a widely adopted strategy aimed at enhancing model performance in semantic segmentation tasks. Backbones, such

as ResNet, InceptionV2, DenseNet, and EfficientNet, are well-established architectures in CNN deep- learning. These models are pre-trained on large-scale datasets (such as ImageNet) and have learned to extract meaningful features from images by encompassing spatial relationships and contextual information crucial for accurate segmentation.

By fine-tuning these pre-trained backbones for specific segmentation tasks, models can efficiently adapt to new datasets and extract relevant features tailored to the nuances in land cover classification. This process leverages transfer learning, where knowledge acquired from previous tasks (e.g., image classification) is transferred to improve performance on current segmentation tasks. This approach not only accelerates model convergence during training but also enhances segmentation accuracy by leveraging the rich feature representations learned by backbone networks.

The choice of ResNet, InceptionV2, DenseNet, and EfficientNet as backbone architec- tures was motivated by their proven performance in various computer vision tasks and their distinct architectural strengths:

A. ResNet

ResNet (He et al., 2016), or Residual Network, is a pioneering convolutional neural network architecture devised to tackle the challenge of vanishing gradients in deep networks. Developed by Microsoft Research, ResNet introduces residual connections enabling the training of exceptionally deep networks by learning residual functions. These connections address the degradation problem associated with increasing network depth, resulting in state-of-the-art performance across various computer vision tasks.

B. Inception

An evolution of Google's Inception architecture, InceptionV3 (Szegedy et al., 2016) is renowned for its computational efficiency and high accuracy. It introduces several novel features, including the inception model, which enables the network to efficiently capture features at multiple scales through parallel convolutions. InceptionV3 employs factorized convolutions, which reduces computational cost

while maintaining expressive power. Additionally, it incorporates batch normalization and auxiliary classifiers, thus facilitating convergence speed and regularization.

C. DensNet

DenseNet (Huang et al., 2018), short for "densely connected convolutional networks", is a convolutional neural network architecture known for its densely connected layers. Unlike traditional architecture where each layer is connected only to the subsequent layers, DenseNet introduces dense connections, where each layer receives direct inputs from all preceding layers. This design fosters feature reuse and facilitates the flow of gradients, leading to improved parameter efficiency and better gradient propagation.

D. EfficientNet

EfficientNet is a family of convolutional neural network architectures developed by (Tan and Le, 2020). It is specifically designed to achieve state-of-the-art accuracy while simultaneously being highly efficient in terms of computational resources. The key innovation behind EfficientNet is the compound scaling method, which uniformly scales network depth, width, and resolution in a systematic manner. This approach ensures that the network's parameters and computational cost are optimized for a given resource constraint, resulting in models that are both accurate and efficient across a wide range of tasks. In our study, we specifically utilized EfficientNetB0, which is the smallest variant in the EfficientNet family. EfficientNetB0 strikes a balance between model complexity and performance, making it suitable for various computer vision tasks, including image classification, object detection, and semantic segmentation.

Semantic Segmentation Models

We selected UNet (Ronneberger et al., 2015), SegNet (Badrinarayanan et al., 2017), and DeepLabV3+ (Chen et al., 2018) for our land cover segmentation due to their proven performance and distinct architectural strengths. By incorporating skip connections, UNet's encoder–decoder structure effectively captures both local and global features, which are essential for precise boundary delineation (Ronneberger

et al., 2015). SegNet strikes a balance between memory efficiency and high-resolution feature preservation, making it suitable for handling complex satellite imagery (Badrinarayanan et al., 2017). DeepLabV3+, which utilizes atrous convolution and atrous spatial pyramid pooling (ASPP) modules, excels in capturing multi-scale contextual information, which is crucial for intricate segmentation tasks (Chen et al., 2018).

- UNet

The UNet (Ronneberger et al., 2015) semantic segmentation model is a deep learning architecture designed for pixel-wise classification tasks, particularly in image segmentation. In this sample, we utilized the UNet model to perform semantic segmentation on UAV RGB images. The model employs a symmetrical encoder–decoder structure, with skip connections between corresponding encoder and decoder layers to preserve spatial information. This aids in capturing both local and global features, making it particularly effective for such tasks as object detection and boundary delineation.

Our UNet semantic segmentation model (Figure 5.1.6) is designed to process 128 × 128-pixel RGB images with a structured architecture aimed at capturing intricate spatial details. The model architecture is structured into two main sections: a contraction path (c1 to c5) and an expansive path (u6 to u9).

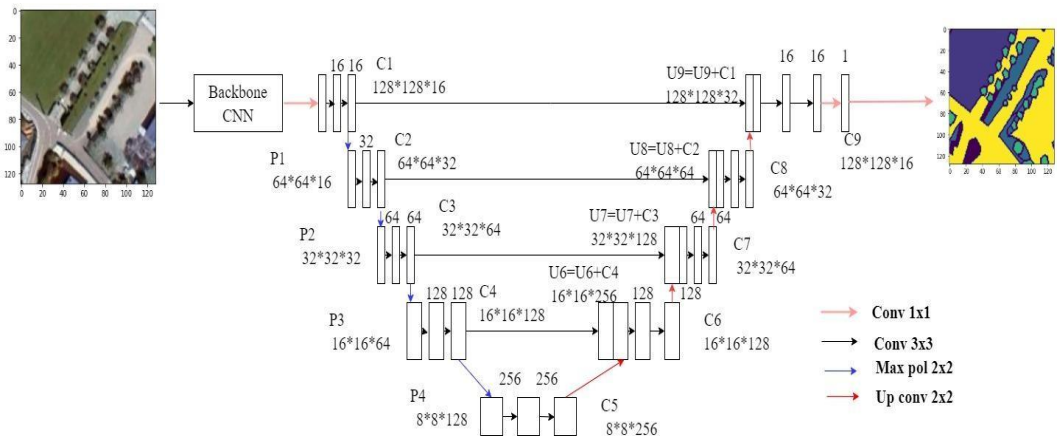


Figure 5.1.6 Architecture of the UNet semantic segmentation backbone model.

In the contraction path, successive convolutional blocks progressively increase the number of filters to extract and encode features from the input image. Max-pooling layers (p1 to p4) are strategically placed to down sample the spatial dimensions, thereby reducing computational load while preserving essential features. At the bottleneck layer (c5), the model captures high-level context and semantic information, which is crucial for accurate segmentation.

Conversely, the expansive path of the UNet model focuses on upsampling the feature maps using transposed convolutional layers. These layers help recover spatial resolution lost during the contraction path and enable the model to reconstruct detailed information. Each block in the expansive path (c6 to c9) sequentially reduces the number of filters, allowing the model to refine segmentation boundaries and enhance localization accuracy.

The final layer of the UNet model (outputs) employs a 1 × 1 convolutional layer

with a sigmoid activation function, facilitating pixel-wise predictions for each class in the segmentation task. This setup enables the model to output probability maps where each pixel indicates the likelihood of belonging to a specific land cover class.

During training, the model is compiled using the Adam optimizer, which efficiently adjusts learning rates for each parameter during training. The choice of binary cross- entropy loss function aligns with the pixel-wise nature of the segmentation task, thereby optimizing the model to produce accurate binary predictions for each pixel. The accuracy metric provides insights into the model's performance by measuring the proportion of correctly classified pixels compared to the total number of pixels.

- SegNet

SegNet (Badrinarayanan et al., 2017) is a convolutional neural network (CNN) architecture specifically tailored for semantic segmentation tasks, where the goal is to assign a class label to each pixel in an image. It features an encoder–decoder structure, which comprises an encoding path to extract hierarchical features from the input image and a decoding path to generate a pixel-wise segmentation map. Our SegNet semantic segmentation model, depicted in Figure 5.1.7, is optimized

with the EfficientNetB0 architecture serving as its foundational backbone, with connected layers fully omitted to streamline feature extraction from input images. The model is structured around an encoder–decoder architecture, each fulfilling distinct roles in the segmentation process.

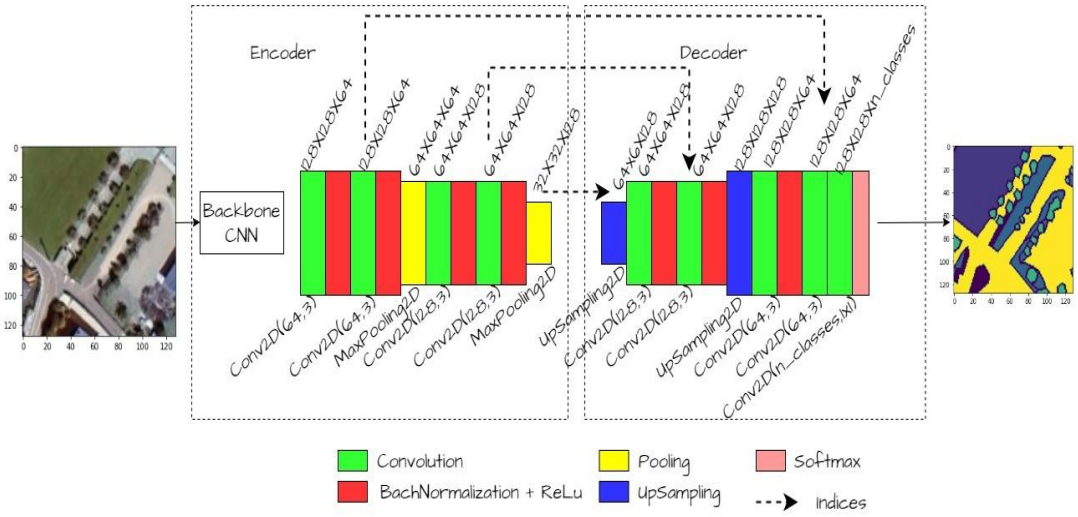


Figure 5.1.7 SegNet block diagram with backbone encoder–decoder CNN architecture.

The encoder, or contracting path, initiates with convolutional layers followed by batch normalization and max-pooling operations. This sequence progressively condenses spatial dimensions while effectively capturing essential features from the input images. By utilizing max-pooling layers, the encoder enhances computational efficiency by reducing the complexity of feature maps without compromising significant visual information.

In contrast, the decoder, or expansive path, employs up sampling layers to restore the spatial resolution of feature maps. These layers are crucial for recovering fine-grained details lost during the down sampling process in the encoder. Furthermore, the decoder integrates features extracted from the EfficientNetB0 backbone with the up-sampled feature maps to refine segmentation accuracy. This fusion of hierarchical features ensures that the model can leverage both high-level semantic information and detailed spatial context for precise pixel-wise predictions. Subsequent convolutional layers further refined the features, and the output layer generates pixel-wise predictions through a softmax activation function. The model

constructed with the backbone input and output layer is designed to classify pixels in images.

- DeepLab

DeepLabV3 (Chen et al., 2018)is a cutting-edge convolutional neural network architecture tailored for semantic image segmentation. It leverages atrous convolution to capture multi-scale contextual information efficiently. Key features include a pyramid network for hierarchical feature extraction, atrous spatial pyramid pooling for multi-scale feature aggregation, and efficient up-sampling methods for high-resolution segmentation maps. Our DeepLabV3+ model (Figure 5.1.8) utilized an EfficientNetB0 backbone for feature extraction without fully connected layers, serving as the encoder. This encoder processes input images and extracts features, which are then passed on to the decoder. The decoder consists of an atrous spatial pyramid pooling (ASPP) module followed by global average pooling and low-level feature concatenation. The ASPP module employs convolutional layers with varying dilation rates to capture multi-scale contextual information. Additionally, global average pooling is performed to capture global context information. The decoder then combines ASPP outputs, global context, and low-level features using concatenation. Further convolutional layers refine the features, followed by up-sampling layers to restore spatial information. Finally, a 1 × 1 convolutional layer with SoftMax activation generates pixel-wise predictions for semantic segmentation. The model is compiled using the Adam optimizer and categorical cross-entropy loss and accuracy function for metrics.

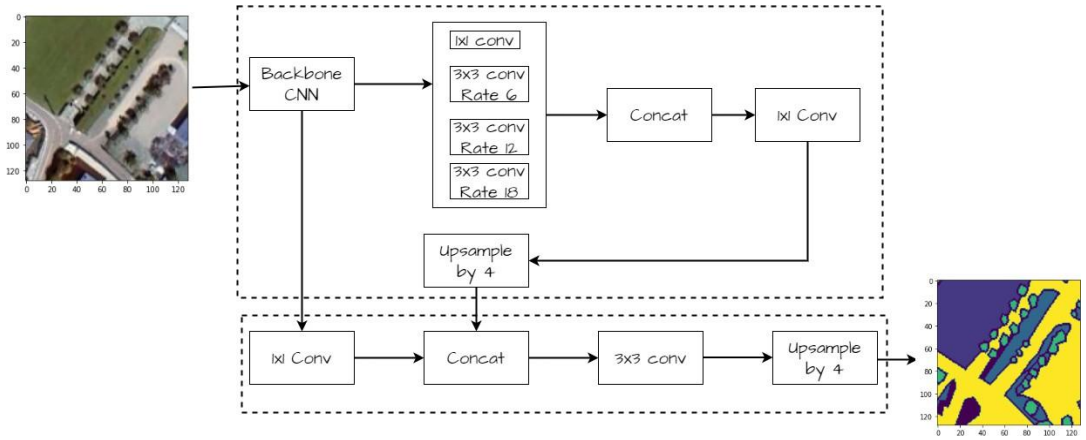


Figure 5.1.8 DeeplabV3 block diagram with backbone encoder–decoder CNN architecture.

We implemented U-Net, SegNet, and DeepLabV3 segmentation models for the semantic segmentation of satellite images. Initially, the image and mask datasets underwent preprocessing by subdividing them into smaller patches to facilitate training. Each patch was then scaled using min–max scaling, and the RGB masks were converted into integer labels based on predefined RGB values. These models were constructed using the Effi- cientNetB0 backbone, with and without encoder and decoder paths. A SoftMax activation function was applied to the output layer for multi-class segmentation. Following compilation with the Adam optimizer and categorical cross-entropy loss function, the model was trained for 100 epochs with batch size 16. The evaluation was made using accuracy and IoU metrics on both training and validation datasets, and the trained model was then saved for future reference. Performance metrics, including accuracy, precision, recall, F1 score, and Jaccard coefficient, were computed, and the segmentation performance was visually demonstrated on randomly selected test images.

Performance Metrics

In this study, several metrics were used to evaluate the performance of the semantic segmentation models:

- Accuracy It measures the overall correctness of the segmentation by calculating the ratio of correctly predicted pixels to the total number of pixels. It is computed as

$$Accuracy = \frac{True\ positives\ +\ True\ Negatives}{Total\ Pixels}$$

- Precision—It quantifies the model's ability to correctly identify positive predictions among all predicted positives. It is computed as

$$\text{Precision} = \frac{True\ positives}{True\ Positive\ +\ False\ Positive}$$

- Recall (Sensitivity) It measures the model's ability to detect all relevant instances of a class in the image. It is computed as

$$\text{Recall} = \frac{True\ positives}{True\ Positive\ +\ False\ Negative}$$

- F1 Score—It provides a balanced measure of precision and recall. It is calculated as the harmonic means of precision and recall:

$$\text{F1} = 2\,x\,\frac{Precision\ \times\ Recall}{Precision\ +\ Recall}$$

- Jaccard Index (IoU)—Also referred to as intersection over union (IoU), it measures the overlap between the predicted and ground truth regions:

$$\text{IoU} = \frac{\text{Intersection of Predicted and Ground Truth Regions}}{\text{Union of Predicted and Ground Truth Regions}}$$

- Mean IoU (mIoU)—It calculates the average IoU across all classes and provides an overall measure of segmentation accuracy across different classes.

These metrics were computed using the trained segmentation models to evaluate their performance on the test dataset. Additionally, class weighting based on Dice scores was applied during training to mitigate the impact of class imbalance.

Result

Our semantic segmentation models (Unet, SegNet, and DeepLabV3) utilized Tensor- Flow and the segmentation-models library to perform image segmentation. The dataset consisted of a total of 765 images, divided into training and testing sets with a ratio of 0.80 and 0.20, respectively. Each image was annotated with one of seven classes: grasslands, arable land, herb-dominated habitats, hedgerows, vineyards, tree-dominated man-made habitats, and *Olea europea* groves. Initially, the images and their corresponding masks were loaded from the specified directories and pre-processed accordingly. The masks were encoded using label encoding and then split into training and testing datasets. Next, the model was configured with specific parameters, including the EfficientNet backbone architecture and a combination of Dice loss and Categorical Focal loss as optimization objectives. To address the class imbalance inherent in the dataset, we

implemented class weighting based on Dice scores. This technique assigns higher weights to classes with lower coverage, ensuring that the model learns effectively from all classes. The model was trained using hyperparameters, as shown in Table 5.1.1. After training, the model was saved for future reference. Performance metrics such as accuracy, precision, recall, F1 score, Jaccard score, and mean IoU were computed using the trained model on the test dataset. Finally, the results were printed to evaluate the segmentation model's performance.

Table 5.1.2 shows a comparative analysis of performance metrics for the three Unet, Seg- Net, and DeeplabV3 semantic segmentation models under two distinct conditions: with and without backbone integration. These metrics serve as quantitative indicators of model effectiveness in accurately segmenting images. Across all models, the incorporation of back- bone architecture consistently leads to improvements in performance metrics. Specifically, models equipped with backbone demonstrate enhanced accuracy, precision, recall, and F1 scores compared to their counterparts lacking backbone integration. Accuracy, which measures correct pixel classification, ranges from 0.638 to 0.763 with backbone and from 0.667 to 0.762 without it. Similarly, precision, recall, and F1 scores exhibit higher values when using backbone architecture. Additionally, metrics like the Jaccard coefficient (IOU) and mean IOU, which evaluate the overlap between predicted and ground truth masks, show substantial improvements with backbone integration. These findings underscore the importance of incorporating pre-trained feature extraction networks, or backbones, to enhance the performance of semantic segmentation models, thereby advancing their applicability in diverse image analysis tasks.

Table 5.1.1 Hyperparameters and configurations used in the semantic segmentation model training with pre-trained backbone for land cover segmentation.

Hyperparameter	**Value**
Number of epochs	100
Batch size	16
Patch size	128
Dice loss weights	[0.1428, 0.1428, 0.1428, 0.1428, 0.1428, 0.1428, 0.1428]

Focal loss	1.0 (weight in total loss calculation)
Loss function	Total loss (Dice loss + focal loss) Optimizer
Input shape	(128, 128, 3)
Number of classes	7

Table 5.1.2 Performance metrics comparison of UNet, SegNet, and DeeplabV3 models with and without a backbone.

Performance Metrics	UNet Without Backbone	UNet with Backbone	SegNet Without Backbone	SegNet With Backbone	DeeplabV3 Without Backbone	DeeplabV3 with Backbone
Accuracy	0.574	0.653	0.564	0.673	0.681	0.763
Precision	0.590	0.657	0.563	0.678	0.6855	0.761
Recall	0.574	0.653	0.566	0.673	0.681	0.763
F1 score	0.573	0.646	0.559	0.672	0.674	0.756
Jaccard coefficient (IOU)	0.411	0.500	0.399	0.528	0.5308	0.626
Mean IOU	0.306	0.323	0.290	0.407	0.410	0.520

Based on the performance metrics provided, it can be observed that the DeeplabV3 model consistently outperformed the Unet and SegNet models across the metrics, especially when backbone integration was considered. With backbone integration, DeeplabV3 achieved the highest values for accuracy, precision, recall, F1 score, Jaccard coefficient (IOU), and mean IOU among the three models. This indicates that DeeplabV3, especially when equipped with backbone architecture, offers superior image segmentation capabilities compared to Unet and SegNet. Therefore, in terms of overall performance and effectiveness in segmenting images, DeeplabV3 stands out as the preferred model choice.

Our investigation also evaluated the effectiveness of various pre-trained backbones for semantic segmentation of land cover using DeepLabV3. As shown in Table 5.1.3, Efficient NetB0 emerged as the leader, achieving the highest overall accuracy (76.35%) and F1-score (75.60%). This indicates its superior ability to accurately segment land cover classes in the imagery. Resnet-34 followed closely with an

accuracy of 70.83% and F1-score of 70.77%. While InceptionV3 and DenseNet exhibited lower overall accuracy (around 71–75%), they maintained good precision and recall values for land cover class segmentation (refer to

Table 5.1.2 for details). Mean intersection-over-union (mIOU) and Jaccard score mirrored these trends, with EfficientNetB0 achieving the highest values (52.05% and 62.60%, respectively). These findings highlight the importance of selecting an appropriate pre-trained backbone for DeepLabV3 in land cover segmentation tasks. The optimal choice can significantly impact the model's ability to differentiate and delineate land cover classes.

Table 5.1.3 Comparison of semantic segmentation performance using DeepLabV3 with different pretrained backbones.

Backbone	Accuracy	Precision	Recall	F1 Score	Mean IOU	Jaccard Coefficient (IOU)
Resnet 34	70.83	73.29	70.84	70.77	46.32	56.90
EfficientNetB0	76.33	76.10	76.30	75.60	52.00	62.60
InceptionV3	71.46	74.00	71.46	72.01	47.50	61.40
Densest	75.07	76.18	75.05	74.66	50.70	61.75

We analyzed the receiver operating characteristic (ROC) curves, as shown in Figure 5.1.9, to evaluate our multi-class classification model's performance. The curves visualize the trade-off between true positive rate (TPR) and false positive rate (FPR) for each class, while the micro-average ROC curve summarizes the overall performance. The area under curve (AUC) quantifies the model's discriminative power. High AUC values, with the micro- average reaching 0.95 and individual class values ranging from 0.93 to 0.94, indicate that our model effectively differentiates between the various land cover classes.

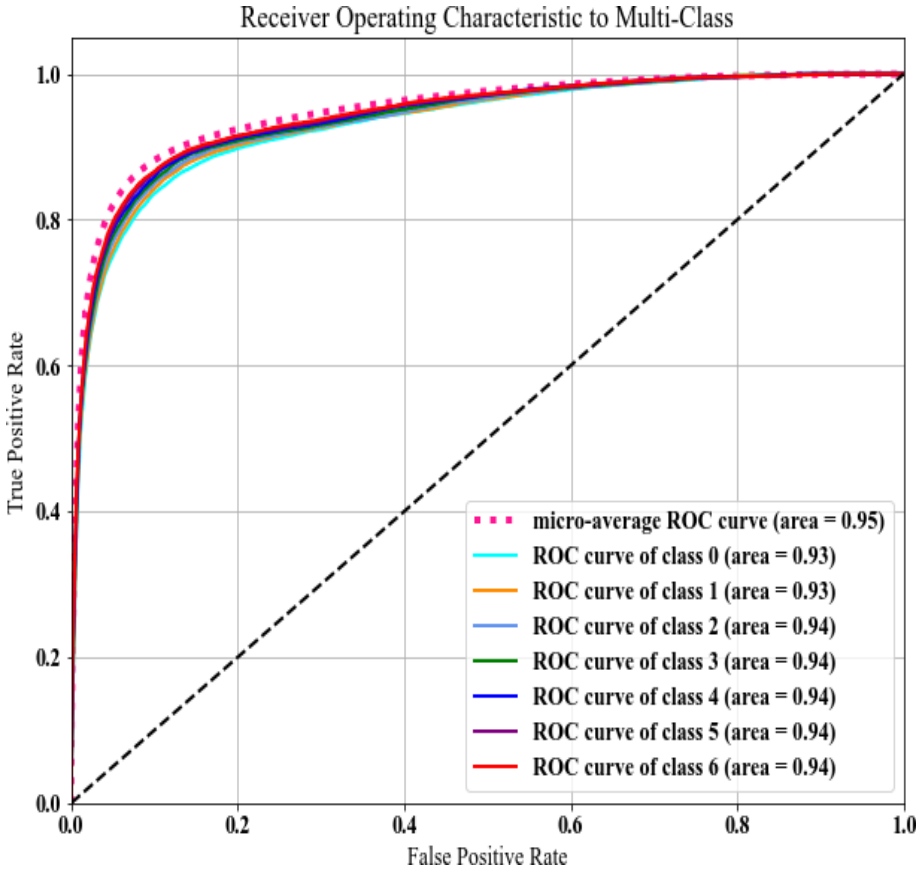


Figure 5.1.9 Receiver operating characteristic (ROC) curves show the performance of the multi-class land cover classification model. The micro-average ROC curve and individual class ROC curves demonstrate the model's strong ability to discriminate between different land cover classes.

After loading the trained model, we generated a batch of test images and their corresponding masks using the validation data generator. Next, we used the loaded model to compute predictions for the test images. Then we converted the predicted masks from categorical format to integer format for visualization and IoU calculation. Finally, in order to qualitatively assess the model's performance, we visualized a randomly selected test image along with its ground truth mask and predicted mask, as shown in Figure 5.1.10.

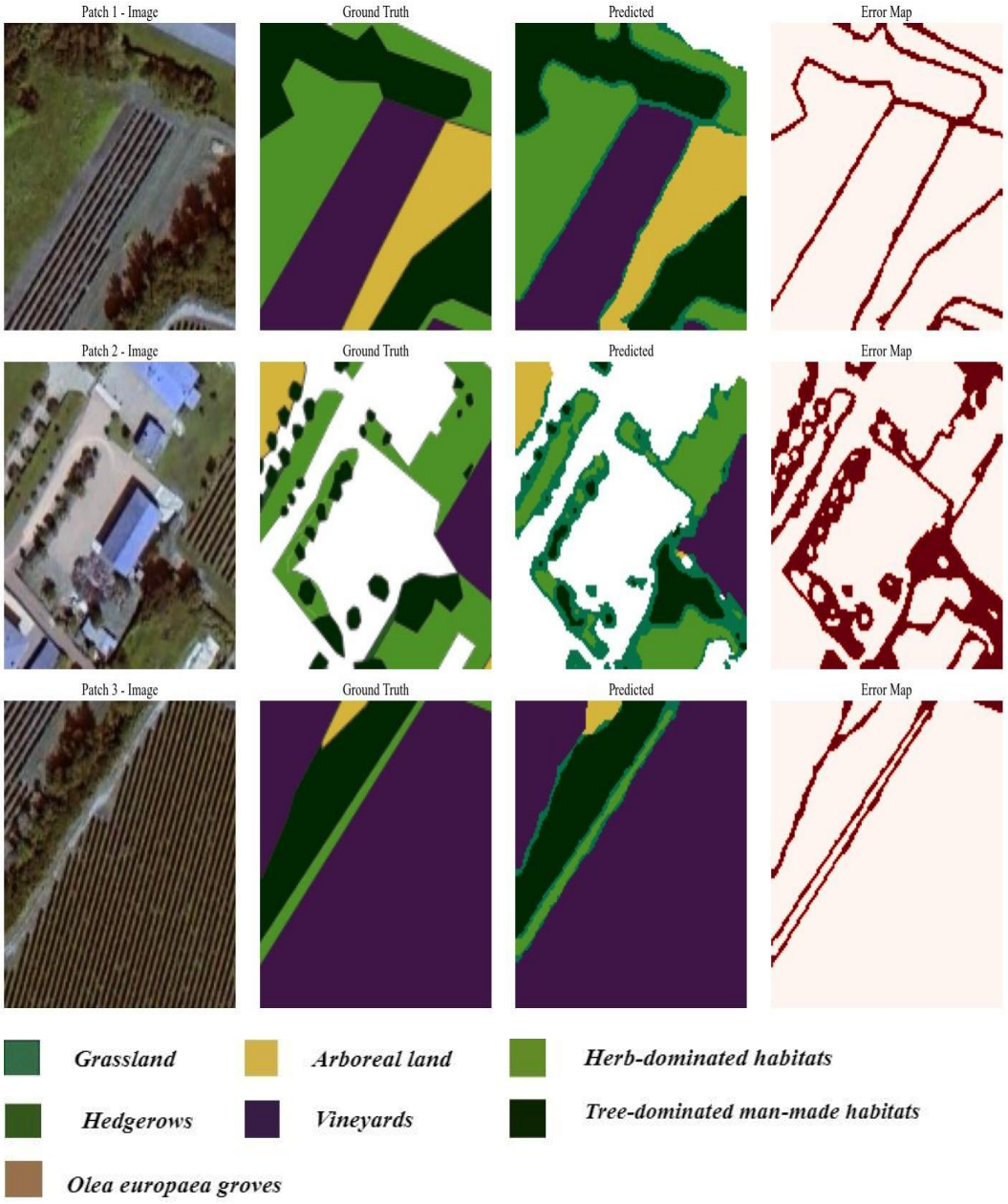


Figure 5.1.10 Display of a randomly selected test image, ground truth mask, predicted mask, and error map. The image illustrates the qualitative assessment of the model's performance, showing the alignment between the original test image, its corresponding ground truth mask, and the predicted mask generated by the model.

Finally, we applied the trained model to a large image (as shown in Figure 5.1.11). To achieve this, we segmented the image into patches of an appropriate size for processing. The prediction process was then carried out on each patch. Finally, the resulting segmented patches were stitched together to reconstruct the predicted

mask for the entire large image. This approach facilitates the application of the model to images beyond the validation dataset's size.

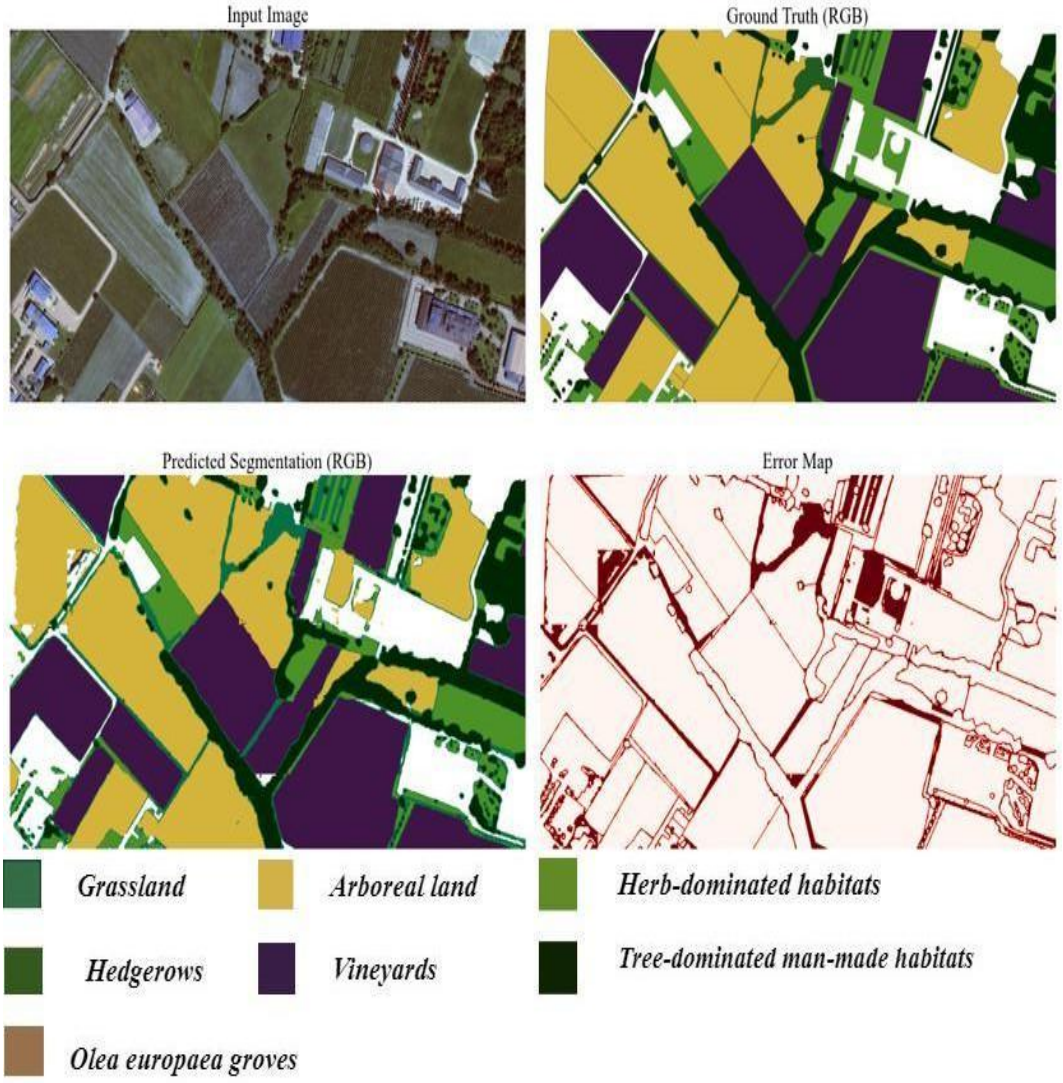


Figure 5.1.11 This figure illustrates the original image, the ground truth mask, the final segmented image mask obtained by applying a trained model, and the error map. The model segments the large image into patches, generates predictions for each patch, and seamlessly stitches the segmented patches together to reconstruct the predicted mask for the entire large image. The colors represent different land cover classes: green for grasslands, yellow for arable land, medium-dark green for herb-dominated habitats, purple for vineyards, black for tree-dominated man-made habitats, and brown for Olea europaea groves.

Discussion

In this study, we addressed key challenges and contributed significantly to the field of land cover mapping in agricultural areas. By focusing on semantic segmentation and using satellite imagery and deep learning models with a transfer learning backbone, we provided insights into the effectiveness of advanced techniques in accurately delineating land cover classes.

We introduced a land cover dataset annotated for seven distinct classes: grasslands, arable lands, herb-dominated habitats, hedgerows, vineyards, tree-dominated man-made habitats, and *Olea europea* groves. This dataset addresses a critical gap in the existing literature (Vali et al., 2020; Zhao et al., 2023) by enabling comprehensive analysis of multiple land cover types within agricultural landscapes. Using this dataset, we developed a methodology for mapping the distribution of key land cover classes (grasslands, herb-dominated, and tree-dominated areas) across large areas of Franciacorta in Lombardy, Northern Italy. This mapping provides a foundational dataset for future research that studies the impact of surrounding land cover on vineyard ecosystem biodiversity and sustainability.

However, our approach also addresses a drawback highlighted in previous studies (Ma et al., 2019; Ouchra et al., 2023). While traditional land cover mapping techniques have utilized classical machine learning algorithms and object-based image analysis (OBIA), they often struggle with spectral signature similarities, class heterogeneity, and limited generalizability. Additionally, acquiring specialized datasets for semantic segmentation has been challenging due to the high costs associated with data collection and manual annotation.

With careful data gathering, preparation, and model selection, we proved that deep learning models like UNet, SegNet, and DeepLabV3 excel in accurately mapping different land cover types from satellite imagery. By integrating pre-trained feature extraction networks, or backbones, into these models, we observed significant improvements in segmentation performance across various metrics. Our findings underscore the importance of leveraging advanced methodologies to achieve more accurate and reliable land cover mapping results. These advanced methodologies offer scalable and efficient solutions for environmental monitoring, conservation,

and land management. By harnessing the power of satellite imagery and deep learning models, we can gain valuable insights into ecosystem health, biodiversity conservation, and land use dynamics.

The performance metrics of various segmentation models, as presented in Table 2, clearly demonstrate the superiority of the DeepLabv3 model with a backbone in achieving higher segmentation accuracy compared to UNet and SegNet. More specifically, DeepLabv3 with a backbone attained an accuracy of 0.763, a precision of 0.761, a recall of 0.763, an F1 score of 0.756, a Jaccard coefficient (IoU) of 0.626, and a mean IoU of 0.520. These metrics consistently outperform those of the other models tested with and without backbones. The enhanced performance of DeepLabv3 can be attributed to its advanced architecture, which integrates atrous spatial pyramid pooling (ASPP) and robust backbone networks, thereby facilitating multi-scale context aggregation and improved handling of complex spatial patterns (Chen et al., 2018). This enables DeepLabv3 to excel in capturing fine-grained details and context, resulting in more accurate and reliable segmentation outcomes.

Among the evaluated backbones presented in Table 3, EfficientNetB0 demonstrates the highest performance across most metrics, including accuracy, precision, recall, F1 score, mean IOU, and Jaccard coefficient. This superior performance is due to EfficientNetB0's efficient use of computational resources while maintaining high accuracy and robustness in feature extraction. EfficientNetB0 leverages a compound scaling method that uniformly scales depth, width, and resolution, enabling it to achieve a balanced trade-off between model complexity and performance (Szegedy et al., 2016). In contrast, while DenseNet and InceptionV3 also perform well, EfficientNetB0's advanced architectural optimizations provide it with a more effective ability to capture detailed and diverse features, resulting in higher overall segmentation accuracy and more reliable performance metrics. ResNet34, while robust, lags in comparison, primarily due to its less efficient scaling and feature extraction capabilities. Looking ahead, future researchers should focus on improving semantic segmentation models for land cover mapping, expanding the dataset to include a more extensive number of land cover classes beyond the seven considered in this study. Additionally, incorporating ground truth data collected through field surveys would enhance the accuracy and reliability of

land cover mapping, particularly for complex and heterogeneous agricultural landscapes.

Conclusions

This study demonstrates the feasibility of employing satellite imagery and deep learning to accurately map land cover in agricultural regions. By developing a cost-effective and reproducible method, we created a novel dataset specifically tailored to wine-growing areas within the Franciacorta area. This dataset comprises seven manually annotated land cover classes, providing a valuable resource for agricultural research. Through rigorous comparison of state-of-the-art deep learning models, our research contributes significantly to advancing land cover mapping techniques.

The results demonstrate the effectiveness of deep learning models, particularly DeepLabv3, in accurately segmenting land cover classes from satellite imagery. DeepLabv3 with an EfficientNetB0 backbone outperformed other models in all performance metrics, making it the most reliable for land cover mapping. Its advanced architecture integrates atrous spatial pyramid pooling (ASPP) and efficient multi-scale context aggregation, enabling it to capture fine-grained details and handle complex spatial patterns effectively. This study highlights the potential of these advanced methods for supporting sustainable land management, environmental monitoring, and agricultural decision making. Furthermore, by analyzing different land cover types such as grasslands, herb-dominated habitats, and tree-dominated areas, we emphasize the importance of understanding how these surrounding habitats contribute to vineyard sustainability, fostering biodiversity, and enhancing ecosystem services like pollination and pest control.

Compared to traditional manual field-based mapping approaches, our methodology reduces the time required for data preparation by automating annotation tasks and utilizing open-access satellite imagery. Performance metrics show that DeepLabv3 with EfficientNetB0 improves segmentation accuracy by 10.9–13.3% and F1 score by 11.0–12.4% over other tested models. Additionally, it significantly lowers costs by avoiding the need for expensive high-resolution proprietary imagery and specialized equipment. While this research offers valuable insights, further

investigations are necessary to enhance the generalizability of the findings to diverse agricultural regions. Expanding the dataset to include additional land cover classes and incorporating ground-truth data through field surveys are essential for refining model performance and expanding the application of these techniques. Moreover, this approach investigates the application of more advanced deep learning architectures.

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5.2. Vineyard Groundcover Biodiversity: Using Deep Learning to Differentiate Cover Crop Communities from Aerial RGB Imagery

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Abstract

Monitoring groundcover diversity in vineyards is a complex task, often limited by the time and expertise required for accurate botanical identification. Remote sensing technologies and AI-based tools are still underutilized in this context, particularly for classifying herbaceous vegetation in inter-row areas. In this study, we introduce a novel approach to classify the groundcover into one of nine categories, in order to simplify this task. Using UAV images to train a convolutional neural network through a deep learning methodology, this study evaluates the effectiveness of different backbone structures applied to a UNet network for the classification of pixels into nine classes of groundcover: vine canopy, bare soil, and seven distinct cover crop community types. Our results demonstrate that the UNet model, especially when using an EfficientNetB0 backbone, significantly improves classification performance, achieving 85.4% accuracy, 59.8% mean Intersection over Union (IoU), and a Jaccard index of 73.0%. Although this study demonstrates the potential of integrating remote sensing and deep learning for vineyard biodiversity monitoring, its applicability is limited by the small image coverage, as data were collected from a single vineyard and only one drone flight. Future work will focus on expanding the model's applicability to a broader range of vineyard systems, soil types, and geographic regions, as well as testing its performance on lower-resolution multispectral imagery to reduce data acquisition costs and time, enabling large-scale and cost-effective monitoring.

Keywords: cover crop communities; deep learning; groundcover diversity; precision agriculture; unmanned aerial vehicle

Introduction

Viticulture, one of the most widespread and economically significant perennial fruit crops globally (Homet et al., 2024), is increasingly the focus of sustainable

management strategies aimed at integrating biodiversity into agricultural systems. A central component of these strategies is the management of inter-row groundcover vegetation, which plays a crucial role in enhancing ecological processes and delivering key ecosystem services.

Whether sown or spontaneous, cover crops can contribute to nitrogen fixation, improve soil structure, reduce erosion, attract pollinators, and support the biological control of pests (Blanco-Canqui et al., 2015; Daryanto et al., 2018; Eckert et al., 2020). Groundcovers also contribute to both planned biodiversity—intentionally introduced by vine-growers—and associated biodiversity, which emerges spontaneously within the vineyard agroecosystem (Novara et al., 2020).

Understanding and managing groundcover diversity is essential to optimize these benefits. However, significant knowledge gaps remain concerning the relationships between different cover crop communities and the provision of ecosystem services in vineyards. One of the main obstacles is the lack of practical tools for accurately assessing groundcover composition over time and space. In particular, there is limited quantitative understanding of how different groundcover types are distributed spatially within vineyards and what proportion of the inter-row area they occupy. Field-based surveys are time-consuming, require botanical expertise, and lack scalability. These limitations restrict the broader adoption of biodiversity-based practices and the ability to monitor their ecological impacts (Crotty and Stoate, 2019; Labeyrie et al., 2021).

Remote sensing technologies and artificial intelligence (AI) now offer promising solutions to address these challenges. In particular, the combination of Unmanned Aerial Vehicles (UAVs) and deep learning (DL) models applied to image analysis enables the automated mapping of vegetation and land cover classification. Deep learning networks, such as convolutional neural networks and recurrent neural networks, are widely used in this context, making them particularly effective in image processing (Du and Swamy, 2019). Although these technologies are increasingly used to monitor vine vigor, disease presence, and soil characteristics, their application to vineyard groundcover classification remains underdeveloped (Epifani and Caruso, 2024; Mărculescu et al., 2024). There is a clear need to design

and test DL models specifically adapted to the spatial variability and structural complexity of herbaceous vegetation in inter-row areas.

This study addresses this gap by developing a deep learning-based approach for groundcover classification using UAV-acquired RGB imagery. We implemented a pixel-wise classification system capable of distinguishing nine classes: vine canopy, bare soil, and seven distinct cover crop communities. The first two categories allow for the separate analysis of the seven categories of cover crops that were chosen according to their functional role in the agroecosystem (Abad et al., 2021).

A key contribution of our work is the comparative evaluation of three UNet-based deep learning architectures, each featuring a different encoder backbone—a pre-trained convolutional neural network used as the feature extractor at the core of the segmentation model—namely, ResNet34, EfficientNet, InceptionV3 and DenseNet.

The objective of this study is to address the knowledge gap in applying DL models to the study of groundcovers in vineyards and to compare these DL models to determine which one is best suited to the case study. Future research should aim to expand the model's applicability across a wider range of vineyard types, soil conditions, and image resolutions. In doing so, this approach could enable large-scale, cost-effective biodiversity monitoring and provide valuable insights into vineyard biodiversity dynamics and their functional implications over time and space.

Materials and Methods

Study Site

This study was conducted in a vineyard belonging to Azienda Agricola Ricci Curbastro in Capriolo, Brescia, Italy (Figure 5.2.1). The vineyard is situated in the Franciacorta wine region, known for its high-quality sparkling wine production.

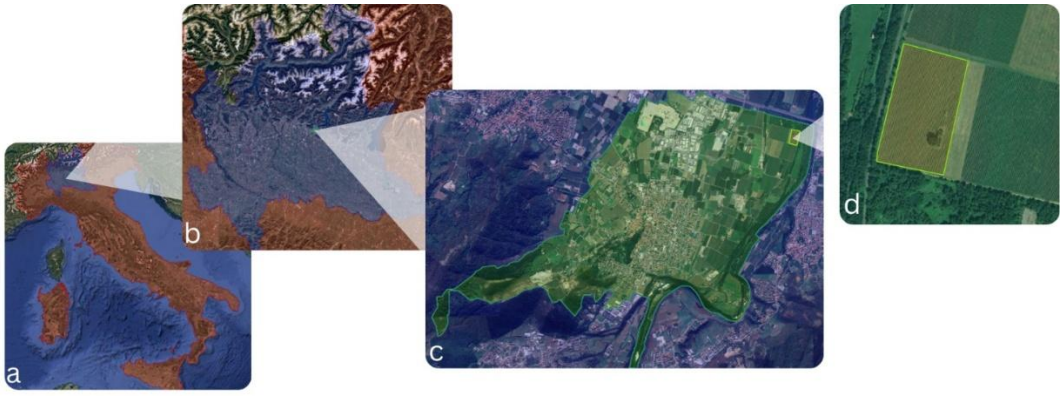


Figure 5.2.1. Progressive zoom into the study site: (a) Italy and the Lombardy region, (b) detail of Lombardy, (c) municipality of Capriolo, and (d) vineyard of interest.

Cover Crop Communities Classification

In this study, we focused on the inter-row areas of vineyards and categorized them into three main components: vine canopy, bare soil, and groundcover vegetation. Within the groundcover category, we further identified seven distinct types of cover crop communities, grouped according to their dominant botanical families or functional traits: graminoids, legumes (Fabaceae), mustards (Brassicaceae), composites (Asteraceae), Polygonaceae, Plantaginaceae, and other forbs. These cover crop communities play different functional roles and provide various ecosystem services (Table 5.2.1).

Table 5.2.1. The cover crops identified in the images and their functional roles.

Cover Crop	**Functional Role**
Graminoids	Combating soil erosion and weed competition (Van Sundert et al., 2021)
Legumes	Nitrogen fixation and the enhancement of soil health and biological fertility (Muhammad et al., 2021; Perrone et al., 2022)
Mustards	Suppression of soil-borne pathogens in vineyards and nurseries (Richards et al., 2020)
Composites	Supporting beneficial insects (Sáenz-Romo et al., 2019)
Polygonaceae	Suppress weeds due to its rapid growth and allelopathic effects, also hosting many arthropods that contribute to pest control (Björkman and Shail, 2013)
Plantaginaceae	Significant suppression of weeds (Miglécz et al., 2015)
Other forbs	Contribute to soil structure improvement and impact on the dynamics of organic carbon in the soil (Lundholm, 2015)

Image Acquisition

To acquire aerial imagery, a drone survey was carried out on 21 September 2023, at noun, on a cloudy day, using an DJI M300 RTK UAV. The flight was autonomously managed via the Litchi application (version 4.25.0, released 4 July 2022, by VC Technology Ltd., London, UK), which enabled the execution of a structured photogrammetry mission. The UAV was flown at an altitude of 8 m above ground level. Four ground control points (GCPs) with known coordinates were used for georeferencing. A total of 24 high-resolution RGB images were acquired, ensuring full coverage of the study area, using a previously available DJI Zenmuse P1 Camera, which has a 35.9 × 24 mm sensor and produces images with a resolution of 45 megapixels and a with a focal length of 35 mm, determining a pixel size of 0.1 cm. These 24 images were curated to ensure full coverage of the study area without overlapping between image footprints.

Data Preprocessing for Cover Crops Segmentation

The study utilized 24 RGB images (8192 × 5460 pixels), each representing 40 square meters, for a total analyzed area of 960 square meters. While DL offers advantages over traditional ML for plant species mapping by handling complex data, the large image size presents computational challenges. To address this, the images underwent preprocessing as follows:

A plant expert manually annotated masks for each training image using Roboflow, a web-based platform for image dataset creation and management.

The high-resolution images and their corresponding masks were partitioned into 256 × 256-pixel patches for training a U-Net segmentation model. This facilitated efficient image segmentation and feature identification. The trained model was then saved.

The saved model was used for the prediction and mapping of the full-size images.

Different types of ground cover (cover crops, vines, and soil) were manually labeled by an experienced botanist with in-depth knowledge of vineyard ecosystems. The expert classified each polygon in the mask image (8192 × 5460 px) by assigning labels corresponding to the established reference categories. Following approaches used in vegetation mapping studies [22,23], each polygon was attributed to the

category whose vegetative morphological traits were visually dominant, that is, recognizable in more than half of the polygon area (≥60%). Subsequently, the image was divided into patches of 256 × 256 pixels, and the classification was verified by the same expert to ensure accuracy and consistency.

Figure 5.2.2 illustrates the core workflow of the semantic segmentation process. Semantic segmentation is a deep learning technique that classifies each pixel in an image into a predefined category, allowing detailed spatial mapping of vineyard groundcover types. A U-Net architecture was employed for model training. Once trained, the model was saved and applied to full-size images for pixel-wise prediction, enabling high-resolution groundcover mapping within vineyard inter-rows

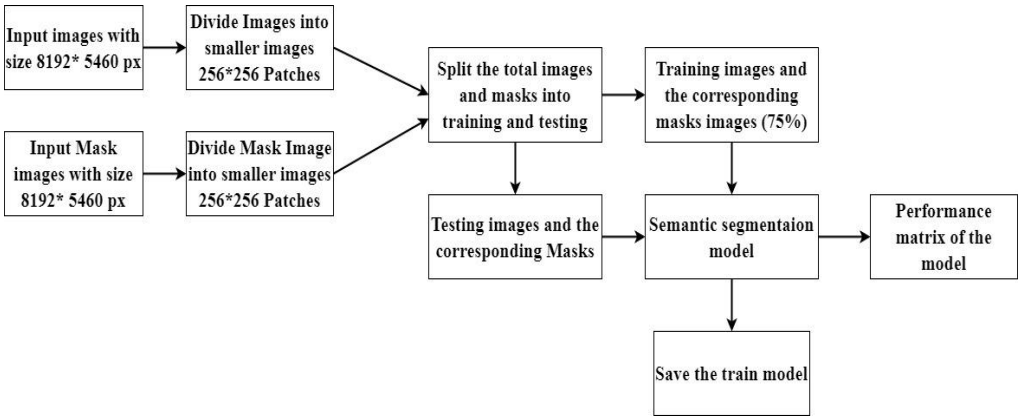


Figure 5.2.2. Workflow of the semantic segmentation process applied to high-resolution UAV images for groundcover classification in vineyard inter-rows.

This study addressed the challenges posed by the large size (8192 × 5460 pixels) of the original images, which resulted in high memory requirements and slow training times in deep learning models. A Python script was developed to efficiently process these images. The script iterated through the image and mask file directories, resizing each image and corresponding mask to the nearest dimensions divisible by 256 pixels (Figure 5.2.3). The patchify library (TensorFlow) was then used to segment the resized images and masks into non-overlapping 256 × 256-pixel patches. These patches were saved individually while maintaining their association with the corresponding masks. Finally, the splitfolders library (TensorFlow) was

used to divide the patches into training (70%), validation (15%), and testing (15%) datasets.

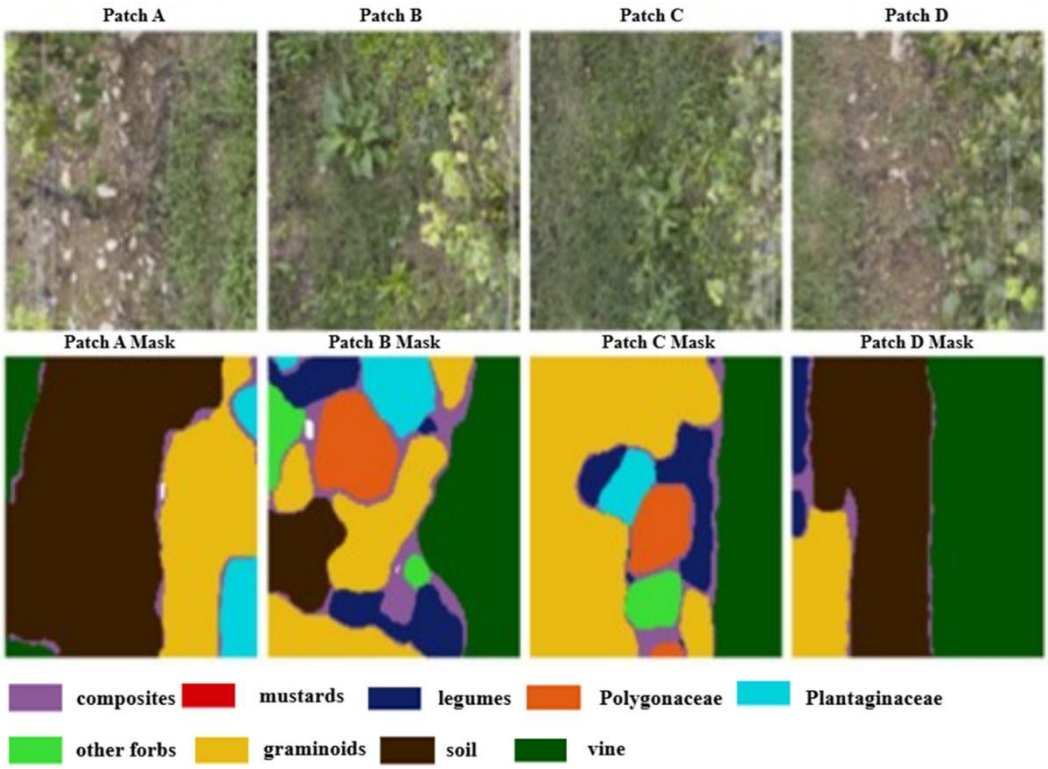


Figure 5.2.3. *Illustration of four randomly selected image patches (A, B, C, D) of size 256 × 256 pixels, extracted from the original vineyard images along with their corresponding ground truth masks. These patches are used to train and evaluate a deep-learning model. The legend describes the color representing each class (In the case of these images, no patches of the mustard variety are observed).*

Semantic Segmentation Model

A UNet semantic segmentation model (Ronneberger et al., 2015), implemented in Keras (Python 3.13.7), was designed for pixel-wise classification of UAV RGB imagery, where each pixel is assigned a class label based on local features such as color, texture, or spatial context. This architecture, illustrated in Figure 5.2.4, comprises encoder and decoder pathways with skip connections to preserve spatial information and effectively capture both local and global features. The model outputs a segmented mask classifying each pixel into one of nine classes: seven cover crop communities (graminoids, legumes, mustards, composites,

Polygonaceae, Plantaginaceae, and other forbs), vine, and soil. The training involved minimizing a loss function (measuring the discrepancy between predicted and ground truth masks), with performance evaluated using Intersection over Union (IoU), accuracy, and Mean IoU. We compared semantic segmentation with and without backbone architectures. The "no backbone" approach trained the UNet from scratch, relying solely on its inherent architecture for feature extraction. This was contrasted against models incorporating backbone architectures. The selection of backbone architectures was guided by their proven performance in semantic segmentation tasks, particularly in agricultural and environmental contexts. ResNet34 offers reliable feature extraction through residual learning (He et al., 2016a), while Incep-tionV3 is noted for its computational efficiency and multi-scale feature processing (Szegedy et al., 2016a). EfficientNet, with its compound scaling method, optimizes performance relative to computational cost (Tan and Le, 2020), and DenseNet promotes gradient flow and feature reuse via dense connectivity (Huang et al., 2018). These architectures have been effectively applied in recent agricultural segmentation studies (Wang et al., 2023; Zuo and Li, 2024), justifying their selection for comparative evaluation in this work.

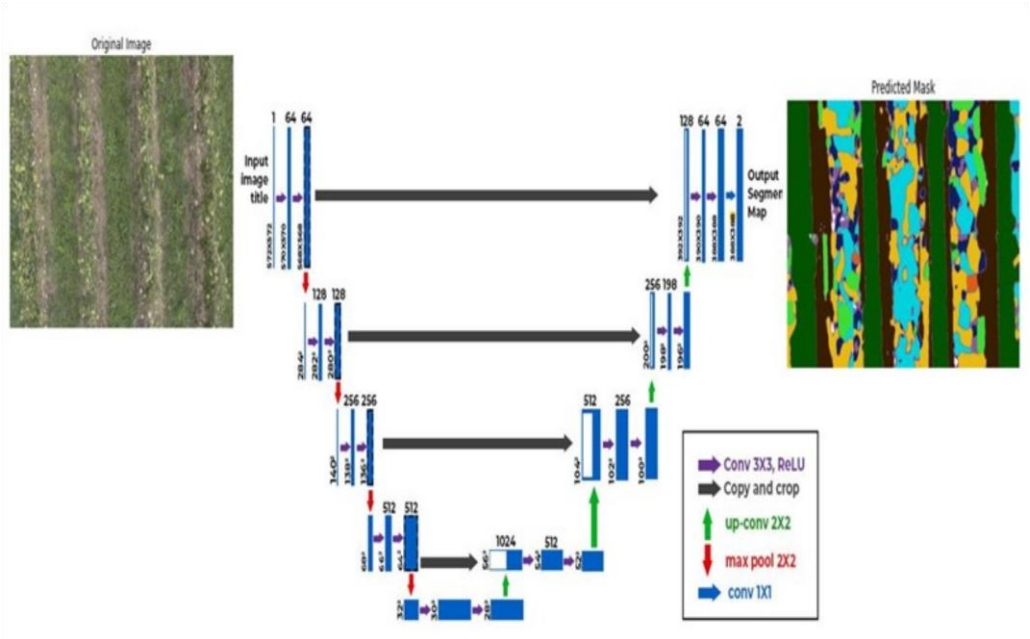


Figure 5.2.4. *The architecture of the UNet Semantic Segmentation Model.*

Metrics

In addition to overall pixel accuracy and mean Intersection over Union (mIoU), we report per-class IoU and a multiclass confusion matrix on the held-out test set to provide class-resolved performance. Accuracy measures the proportion of correctly labeled pixels over the entire image; it can be influenced by abundant classes (e.g., soil). Mean IoU averages the IoU across classes and thus better reflects species-level segmentation quality, particularly for minority classes (e.g., Mustards, Polygonaceae, Plantaginaceae)

Training Parameters

Model training was performed using the Adam optimizer with a learning rate of 0.001, $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\varepsilon = 1 \times 10^{-7}$. The batch size was set to 16, and training ran for 100 epochs with early stopping (patience = 10) based on validation loss. The loss function combined class-weighted Dice Loss and Categorical Focal Loss, and model performance was monitored using accuracy and Intersection-over-Union (IoU) metrics. All images were normalized to a [0, 1] range, and the dataset was split into 70% training, 15% validation, and 15% testing subsets. Batch normalization layers were included throughout the architecture to improve training stability and generalization.

For each backbone (U-Net without backbone, ResNet34, EfficientNet-B0, Inception-V3, DenseNet-121), models were trained with Adam (learning rate 0.001, $\beta_1 = 0.9$, $\beta_2 = 0.999$), batch size 16, and a composite loss of class-weighted Dice plus Categorical Focal. Early stopping monitored the validation loss (patience = 10, restore_best_weights = True). For reporting, the 'stopped epoch' is defined as the epoch attaining the minimum validation loss; all validation metrics (Accuracy, Precision, Recall, F1, Mean IoU) are computed from that checkpoint. We provide the full learning curves (training/validation loss and Mean IoU) for each backbone.

Results

Our UNet semantic segmentation model was trained on a dataset comprising 15,600 image patches. These patches were derived from 24 high-resolution RGB images (8192 × 5460 pixels) by dividing them into smaller 256 × 256-pixel sections. To ensure rigorous evaluation, the dataset was divided into a training set (70%), a

validation set (15%), and a test set (15%). The model is configured with specific parameters, including the DensNet121, ResNet34, InceptionV3, and EfficientNet backbone architecture, with a combination of Dice loss and Categorical Focal loss as the optimization objective. The model is trained over 100 epochs, and the training progress is visualized using plots for loss and IOU score. After training, the model is saved for future use. Performance metrics such as accuracy, precision, recall, F1 score, Jaccard score, and Mean IoU are computed using the trained model on the test dataset. Finally, the results are printed to evaluate the segmentation model's performance.

Class Imbalance and Data Augmentation

To address the class imbalance evident in Table 5.2.2, where certain classes (e.g., mustards, Polygonaceae, and Legumes) have significantly lower coverage areas than others, we implemented a class-balanced data augmentation strategy. Augmentation is strictly label-preserving and applied jointly to the RGB image and its ground-truth mask using only rigid transforms (rotations by 0°/90°/180°/270° and horizontal/vertical flips); no elastic/non-rigid warps or mask repainting are used, so the spatial arrangement of vegetation is preserved. This involved selectively augmenting the training data by creating new image patches that focused on the under-represented classes. Specifically, we modified the existing masks to temporarily ignore highly represented classes, effectively creating new masks where the under-represented classes became the dominant features. These temporary "ignore" masks were used only to guide patch selection (sampling) and were never used as training targets; the model was always supervised with the original, unmodified pixel-wise masks. This process increased the number of training samples for the under-represented classes without altering the original dataset. New image patches were then generated from these modified masks, thus enriching the training data with a more balanced representation of all classes. For clarity, while patch selection could be guided by temporary masks, the labels fed to the network were the original masks, ensuring that no class areas were synthetically inflated or spatially altered. This targeted approach ensured that the model received sufficient training examples for even the least prevalent classes, improving its ability to accurately segment these features.

Table 5.2.2. Presents the coverage area distribution for various classes in different images, measured as a percentage. Each row represents a distinct image, while the columns indicate the coverage area percentage for different classes, including graminoids, forbs (composite, mustards, legumes, Polygonaceae, Plantaginaceae, and other forbs), vine, and soil, respectively.

Image	Composite (%)	Mustards (%)	Legumes (%)	Polygonaceae (%)	Plantaginaceae (%)	Other Forbs (%)	Graminoids (%)	Soil (%)	Vine (%)
1	14.56	0.18	0.54	0.38	0.62	20.06	3.09	9.92	29.18
2	7.12	0.11	0.27	1.5	0.37	1.03	6.44	8.85	25.54
3	7.07	0.0	7.54	1.91	18.42	7.73	15.25	16.44	25.32
4	8.23	0.04	6.39	5.47	12.1	2.9	13.95	19.68	28.29
5	9.7	0.12	1.075	0.76	1.286	24.27	4.486	11.29	36.706
6	1.64	0.82	1.7	0	2.72	8.38	4.87	25.44	44.36
7	4.3	0.01	0.19	0.11	6.18	12.94	24.22	4.75	21.69
8	11.32	0.02	7.09	6.9	6.86	7.84	11.97	15.91	31.06
9	7.64	0.0	3.69	0.87	11.68	15.48	19.85	16.77	23.76
10	14.56	0.18	0.54	0.38	0.62	20.06	3.09	9.92	29.18
11	5.6	0.01	2.51	2.81	10.7	9.98	21.69	17.73	28.39
12	5.72	0.0	3.81	3.67	10.71	4.19	16.06	21.83	33.9
13	24.56	0.0	1.64	0.29	0.95	15.7	20.71	0.92	24.24
14	8.14	0.0	5.25	0.3	12.59	4.98	14.86	23.11	30.42
15	12.87	0.05	1.71	1.207	1.52	23.5	3.65	7.76	19.29
16	4.31	0.01	0.19	0.11	6.18	12.94	24.22	4.75	21.69
17	8.98	0.26	0.25	2.45	0.04	11.97	7.64	13.33	27.78
18	0.82	0	3.21	0.66	17.08	4.53	15.66	22.07	28.22
19	8.98	0.26	0.25	2.46	0.05	11.97	7.64	13.33	27.78
20	7.07	0.0	7.54	1.91	18.42	7.73	15.25	16.44	25.32

21	8.23	0.04	6.39	5.47	12.1	2.9	13.95	19.68	28.29
22	11.32	0.03	7.09	6.9	6.86	7.84	11.97	15.91	31.06
23	5.6	0.02	2.51	2.81	10.7	9.98	21.69	17.73	28.39
24	0	0	0	0	4.54	1.5	0	0.01	0.0

Overfitting Prevention Strategies

To mitigate overfitting, we implemented early stopping. Training was halted when the validation loss stopped decreasing for a specified number of epochs (e.g., 10 epochs), ensuring that training continued only as long as the model was improving its performance on unseen data. Additionally, batch normalization was employed to stabilize and accelerate training, and class weighting in the loss function helped manage class imbalances. These strategies collectively contributed to preventing overfitting and enhancing the model's generalization ability.

Model Performance

The comparison of UNet semantic segmentation models using different backbone architectures reveals nuanced differences in performance metrics (Table 5.2.3). Across all backbone configurations, including ResNet34, EfficientNet, InceptionV3, DenseNet, and a version without a specified backbone, there is a notable consistency in accuracy, precision, recall, and F1 score, with variations typically within a range of 1–2 percentage points. However, when assessing metrics more tailored to semantic segmentation tasks, such as mean IOU and Jaccard score, subtle disparities emerge. EfficientNet and DenseNet exhibit slightly higher mean IOU and Jaccard scores compared to ResNet34 and InceptionV3, highlighting their marginally superior ability to accurately segment objects in images. For instance, EfficientNet achieves an accuracy of 85.4%, while DenseNet reaches 83.6%, both with corresponding mean IOU scores of 59.8% and 52.1%, respectively. These results underscore the importance of selecting an appropriate backbone architecture, as models with dedicated architectures designed for image segmentation tasks demonstrate enhanced performance, particularly in terms of mean IOU and Jaccard score, compared to models without a specified backbone.

Table 5.2.3. Performance Metrics of UNet Semantic Segmentation Models with Different Backbone Architectures and without.

Backbone	Accuracy	Precision	Recall	F1 (Correct)	Mean IOU	Jaccard Score
ResNet34	80.0	79.8	79.3	79.5	50.5	63.1
EfficientNet B0	85.4	84.97	75.9	80.2	59.8	73.0
Inception V3	82.9	82.3	82.6	82.4	53.8	66.4
DenseNet	83.6	83.9	83.4	83.6	52.1	65.1
Without Backbone	78.0	77.9	77.8	77.8	48.9	61.2

Accuracy: This metric measures the overall correctness of the segmentation by calculating the ratio of correctly predicted pixels to the total number of pixels. Precision: Precision quantifies the model's ability to correctly identify positive predictions among all predicted positives. It's calculated as the ratio of true positives to the sum of true positives and false positives. Recall: Recall, also known as sensitivity, measures the ability of the model to detect all relevant instances of the class in the image. It's calculated as the ratio of true positives to the sum of true positives and false negatives. F1 Score: The F1 score is the harmonic mean of precision and recall. It provides a balanced measure between precision and recall and is calculated as 2 * (precision * recall)/(precision + recall). Mean IoU: Mean IoU calculates the average IoU across all classes. It's a popular metric for semantic segmentation tasks as it provides an overall measure of segmentation accuracy across different classes. Jaccard Score (IoU): The Jaccard score, or Intersection over Union (IoU), measures the ratio of the intersection of the predicted and ground truth segmentation masks to their union. It evaluates the overlap between the predicted and ground truth regions.

The training and validation loss curves for all backbone architectures (Figure 5.2.5) show a consistent decrease over epochs, indicating effective convergence without severe overfitting. Models with pretrained backbones particularly EfficientNet-B0 and ResNet50 achieved faster loss reduction and lower final validation loss compared to those without a backbone, reflecting more efficient feature learning. DenseNet-121 and Inception-V3 also demonstrated stable convergence, though with slightly higher final losses. The no-backbone model exhibited the slowest

convergence and highest validation loss, confirming the benefit of transfer learning in improving model generalization and segmentation performance.

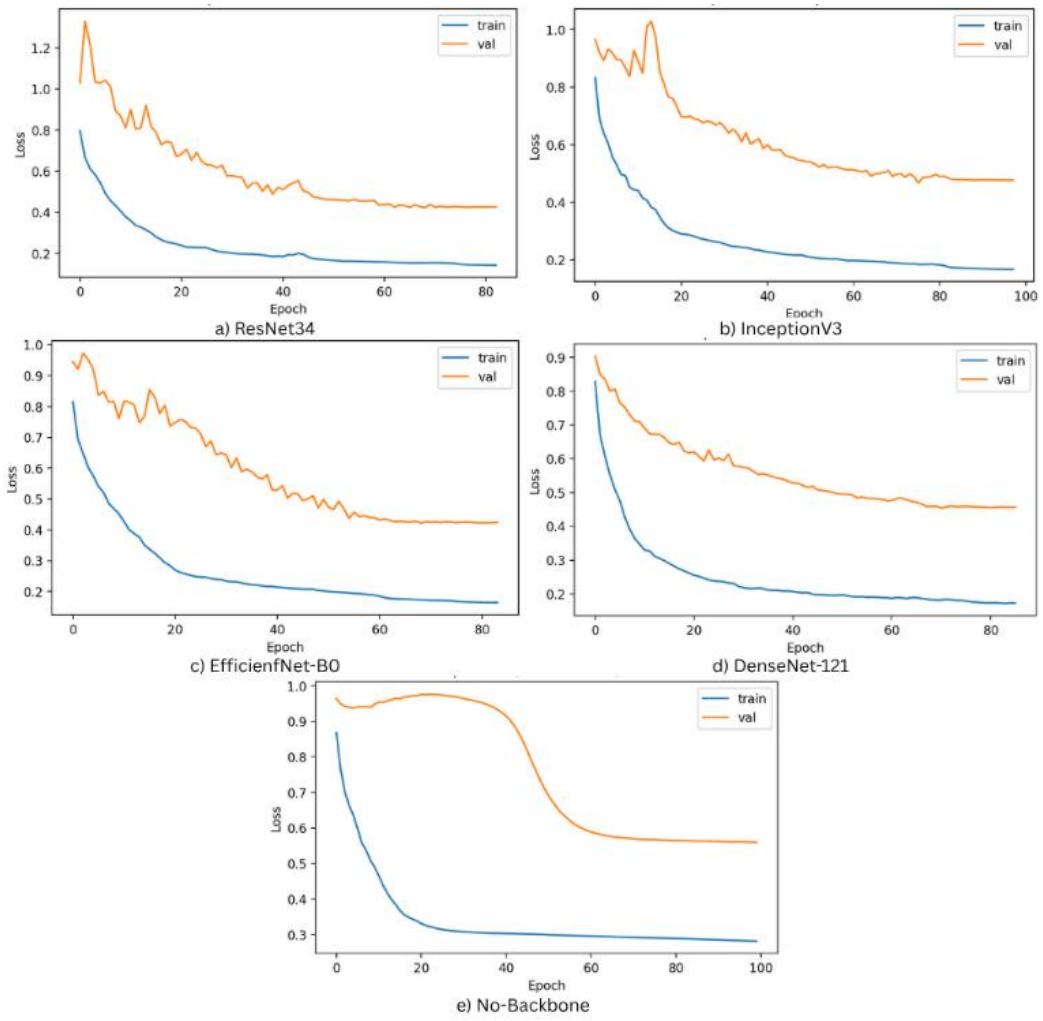


Figure 5.2.5. Training and validation loss curves for U-Net models with different backbone architectures: a) ResNet34, b) InceptionV3, c) EfficientNet-B0, d) DenseNet121, and e) no-backbone configuration. The steady decline in both training and validation losses indicates stable convergence across all models, with pretrained backbones (ResNet34, InceptionV3, EfficientNet-B0, and DenseNet121) achieving faster convergence and lower final validation losses compared to the model without a backbone.

As shown in Table 5.2.4, all backbone architectures achieved high accuracy across most vegetation classes, with particularly strong performance for Plantaginaceae, vine, and mustards (IoU > 0.80 for the best-performing models). Among the architectures, EfficientNet-B0 and ResNet50 consistently produced the highest per-class precision and IoU values, indicating superior discrimination of vegetation types. In contrast, classes with limited spatial coverage, such as Polygonaceae and

legumes, exhibited lower recall and IoU across all models, reflecting the effect of class imbalance on segmentation accuracy. Overall, backbone-based models outperformed the no-backbone configuration, confirming the benefit of transfer learning for fine-scale vegetation mapping.

Table 5.2.4. Per-class accuracy, precision, recall, and IoU values for U-Net models with different backbones on the test dataset.

Backbone	Class	Accuracy	Precision	Recall	IoU
EfficientNet-B0	Plantaginaceae	0.994	0.917	0.91	0.841
EfficientNet-B0	Polygonaceae	0.99	0.961	0.398	0.392
EfficientNet-B0	composite	0.872	0.561	0.648	0.43
EfficientNet-B0	graminoids	0.942	0.847	0.461	0.426
EfficientNet-B0	legumes	0.996	0.747	0.534	0.452
EfficientNet-B0	mustards	1.0	0.862	0.859	0.754
EfficientNet-B0	other forbs	0.944	0.829	0.793	0.682
EfficientNet-B0	soil	0.952	0.834	0.844	0.723
EfficientNet-B0	vine	0.929	0.877	0.956	0.843
DenseNet-121	Plantaginaceae	0.994	0.917	0.925	0.854
DenseNet-121	Polygonaceae	0.991	0.943	0.473	0.46
DenseNet-121	composite	0.862	0.544	0.534	0.369
DenseNet-121	graminoids	0.929	0.632	0.551	0.417
DenseNet-121	legumes	0.996	0.766	0.464	0.407
DenseNet-121	mustards	1.0	0.831	0.825	0.706
DenseNet-121	other forbs	0.945	0.817	0.801	0.679
DenseNet-121	soil	0.943	0.805	0.817	0.682
DenseNet-121	vine	0.935	0.893	0.951	0.854
Inception-V3	Plantaginaceae	0.994	0.937	0.911	0.858
Inception-V3	Polygonaceae	0.983	0.84	0.184	0.178
Inception-V3	composite	0.863	0.517	0.603	0.386
Inception-V3	graminoids	0.939	0.804	0.45	0.405
Inception-V3	legumes	0.996	0.767	0.494	0.429
Inception-V3	mustards	1.0	0.661	0.879	0.606
Inception-V3	other forbs	0.925	0.751	0.748	0.599
Inception-V3	soil	0.938	0.777	0.819	0.663
Inception-V3	vine	0.932	0.888	0.95	0.849
No-backbone	Plantaginaceae	0.992	0.919	0.854	0.794
No-backbone	Polygonaceae	0.992	0.887	0.427	0.405
No-backbone	composite	0.875	0.58	0.475	0.354
No-backbone	graminoids	0.931	0.684	0.507	0.411
No-backbone	legumes	0.996	0.665	0.435	0.357
No-backbone	mustards	0.999	0.0	0.0	0.0
No-backbone	other forbs	0.924	0.745	0.718	0.576

No-backbone	soil	0.923	0.733	0.772	0.603
No-backbone	vine	0.894	0.823	0.943	0.784
ResNet50	Plantaginaceae	0.994	0.906	0.933	0.851
ResNet50	Polygonaceae	0.985	0.963	0.215	0.213
ResNet50	composite	0.865	0.544	0.58	0.39
ResNet50	graminoids	0.939	0.725	0.549	0.455
ResNet50	legumes	0.997	0.796	0.588	0.511
ResNet50	mustards	1.0	0.874	0.941	0.829
ResNet50	other forbs	0.938	0.825	0.748	0.646
ResNet50	soil	0.946	0.827	0.808	0.691
ResNet50	vine	0.918	0.856	0.954	0.822

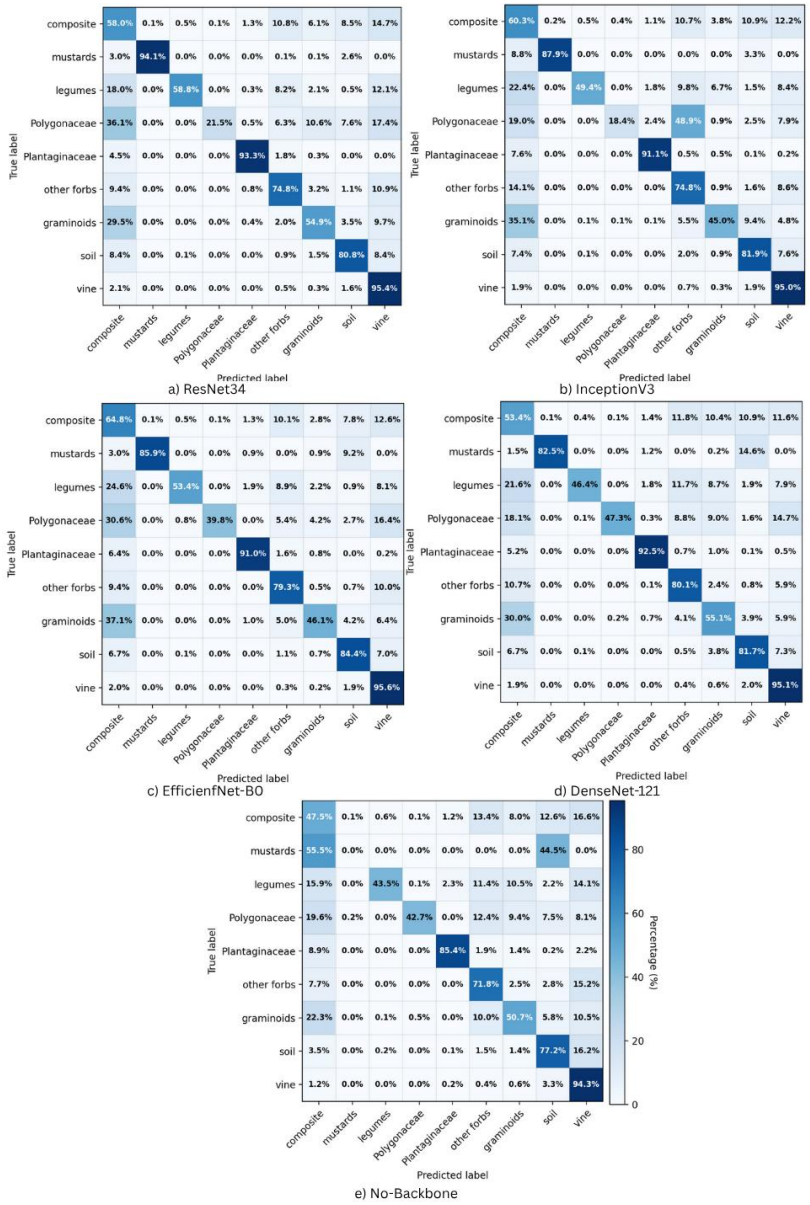


Figure 5.2.6. Confusion matrices for U-Net models with different backbone architectures: a) ResNet34, b) InceptionV3, c) EfficientNet-B0, d) DenseNet121, and e) no-backbone configuration. The matrices illustrate class-wise prediction performance across nine vegetation and soil categories. High diagonal values indicate accurate classification, with Plantaginaceae, vine, and mustards showing the highest true positive rates, while classes with smaller spatial coverage, such as Polygonaceae and legumes, exhibited higher misclassification rates.

The confusion matrices (Figure 5.2.6) demonstrate that all backbone-based U-Net models achieved strong class discrimination, with the highest accuracy for Plantaginaceae, vine, and mustards, which showed clear diagonal dominance and minimal misclassification. Misclassifications were more common among visually similar or spatially co-occurring vegetation classes such as graminoids, composite, and other forbs. Among the architectures, EfficientNet-B0 and ResNet50 exhibited the most distinct class separation, while the no-backbone model showed higher confusion across categories. Overall, the results confirm that transfer learning significantly enhances the model's ability to differentiate vegetation types at fine spatial scales. After loading the trained model, we generate a batch of test images and masks using the validation data generator. Next, we compute predictions for the test images using the loaded model and convert the predicted masks from categorical to integer format for visualization and IoU calculation. Finally, we visualize a randomly selected test image along with its corresponding ground truth mask and predicted mask for a qualitative assessment of the model's performance (Figure 5.2.7). Finally, the trained model was loaded to apply it to a large image, where it was segmented into patches of appropriate size for processing.

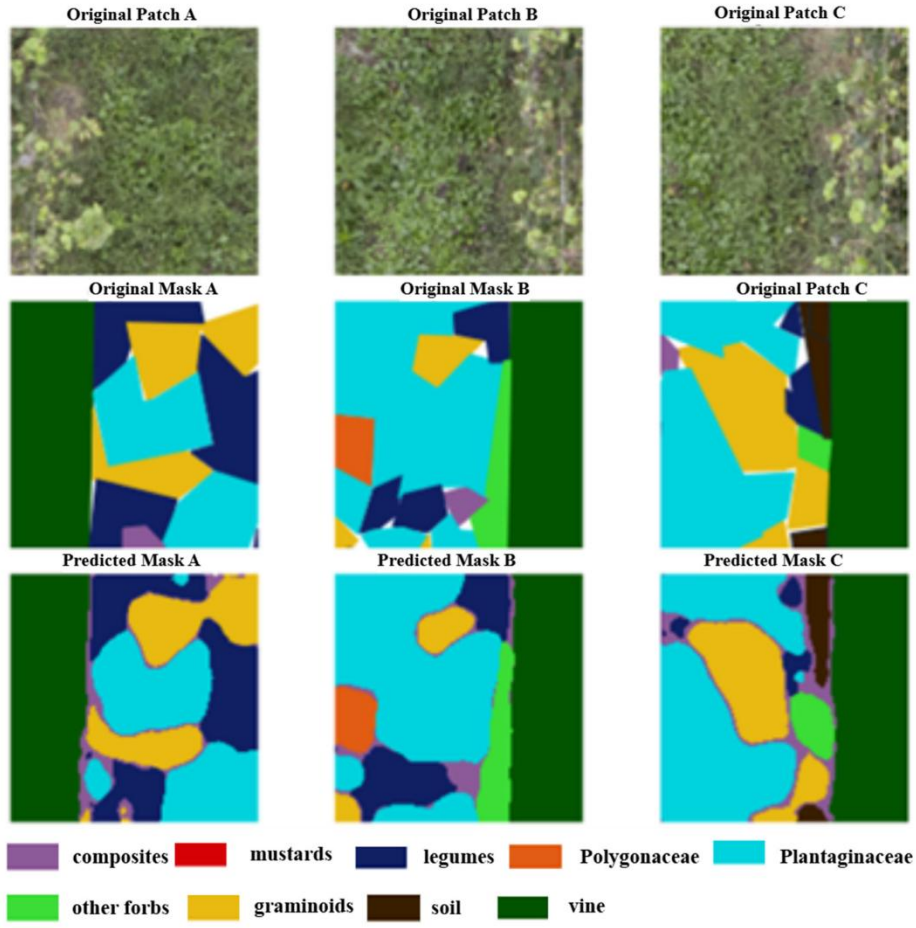


Figure 5.2.7. Visualization of a randomly selected test image, ground truth mask, and predicted mask. The Figure 5.2.illustrates the qualitative assessment of the model's performance, comparing the original test image to its corresponding ground truth and predicted masks. The legend describes the color representing each class.

The prediction process was conducted on each patch, and the resulting segmented patches were then stitched together to reconstruct the predicted mask for the entire large image, facilitating the application of the model to images beyond the validation dataset (see Figure 5.2.7).

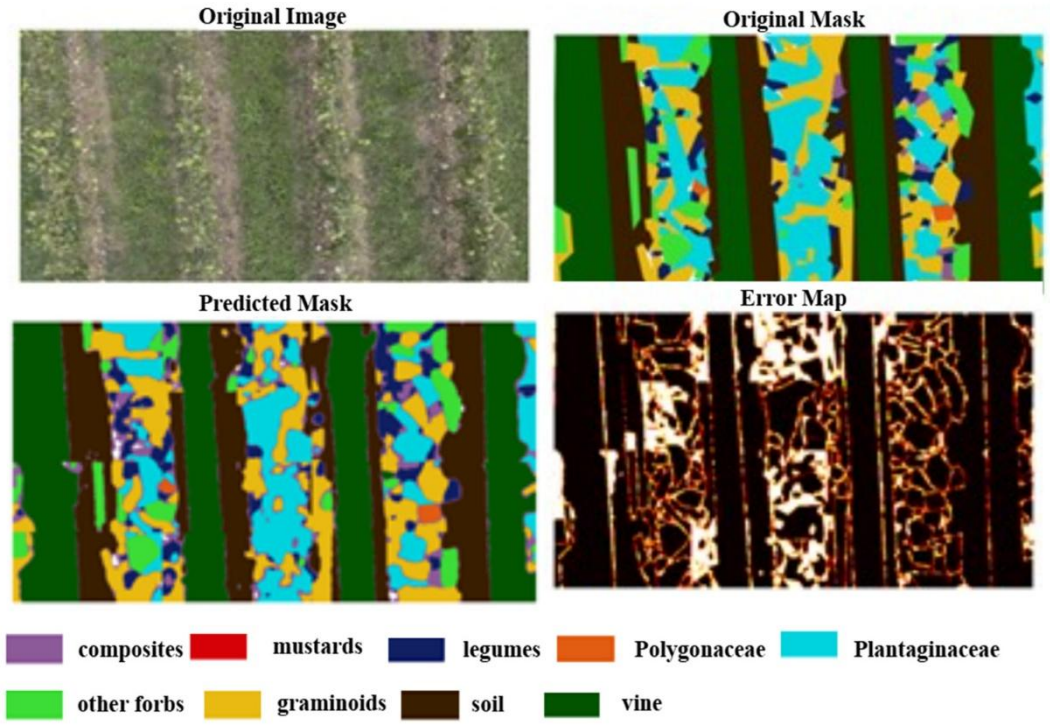


Figure 5.2.8. Illustrates the original image, ground truth mask, and the final segmented image mask obtained by applying a trained model. The model segments the large image into patches for processing, generates predictions for each patch, and seamlessly stitches together the resulting segmented patches to reconstruct the predicted mask for the entire large image. The legend describes the color representation of each class.

Discussion

Our study aims to establish a method for identifying vineyard inter-row groundcovers, with the ultimate goal of creating a comprehensive groundcover map and supporting decision-making for soil and cover crops management in viticulture. The management of cover crops in vineyards is an increasingly widespread agronomic practice, as it enhances soil fertility, increases biodiversity, and mitigates the effects of climate change, with particular attention to water availability management and erosion control (Abad et al., 2021). The adoption of cover crops between vineyard rows helps restore soil ecosystem functions, contributing to a more sustainable and resilient viticulture (Novara et al., 2020). However, the specific composition of plant communities significantly influences the benefits obtained. For this reason, it is crucial to develop advanced tools for classifying and monitoring soil biodiversity, enabling agronomic decisions based on precise and georeferenced data.

In this work, the potential of DL techniques applied to RGB images was evaluated in a vineyard located in the Franciacorta wine-growing area.

The use of artificial intelligence for cover crop recognition represents an innovative approach that enables the automation of vegetation analysis, significantly reducing monitoring time and costs compared to traditional methods based on manual sampling and field botanical analysis.

The main focus of the study was to distinguish between nine classes of groundcover. Beyond the two classes vine and bare soil, other seven different groups of cover crops communities were distinguished: graminoids, composite, mustards, legumes, Polygonaceae, Plantaginaceae, and other forbs. This classification is essential, as the phenology, morphology, and functional traits of plants within each group determine their contribution to ecosystem services in the vineyard. Cover crop communities play a crucial role in maintaining agroecosystem balance. Morphological and functional differences among species directly influence the ecosystem services they provide, including soil fertility regulation, improvement of soil physical structure, and control of interspecies competition. Graminoids, with their fibrous root systems, enhance the structural stability of the upper soil layers, contributing to erosion reduction and increased water infiltration capacity (Martin and Isaac, 2018). Brassicaceae, on the other hand, can aid in soil biofumigation, reducing pathogen presence and promoting a better microbial balance (O'Farrell et al., 2023). Legumes, through atmospheric nitrogen fixation, improve nutrient availability and reduce dependency on chemical fertilizers, supporting a more sustainable agricultural model (Ghafoor et al., 2024). Polygonaceae and Plantaginaceae play a complementary role by enhancing soil structure at greater depths and improving functional biodiversity through their ability to attract pollinators and natural predators of pests. The precise identification and mapping of these plant communities are therefore fundamental for optimizing vineyard management, allowing for the selection of the most suitable species combinations based on local pedoclimatic conditions and specific agronomic objectives.

Using a total of 24 RGB images, taken with a drone at 8 m height, five UNet-based deep learning models with different encoder backbones (Ronneberger et al., 2015)

were trained and tested to assess their accuracy in predicting the observed soil cover. By employing a UNet architecture, which excels in pixel-wise classification tasks through its symmetrical encoder–decoder structure and skip connections, the model effectively segments UAV RGB images into predefined classes such as vine, soil, and various vegetation types. The integration of advanced DL techniques, such as semantic segmentation with backbones, offers a notable improvement in accuracy over methods without backbones, as evidenced by performance metrics. The use of backbones like EfficientNet (Tan and Le, 2019), ResNet34 (He et al., 2016b), InceptionV3 (Szegedy et al., 2016b) and DenseNet (Huang et al., 2017) provided a robust foundation for feature extraction, enhancing the model's ability to capture hierarchical features and spatial relationships within the images. Even though all the architectures analyzed showed high performance, exceeding an accuracy of 70%, the UNet model with an EfficientNet backbone stood out above the rest, achieving an accuracy of 85.4%, with a precision of 84.97%. Unlike generalized datasets, ours is tailored to the unique ecological conditions and management practices of vineyards, making direct comparisons with other segmentation benchmarks difficult. To assess our UNet model, we therefore had compared it to relevant studies in agricultural image segmentation using aerial imagery. While many studies, like those by Zuo and Li (Zuo and Li, 2024) on weed segmentation in corn fields and Shai et al. (Shahi et al., 2023) on weed detection using UAV images, focus on different crop types and scales, our dataset's emphasis on vineyard cover crops requires a more granular analysis. Our UNet architecture aligns with common practices in image segmentation, as exemplified by Wang et al. and Zhao et al. (Wang et al., 2023; Zhao et al., 2019).

The integration of advanced deep learning and remote sensing techniques opens new possibilities for vineyard management. Automating biodiversity mapping enables real-time monitoring of the evolution of plant communities within the vineyard, facilitating adaptive management strategies by adjusting cover crop selection based on actual agronomic needs. This approach reduces monitoring costs by eliminating the need for extensive manual sampling and optimizes resource management, such as fertilization and irrigation, based on the composition of plant communities and their interactions with the soil. Although the specific case

analyzed here concentrates on the inter-row zones, since the under-vine (in-row) areas were tilled and thus classified as soil, the broader goal of this research is to monitor the entire vineyard groundcover, including all cover crop communities visible from aerial imagery. In situations where vegetation is also present beneath the vines, these areas could either be included in the analysis, at least for the portions visible from above and not obscured by the canopy, or excluded during the image pre-processing phase, depending on the study objectives.

The results of this study highlight the potential of DL models, particularly those utilizing advanced backbone architectures, to enhance the precision and efficiency of groundcover classification in vineyards. This advancement in technology provides valuable insights into the spatial distribution and ecological roles of different groundcover types, which can significantly aid vineyard management practices. Specifically, this study represents the first step in applying DL to the classification of cover crop communities in vineyard agroecosystems. The results demonstrate that innovative application of these technologies can address complex, long-standing challenges such as monitoring vineyard biodiversity. Moreover, results obtained in the present study provide the groundwork for future studies on how cover crops may contribute to the ecological balance and sustainability of vineyard ecosystems through ecosystem services provision. However, some limitations have to be underlined. The first key limitation is the potential for bias arising from class imbalance in the dataset. While class-balancing techniques (targeted data augmentation and class weighting) were employed, under-represented classes may still bias predictions, particularly with unseen data. Future research should address this by expanding the dataset to encompass a broader range of vineyard types, soil conditions, and geographic locations. In terms of outputs obtained, although the DL model developed is able to automatically discriminate among nine classes of groundcover, it needs to be evolved in order to generate a real operational tool. Specifically, the results obtained from high-resolution images need to be replicated on lower-resolution images to make the system applicable to much larger areas in hectares, significantly reducing the costs and time required for UAV image acquisition.

This study proved the potential of RGB images in the identification of the seven types of cover crops that can be associated with specific botanical families, and when combined with additional data sources such as multispectral or LiDAR imagery, can be further correlated with ecological traits of the vineyard. This information enables a better understanding of the agroecosystem's health status and biodiversity. From a decision-making perspective, these results can support vineyard managers at both operational and strategic levels. Operationally, they can be used to adjust mowing or tillage schedules based on the spatial distribution and growth dynamics of cover crops and for the planning of sowing operations, supporting the selection of optimal species mixtures. Strategically, this approach can support the evaluation of the relationship between cover crop performance and vine development. and encourage the adoption of more sustainable vineyard management practices aimed at improving soil health, biodiversity, and overall vineyard resilience.

This study represents a step forward in the application of artificial intelligence to vineyard management, providing an innovative approach for soil biodiversity monitoring. The integration of deep learning, UAVs, and remote sensing enables the development of operational tools for more sustainable viticulture, based on precise and up-to-date data (Shahi et al., 2022). Our approach provides a solid scientific foundation for future developments, with the goal of expanding research across different vineyard types and pedoclimatic conditions, optimizing segmentation models for large-scale operational applications, and promoting the adoption of AI in agriculture to enhance biodiversity management and support more sustainable practices.

Conclusions

This study validates the potential of applying DL models to soil cover classification (proving the U-Net model with the EfficientNet backbone to be the most appropriate to apply in the case study), which would simplify the work of winegrowers when monitoring biodiversity in the field and provides valuable information for decision-making related to soil and vegetation management in viticulture. Future research should focus on extending the model's capacity to cover

larger areas more efficiently, incorporating multispectral images, while optimizing processing time and costs. Additionally, expanding the dataset to include a wider variety of vineyard types, managements, soil conditions, and geographical contexts will be essential to improve the model's generalizability and applicability across different viticultural environments.

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5.3. Are Biodiversity and Agriculture in Conflict? Insights from the Farmland Biodiversity Support Index in Lombardy

Chapter 5.3 is currently under review in the journal Agricultural Systems.

Abstract

Agriculture plays a dual role in biodiversity: on the one hand, it is one of the causes of loss due to landscape simplification; on the other, if managed accurately, it can serve as one of the most important allies among human-managed productive activities in valorization of biodiversity. Biodiversity in agriculture is assumed as the variety of biological elements present, that is, the number and identity of components within a given territory, a fundamental component for ecological resilience, productive stability, and the maintenance of ecosystem services. In this context, the Farmland Biodiversity Support (FBS) index is proposed as an assessment tool designed to estimate the potential contribution of farmland areas to support biodiversity. The index integrates three components of the rural mosaic — agricultural areas, permanent meadows and managed forest areas — considering for the agricultural part five functional aspects: crop diversity, resources provided to pollinators, linear elements, riparian-wet areas and habitat suitability for avifauna. Applied to Lombardy municipalities for 2021, the FBS highlights a marked territorial gradient, with higher values in pre-Alpine areas rich in semi-natural elements and heterogeneous values in the lowland, with significant local differences attributable to crop diversification and the presence of ecological infrastructure. The FBS is an operational and scalable tool, useful for supporting spatial planning and agroecological management strategies, enabling an integrated assessment of the potential capacity of farmland areas to support biodiversity.

Introduction

Biodiversity in farmland areas includes the variety and variability of life they contain, including both cultivated or bred species and wild organisms associated with agricultural systems (FAO, 2005; Vandermeer and Perfecto, 1995). During the second half of the 20th century, agricultural intensification, characterized by increased application of mineral fertilizers, and synthetic pesticides, widespread mechanization, and marked reduction in crop diversity, boosted yields but

generated substantial negative impact on biodiversity (Pretty, 2018). Cultivation specialization and the growing synchronization of agricultural practices (eg, harvest or mowing dates) further contributed to the simplification of the rural landscape (Gepts, 2023). Across many regions, traditional agricultural mosaics (including small fields, diversified crop rotations, meadows, pastures, hedgerows, and other marginal areas) have progressively been replaced by extensive monocultures (Marja et al., 2022). Linear elements such as hedges, field trees and riparian buffer strips have often been removed to maximize arable land and facilitate the machinery movement (Prangel et al., 2023). This structural homogenization directly affects biodiversity, as simplified landscapes generally host fewer species than complex and heterogeneous ones (Song et al., 2016). In Europe, for example, the farmland bird index (which tracks populations of common bird species associated with rural environments) has declined by roughly 60% since 1980 (Burns et al., 2021). Intensive agricultural practices and the resulting degradation of rural habitats are consistently identified as the main drivers of this trend. The disappearance of grassy margins, isolated trees, and fallow areas eliminates essential nesting and foraging sites (Dainese et al., 2019); the shift toward genetically uniform crop varieties and the reduction of permanent fodder crops diminish the availability of seeds and insects required by many species (Benton et al., 2003); and the widespread pesticide use reduces insect and invertebrate populations, thereby limiting food resources for birds, bats, and small mammals (Kleijn et al., 2015). The ecological costs of these processes are increasingly evident. Globally, for example, the decline in pollinators threatens an estimated 235–577 billion dollars in agricultural production each year (Brondízio et al., 2019). At the same time, ecological simplification heightens the vulnerability of agrarian systems to pests, diseases, and climate-related stresses, ultimately reducing their resilience (Bélanger and Pilling, 2019). Yet agriculture remains uniquely positioned to safeguard and enhance biodiversity when managed sustainably and within more structurally complex landscapes. Extensive scientific evidence demonstrates that increasing landscape heterogeneity has consistently positive effects on biodiversity (Lecoq et al., 2022; Sirami et al., 2019). Farming systems that integrate diverse land uses and structural elements support richer biological communities than uniform, monofunctional systems (Fahrig et al., 2011).

Habitat diversity provides food resources and refuge, enabling the persistence of a wide range of species and sustaining ecological processes (Kratschmer et al., 2024; Staley et al., 2023). These semi-natural elements also act as ecological corridors, promoting organism movement and enhancing landscape connectivity (Devictor and Jiguet, 2007). At the field scale, diversification through crop rotations or intercropping limits the spread of crop-specific pests and pathogens while increasing the variety of microhabitats within soils and vegetation. This, in turn, supports greater richness of soil organisms and beneficial arthropods (Bosem Baillod et al., 2017; Jeanneret et al., 2021). Complex agricultural landscapes, such as the traditional mosaics of fields, woods and pastures, illustrate how agricultural production and biodiversity conservation can coexist, maintaining substantial populations of wild species alongside crops (Sirami et al., 2019). Strengthening the ecological resilience of agricultural systems through crop diversification and integration of functional biodiversity can make it possible to increase productivity without expanding cultivated areas (FAO, 2011), regenerating natural capital, improving soil quality, reducing ecological risks and increasing climate resilience, and at the same time optimizing the provision of ecosystem services and the multifunctional potential of agriculture. Several indicators are available for assessing biodiversity in farmland areas, each capturing different aspects of landscape composition and structure. Among the most widely used are habitat richness and diversity indices, which quantify the number and distribution of environmental types within the agricultural mosaic (Billeter et al., 2008). Additional structural descriptors, such as mean patch size and landscape connectivity, are essential for evaluating fragmentation and ecological continuity (Martel et al., 2019). The density of linear elements, including hedges, ditches, tree-lined rows, provides a measure of structural connectivity between cultivated and semi-natural habitats and supports species dispersal (Billeter et al., 2008; Herzog et al., 2012). Other relevant indicators are the percentage of semi-natural habitats, crop diversity and the presence of trees or shrubs, which increase the ecological complexity of the landscape (Jeanneret et al., 2021; Soulé et al., 2023). At a biological level, the Farmland Bird Index represents a synthetic indicator of biodiversity, as it reflects the response of typical farmland bird populations to

structural and managerial variations in the agricultural landscape (Campedelli et al., 2009). Despite the availability of these tools, current approaches to biodiversity assessment in agricultural environments present important limitations. Most rely on multiscale modelling frameworks that analyse patterns from field to landscape level but often overlook the integration of habitat-level sub-indicators directly linked to land use. As a result, they tend to privilege structural metrics, such as connectivity, or include only a single, generic compositional component, typically the proportion of semi-natural areas. This narrow focus constrains their ability to capture the full spectrum of ecological factors that support biodiversity in agricultural landscapes, particularly the combined roles of land-use composition, agronomic diversity and availability of trophic resources for key taxa. Addressing these gaps requires a more comprehensive and operationally applicable measure capable of integrating multiple dimensions of compositional diversity. The objective of this study is therefore to develop an index that reflects the capacity of farmland to support biodiversity through a combined assessment of land-use patterns, agronomic heterogeneity and trophic resource availability for functionally relevant organisms such as pollinators and birds. Using high-resolution spatial and agricultural datasets together with environmental suitability maps derived from species distribution models, we propose the Farmland Biodiversity Support (FBS) index, a tool designed to assess the contribution of agricultural production, broadly conceived to include croplands, coppice woodlands, and semi-natural habitats, to the biodiversity of a given area. To demonstrate its operational potential, we applied the index to the assessment of farmland biodiversity support at the municipal scale across the Lombardy Region (Italy).

Material and methods

Conceptual framework of the Farmland Biodiversity Support Index

In this study, we consider the Farmland Area (FA), defined as the set of land surfaces dedicated to the production and supply of food, feed, and fibers (Bunce, 2009; EC, 2021; World Bank Group, 2025). Within this framework, FA is composed of three main components: agricultural areas (AA), grassland areas (GA), and coppice-managed woodland areas (WA).

The Farmland Biodiversity Support (FBS) index is proposed to quantify the potential contribution of FA to biodiversity, understood as the variety of biological elements present, namely, the number and identity of components within a given area (Duelli and Obrist, 2003). The AA component captures the contribution of strictly agricultural areas to farmland biodiversity by integrating several functional aspects relevant to the ecological quality of cultivated land, which can influence the biodiversity supported within these areas (see Section 2.2). In contrast, the assessment of GA and WA, considered semi-natural elements of the rural landscape, is based solely on their spatial extent, reflecting their structural contribution to the farmland mosaic.

By integrating these three components, the FBS index provides a synthetic measure of the overall potential of farmland to support biodiversity. The index is defined as:

$$FBS = \mathrm{AA} + \mathrm{WA} + \mathrm{GA} \quad [1]$$

All indices and index components are time-dependent variables and would, in principle, carry a subscript *t* indicating the temporal reference of the assessment (typically a calendar year). For simplicity, this subscript is omitted throughout the text except where explicitly needed for clarity.

Quantification of three components of FBS index

The assessment of the AA contribution to biodiversity evaluates agricultural areas through five aspects relevant to farmland biodiversity, integrating information on crop diversity (CD), resources for pollinators (RP), linear elements (LE), riparian–wet features (RW), and suitable bird habitat (HB). The component was calculated by relating the proportion of agricultural land surface within the assessed spatial unit (SU_{AA}) to the total surface of that unit (SU_{Tot}), and by integrating the mean contribution of these five functional aspects:

$$AA = \frac{CD_{AA} \cdot RP_{AA} \cdot LE_{AA} \cdot RW_{AA} \cdot HB_{AA}}{5} \cdot \frac{SU_{AA}}{SU_{Tot}} \quad [2]$$

Crop diversity (CD_{AA}) was measured using Simpson's index (Simpson, 1949), which expresses the probability that two individuals randomly selected from a community belong to different types of crops. Applied to agricultural systems, this

index captures crop diversity as an indicator of the ecological complexity of the rural landscape. For this purpose, taxonomic crop categories were grouped into functional crop types (listed in Table 5.3.1), based on agronomic and ecological traits relevant for agricultural production and ecosystem functioning, as discussed by Jones et al., (2021). Each class represents a crop type or agricultural cover, and the relative proportion of each to the total agricultural area is used to determine the index. The relative proportion of i-th crop type within the total agricultural area (p_i) was then used to compute the index:

$$CD_{AA} = 1 - \sum_i p_i^2 \quad [3]$$

CD values range from 0 to 1, with higher values indicating more diverse agricultural systems, typically associated with lower monoculture and higher ecological value for diversification (Lazzerini et al., 2015; O'Neill et al., 1988).

Table 5.3.1 - Crop categories used for the calculation of the Crop Diversity Index

Crop Type	**Description**
AROM	Aromatic and medicinal crops
BRAS	Brassicaceae (oilseed/vegetable)
CERE	Annual cereals for grain and forage grasses
ENER	Industrial/energy/fibre/dye crops
FLOR	Open-field floricultural crops
FRUT	Fruit trees and berries
HORT	Annual vegetables (fruit/leaf/bulb)
LEGU	Legumes (grain/vegetable/forage)
NUTS	Nuts and perennial oilseed arboreal crops
OLIV	Olive groves
TUBR	Non-Brassicaceae roots and tubers
VINE	Grapevine/vineyards

For crop-related Resources for Pollinators (RP_{AA}), each crop category (**Errore. L'origine riferimento non è stata trovata.**) was evaluated based on its attractiveness to pollinating insects for nectar and/or pollen collection. Attractiveness was assessed on a three-level scale: 0 = not attractive,1 = moderately attractive (limited or seasonal nectar/pollen availability), and 2 = highly attractive (abundant and consistent nectar/pollen resources). Each crop type was evaluated

separately for four pollinator groups-honeybees (HB), bumblebees (BB), solitary bees (SB), and wild pollinators (WP):

$$RP_{AA} = \sum_{i} p_i \cdot \frac{s_i}{8} \quad [4]$$

where $s_i = \sum_{j=1}^{4} s_{ij}$ represents the sum of the pollinator-attractiveness scores (s_{ij}) assigned to crop *i* for each *j*-th pollinator group. RP ranges from 0 to 1, with values close to 1 indicating areas that provide a high level of attractiveness for all four pollinator groups. The LE_{AA} indicator measures the share of the agricultural area (AA) influenced by the presence of linear structures such as hedges and tree-lined rows. To quantify this influence, a 2.5 m buffer was applied around all linear elements, and the resulting surface of the buffered area (SU_{LE}) was calculated. LE was then expressed as the proportion of this buffered area relative to the total agricultural area. To normalize the indicator, a theoretical maximum value was defined for each spatial unit, assuming the presence of one standard linear element per hectare, with a reference dimension of 100 m in length and 5 m in width (i.e., 500 m² per hectare):

$$LE_{AA} = min\left(1, \frac{SU_{\mathrm{LE}}}{0.05 \cdot SU_{\mathrm{AA}}}\right) \quad [5]$$

The Riparian–Wetland component (RW_{AA}) represents the share of agricultural land influenced by nearby water bodies. We first compute SU_{RW} as the portion of SU_{AA} that falls within a 20-meter buffer around lotic and lentic water bodies, including any wetlands within the agricultural mosaic. RW_{AA} is then defined as the ratio of SU_{RW} to SU_{AA}. Because agricultural landscape datasets generally report very small areas of riparian and wetland features—typically between 0.1% and 0.5% of the agricultural area and rarely more than 1% (Kałuża et al., 2025; Robotham et al., 2021), we normalize the indicator by using 1% of SU_{AA} as the upper reference value. This scaling ensures that RW_{AA} reflects the relative completeness of riparian and wetland features with respect to an indicative ecological benchmark. The normalized form is then defined as:

$$RW_{AA} = min\left(1, \frac{SU_{\mathrm{RW}}}{0.01 \cdot SU_{\mathrm{AA}}}\right) \quad [6]$$

The final element of **AA** is HB_{AA}, the habitat-based indicator of farmland bird suitability. The HB_{AA} component estimates the potential availability of suitable habitats for farmland bird species within each spatial unit. When available, FBI values at the highest spatial resolution can be used to directly adjust habitat suitability to the ecological conditions of the target year.In our case study, high-resolution habitat suitability was derived from the maps developed by Brambilla et al., (2025),based on species distribution models calibrated with validated occurrence data from the 2010–2016 breeding seasons. For each municipality, we calculated the mean suitability across the 43 farmland-associated bird species identified by Campedelli et al., (2009). To obtain habitat suitability values that vary over time, we implemented a correction procedure that adjusts HB to the target year using the Farmland Bird Index (FBI). Specifically, HB is scaled by the ratio between the FBI of the target year and the mean FBI of the 2010–2016 reference period. The regional FBI for Lombardy (Lipu, 2024) was used as the population trend indicator. For clarity, in this formulation we explicitly include the **subscript *t*** to represent the temporal resolution of the analysis. The year-adjusted habitat suitability index is therefore expressed as:

$$HB_{AA,t} = \left(\frac{1}{43}\sum_{i=1}^{43}\bar{S}_i\right)\cdot\frac{FBI_t}{FBI_{\text{ref}}} \qquad [7]$$

where $\bar{S}_i$is the mean suitability value of i-th species, FBI_t is the Farmland Bird Index value for the t-th year, and FBI_{ref} is the mean FBI over the 2010–2016 reference period.

This procedure can be adapted to other regions by substituting the FBI with equivalent local or national bird population indices. The second FBS component (WA) captures the extent of coppice-managed woodland within the agricultural landscape. Wooded areas (SU_{WA}) include timber plantations, poplar groves, chestnut orchards, shrub formations, and broadleaf forests managed as low-, medium-, or high-density coppices. WA was computed as the ratio between woodland surfaces inside the farmland and the total municipal area. This metric expresses the structural role of woodland elements within the farmland mosaic:

$$WA = \frac{SU_{WA}}{SU_{Tot}} \quad [8]$$

The third FBS component (GA) corresponds to permanent grassland areas. It was calculated as the proportion of permanent grasslands within the farmland relative to the total municipal area. Permanent grasslands include permanent meadows and natural pastures. This metric reflects the contribution of semi-natural grassland habitats within the local agricultural landscape:

$$GA = \frac{SU_{GA}}{SU_{Tot}} \quad [9]$$

Data collection

To illustrate the functionality and potential of the FBS index, we applied it to assess farmland biodiversity in the Lombardy Region for the year 2021. All datasets refer to 2021 and were obtained from publicly available regional sources. Municipal administrative boundaries were used to define both the total area and the farmland components included in the analysis. Land-cover information was derived from the DUSAF classification system, which enabled the identification of farmland-relevant categories, including riparian zones and linear elements such as hedges and tree rows. Data on crop types and associated taxonomic groups were extracted from SIARL land-use records, which provide detailed information on cultivated parcels and were used to assign pollinator resource scores. Finally, high-resolution environmental suitability maps by Brambilla et al. (2025) supported the estimation of suitable bird habitats (HB) within each municipality.

Results and Discussion

To explore the spatial patterns emerging from the application of the FBS index, we examined its distribution across all municipalities of the Lombardy Region. Figure 5.3.1 highlights a marked territorial variability of the FBS index across Lombardy. The highest values occur in the pre-Alpine belt, where the extensive presence of wooded areas, permanent meadows and other semi-natural elements enhances landscape heterogeneity and increases the capacity of rural mosaics to support biodiversity.

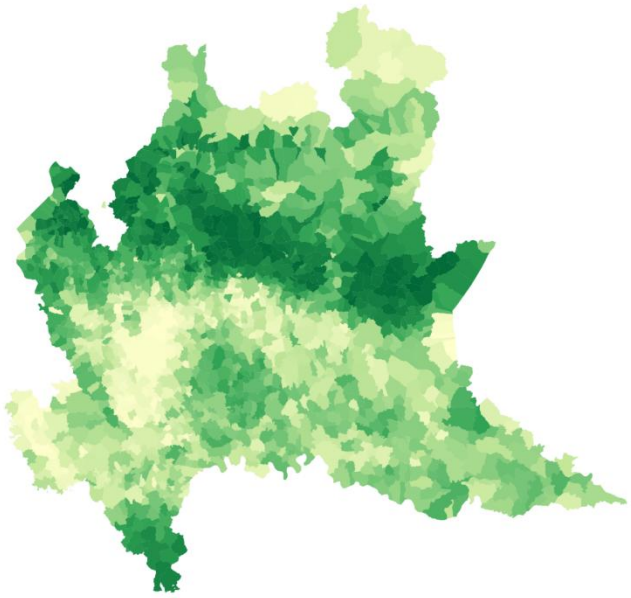


Figure 5.3.1- Spatial distribution of the Farmland Biodiversity Support (FBS) index across municipalities of the Lombardy Region (year 2021)

Moving towards the lowland, the index shows a progressive decline. Here, the expansion of urbanized areas and transport infrastructure, especially in metropolitan and peri-urban contexts, reduces the continuity of rural environments and limits the availability of functional habitats, significantly lowering the indicator values. Settlement pressure combines with increased simplification of cropping systems, resulting in lower FBS levels overall. Within the southern lowland, however, notable differences emerge. Some areas maintain a more heterogeneous agricultural structure, characterized by relatively diverse cropping systems, functional irrigation networks, linear elements and residual portions of stable meadows. This local variability underscores how the capacity to support biodiversity arises from the interplay between agricultural land use, urbanization intensity, and the broader configuration of the rural landscape. To better understand how each element contributes to the overall FBS index, we examined separately the spatial patterns of the three components (**WA**, **GA**, and **AA)**. This disaggregated analysis allows us to identify the specific landscape features driving local variations in farmland biodiversity potential and to clarify the distinct ecological roles played by woodland areas, permanent grasslands, and agricultural area. The distribution of component WA, shown in Figure 5.3.2a, highlights a clear geographical gradient in the presence of wooded areas, including coppice forests, chestnut groves, riparian

formations and other managed forest types. The darker shades, concentrated in the pre-Alpine and foothill areas, correspond to territories historically characterized by extensive and continuous forest cover, where the landscape mosaic includes large woody surfaces shaped by traditional forest management and by topographic constraints that limit agricultural and urban expansion. Moving towards the plain, the WA component declines markedly due to greater urbanization and intensive agricultural use, which have progressively reduced forest spaces. Nonetheless, some lowland municipalities show higher values than their surrounding context. In these contexts, wooded strips along major waterways, riparian corridors, and tree plantations (such as poplar groves) make a substantial contribution to the land classified as "wooded area.". In particular, the forest complexes associated with major river systems constitute some of the few extensive wooded areas in the plain, thereby elevating W relative to fully agricultural or heavily urbanized contexts. Conversely, the central and eastern lowlands exhibit consistently low values, reflecting landscapes where the continuity of forest areas has long been disrupted by agricultural expansion and urban development. In these territories, residual woody formations are typically fragmented, scattered, or confined to narrow linear features, resulting in minimal influence on the indicator.

Component **G** (Figure 5.3.2b) shows a pattern partly complementary to that of component W, although with distinctive features. Higher values are concentrated in Alpine and pre-Alpine areas, where permanent pastures and meadows constitute a structural element of agro-silvo-pastoral systems, supported by extensive management practices that maintain these grasslands over time. However, darker shades also appear in parts of the plain, indicateing that some lowland areas maintain a significant share of permanent meadows. darker shades also appear in parts of the persistence of consolidated forage systems, irrigated permanent meadows, and livestock-oriented agricultural contexts in which multi-year grasslands remain an integral part of crop rotations. In these municipalities, permanent meadows still play a significant role in the rural mosaic, contributing to relatively high farmland values even outside mountainous areas. In contrast, areas dominated by specialized crops, urbanization, or high-intensity agricultural systems exhibit lighter tones, reflecting both the reduced extent and greater fragmentation

of permanent grassland habitats. Taken together, the distributions of the W and G components confirm the presence of a strong territorial gradient, but also highlight how, in some parts of the plain, the permanence of traditional grassland systems locally maintains a significant contribution to the potential support of biodiversity.

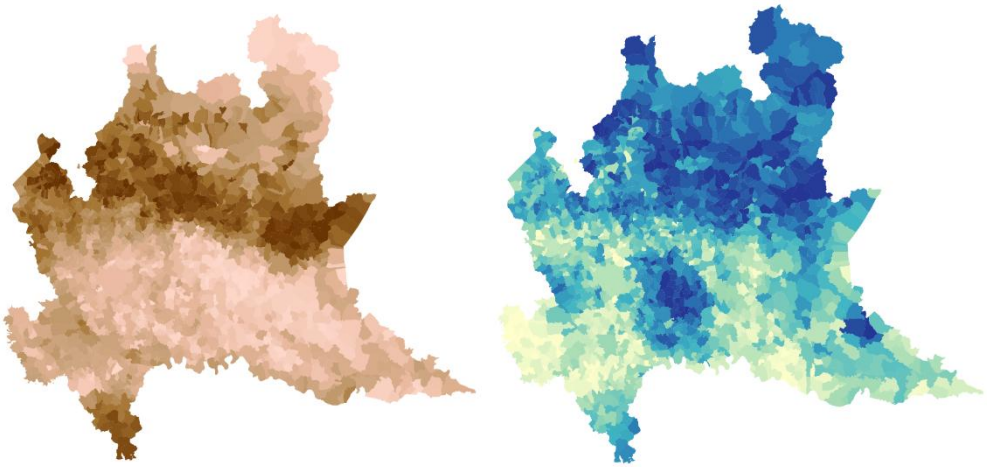


Figure 5.3.2 – (a): Spatial distribution of the woodland component (W) across Lombardy, showing the gradient from extensive pre-Alpine forest cover to more fragmented lowland wooded areas. (b): Spatial distribution of the grassland component (G), highlighting the concentration of permanent meadows and pastures in Alpine and pre-Alpine areas and their persistence in selected lowland municipalities.

Focusing on agricultural areas, Figure 5.3.3 details component AA estimates. As expected, the very low values in the Alpine and pre-Alpine zones reflect above all the limited extension of the areas to arable land or permanent fruit crops compared to other land covers. In the lowland, where agricultural area predominates, the score becomes more varied: darker shades and greater heterogeneity emerge, indicating marked differences in the composition and effect of individual functional aspects. Some municipalities show high values, suggesting a strong incidence of the indices underlying the score, while others show lower values, revealing differentiated agricultural systems even over small territorial distances.

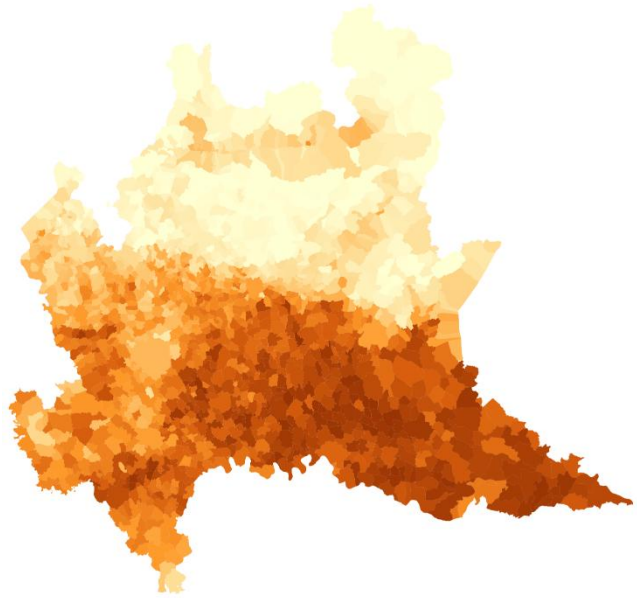


Figure 5.3.3 - Spatial distribution of component A across Lombardy

To further explore the internal variability of the agricultural component (AA), Figure 5.3.4 illustrates the distribution of its five functional sub-components across all municipalities in the Lombardy Region. LE_{AA} has a high variability, characterized by generally low values but with some municipalities showing high percentages of hedges and rows. The low median and the presence of many values close to zero highlight a poor diffusion of linear elements in the regional agricultural landscape, while only a few local contexts retain a more complex and complex ecological structure. Hedges and rows play crucial ecological roles in agricultural systems, contributing to ecological connectivity and landscape functionality. They act as habitat corridors and refuges for numerous faunal groups, improve the landscape's ability to support biodiversity and promote the movement of organisms through the agricultural matrix (Collier et al., 2021; Olivier Lourdais, 2025). In this sense, they represent living ecological infrastructures, often intentionally introduced into ecological intensification programs and environmental mitigation measures. In addition to their connectivity function, hedgerows and rows provide a wide range of ecosystem services: supporting biological pest control, wind attenuation, creating favorable microclimates, reducing erosion, soil stabilization, and increasing botanical diversity along crop margins (Larkin et al., 2022). Their presence also helps improve the overall resilience of agricultural systems, providing

heterogeneous habitats that favor beneficial insects, pollinators, birds, and small mammals. The ecological effectiveness of hedgerows and rows ultimately depends on a variety of local factors, including orientation, vegetation composition and structure, breadth, management methods, and characteristics of the surrounding agricultural matrix. These elements directly influence the faunal suitability and ability of linear structures to serve as habitats, corridors and refuge zones (Perrot et al., 2024). Their adequate design and management is therefore essential to maximize the ecological benefits and ecosystem services provided.

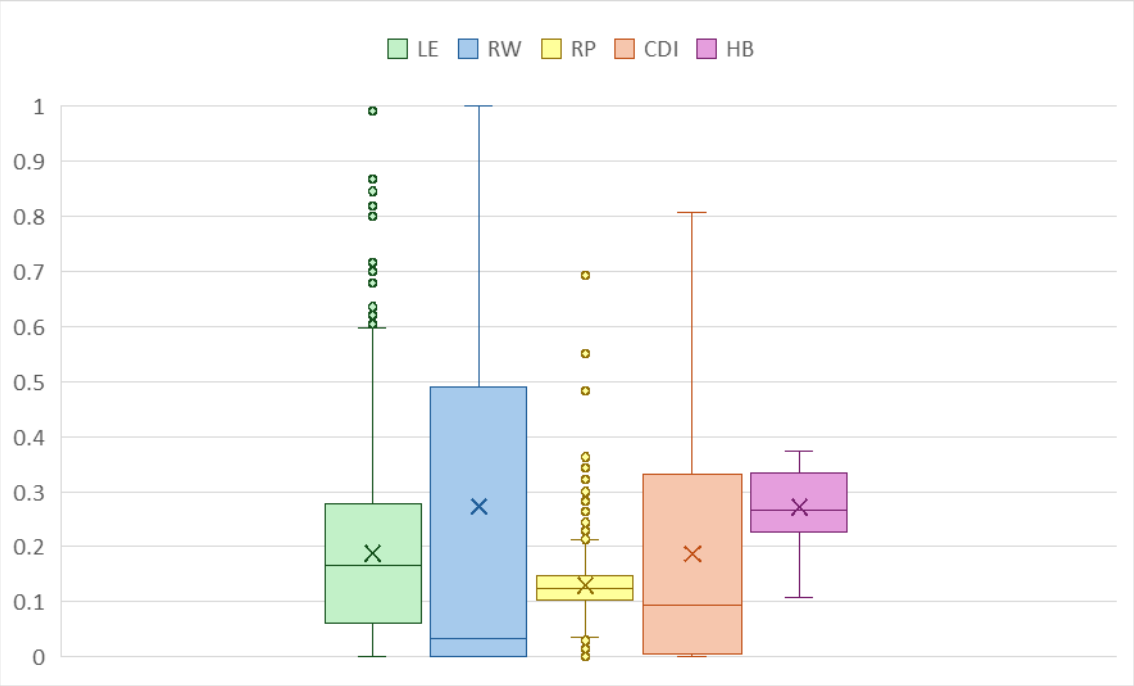


Figure 5.3.4 - Distribution of the estimated values of the five AA functional aspects across all municipalities of the Lombardy Region.

RW_{AA} has the highest variability among all indicators, with a wide dispersion and some very high maximum values. This behavior reflects the punctual and spatially inhomogeneous nature of riparian belts, wetlands, and hygrophilous environments, which tend to be concentrated along major river systems and are almost absent in most municipalities. The very low median confirms that these habitats constitute a generally limited component of the regional agricultural landscape, strongly influenced by the territorial context: local morphology, natural hydrographic network and water availability in fact influence the presence of water bodies to a greater extent than direct management choices. These elements should not be

considered in isolation, but as integrated parts of the river basin, connected to the hydrological, pedological and ecological processes that characterize it (Halsema and Wood, 2008). Although often small-scale, such elements can bring significant benefits to the ecosystem: they increase environmental heterogeneity, provide habitats for aquatic fauna and pollinators, improve nutrient retention, and strengthen ecological connectivity in the agricultural matrix (Blackwell, 2011). From this perspective, the further development of the RW_{AA} indicator should consider territorial specificity, integrating climatic aspects (precipitation, evapotranspiration), soil properties (water retention capacity, texture, soil depth) and local hydrological characteristics. The inclusion of these factors would allow us to better calibrate the riparian-wetland potential in different contexts and make the indicator more sensitive to the ecological and hydrological conditions that regulate the presence, quality, and functioning of wetland habitats in the agricultural landscape.

Of particular interest are the indices linked to crop choices, in particular Crop Diversity (CD_{AA}). The CD_{AA} shows wide variability among municipalities, with few territories characterized by high crop diversity and many others with lower values. This reflects the coexistence of highly specialized areas and contexts in which the production structure is more complex. Crop change, a well-established practice in European agriculture, is taking on an increasing role thanks to the adoption of strategies geared towards soil conservation and the optimization of agronomic efficiency. Crop rotation, achieved through larger rotations or intercropping, is recognized as a key factor in increasing the stability and productivity of agricultural systems. Experimental studies show that species-rich rotations increase yields and reduce interannual variability (Bowles et al., 2020), making systems less vulnerable to biotic and abiotic stresses. The ability to reduce pathogen and pest pressure (Peralta et al., 2018) and improve soil quality (Venter et al., 2016; Wooliver et al., 2022) gives crop diversification a strategic role in agronomic management oriented towards supporting biodiversity. Overall, more complex rotations, intercropping, and diverse production systems represent effective strategies for integrating productivity, soil health, and functional biodiversity into agroecosystems (Gawdiya et al., 2025; Struijk et al., 2026).

The RP_{AA} index shows overall low values and reduced variability, indicating that the supply of nectar and pollen resources provided by crops is modest on average. The few high values reflect the local presence of crops that are particularly attractive to pollinators or greater functional diversification of agricultural areas. Although many crops are not directly dependent on entomophilous pollination, the availability of floral resources is essential to maintain stable populations of pollinating insects and ensure the resilience of pollination services in the agricultural landscape (Katumo et al., 2022). Pollinator abundance and diversity are indeed influenced not only by proximity to natural habitats and management but also by crop choice (Duque-Trujillo et al., 2023). A relevant aspect concerns the diversity of trophic preferences between different pollinator groups. Domestic bees, bumblebees and solitary bees do not use the same resources and have different nutritional and behavioral needs (Bänsch et al., 2021). To optimize pollinator contributions and improve population health, management interventions must consider the availability of floral and non-floral resources, micronutrients, nest materials, and shelters (Jones and Rader, 2022). Crop diversification further contributes to the temporal continuity of blooms, increasing spatial and seasonal availability of nectar and pollen and thus improving functional connectivity for pollinators (Fijen et al., 2025). Future adaptations of the RP_{AA} functional aspect could explicitly integrate the duration and flowering periods of crops. Overall, despite its average low values, crop choice emerges as one of the most strategic levers for strengthening the capacity of agricultural areas to support biodiversity, in line with recent international policies that promote more complex rotations and dedicated areas to support pollinators.

The HB_{AA} functional aspect shows relatively high mean values and characterized by limited variability compared to other parameters. This distribution suggests that the potential habitat quality for agricultural avifauna is determined by ecological processes and factors operating at large scales, attenuating the more marked regional differences found in other indicators. The interpretation of the indicator is more complex than other components, because it simultaneously incorporates the

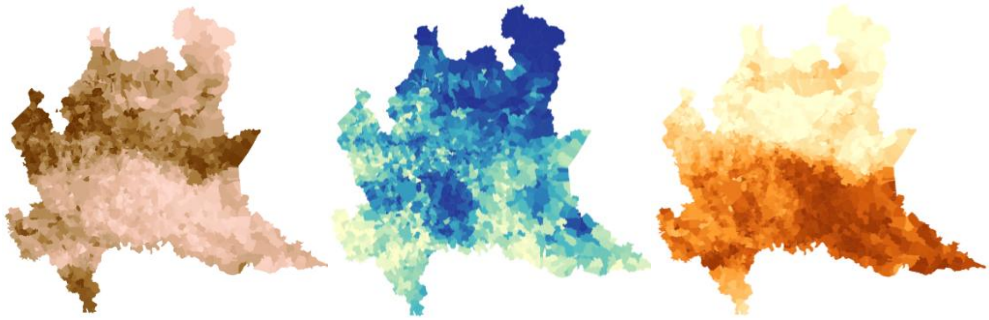


Figure 5 - Relative contribution of the three FBS components (W, G and A) to the total index (W+G+A) across all municipalities of the Lombardy Region.

availability of refuge habitats, the presence of water bodies and trophic resources distributed across the landscape, and the observed distribution of species across different types of agricultural areas. HB_{AA} therefore, represents an integrated measure that reflects both the structural characteristics of the agricultural environment and the ecological response of bird communities, proving to be an effective indicator of the overall state of functionality of agroecosystems.

Finally, Figure 5.3.5 shows the relative contribution of the three index components (W, G and A) to the formation of the final FBS value. The joint reading of the three components confirms the gradient already highlighted by previous analyses, but allows us to clarify which landscape elements actually support the biodiversity potential of farmlands in different municipalities. In the pre-Alpine and hilly areas, the W component clearly prevails, reflecting the structural role of wooded surfaces and riparian belts in defining the ecological potential of the territory. Component G, on the other hand, is decisive in the Alpine municipalities and in some portions of the plain where traditional fodder systems persist. In the agricultural plain, the predominance of component A clearly emerges, with the effects of functional elements observed in the boxplot analysis. In the absence of significant shares of semi-natural areas, local differences in biodiversity support potential depend almost entirely on the functional quality of agricultural systems. In these municipalities, the variability of values is mainly attributable to the presence of linear elements, cultural diversification and the resources offered to pollinator and bird communities. Taken together, Figure 5.3.5 offers a useful interpretative key for developing targeted decisions and policies: it allows us to immediately identify

which components of the index are actually active in different contexts and which levers are most effective for increasing the potential for supporting biodiversity. In mountain areas, this mainly concerns the protection of forest systems, in the irrigated plain the conservation of residual permanent meadows, while in the most intensively cultivated areas the scope for action falls above all on improving the agro-ecological components of agriculture.

Conclusion

The index proposed in this study provides a flexible and operational tool for assessing how different farmland components contribute to biodiversity support across diverse territorial contexts. A key strength of the FBS framework lies in its ability to be calculated at multiple spatial and temporal resolutions, making it suitable for both regional-scale assessments and fine-grained local analyses. The detailed structure of its three farmland components, AA, GA, and WA, enables a differentiated reading of the landscape: each component isolates specific ecological functions and pressures, allowing for an accurate identification of both critical issues and strengths at the municipal scale or within finer spatial units. This level of detail enhances the capacity of the index to guide targeted and evidence-based decision-making, supporting policymakers in designing interventions where they are most effective and in tailoring strategies to the ecological characteristics of each area. In territories lacking semi-natural features such as managed forests, pastures, or permanent meadows, the results show that diversification of arable land and permanent fruit crops can play a key role in strengthening biodiversity support. This pattern is already emerging in several parts of Lombardy, and further improvements are possible by integrating ecological infrastructures and adopting ecological intensification practices. In this way, agriculture does not merely adapt to ecological challenges but can actively contribute to biodiversity conservation while enhancing the delivery of ecosystem services. Extending the assessment over a longer time span—provided that suitable data are available—would allow the index to capture temporal dynamics in landscape structure and management. This would make it possible to distinguish long-term structural changes from short-term fluctuations and to better evaluate how land-use transformations affect the capacity of agricultural areas to support biodiversity.

Future developments should also explicitly incorporate management practices. While crop composition and landscape structure strongly influence biological communities, inappropriate management can reduce or annul these benefits, whereas practices aligned with ecological goals can enhance biodiversity support even in more intensive agricultural systems.

Overall, the FBS index represents a versatile, scalable, and decision-oriented instrument, capable of supporting the integration of production and biodiversity objectives and of guiding agricultural landscapes toward more resilient and ecologically functional configurations.

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6. Conclusion

The activities carried out within this PhD project, coherently framed within the integrated sustainability assessment framework, enabled a systemic analysis of the environmental integrity of the four natural capitals—atmosphere, water, soil, and biodiversity. The integration of farm-level data, sustainability indicators, statistical models, and remote sensing tools made it possible to adopt a multidimensional perspective, oriented not only toward impact reduction but also toward evaluating the regenerative capacity of agroecosystems. This integrated approach is synthetically illustrated in Figure 5, which links the main topics to their associated results, highlighting key drivers, interactions between agronomic practices and natural capitals, and the resulting management implications. Taken together, the studies provide a comprehensive overview of sustainability in relation to environmental integrity. However, the interpretation of results must explicitly account for the role of the environmental and production context in which the methods were applied, as well as the potential limits of replicability and transferability of the proposed assessment tools across different settings.

Regarding the **atmosphere**, the carbon footprint analysis of 25 Italian wineries revealed no statistically significant differences in total emissions between organic and conventional systems, while highlighting distinct emission patterns at the level of individual sources. This outcome underscores the need to move beyond binary comparisons between production models, as emissions depend on specific technical and managerial configurations. Interpretation must therefore account for winery characteristics (e.g., size, mechanization, production strategies) and pedoclimatic context, reinforcing clarity in cause–effect relationships.

For the **water**, the study conducted on non-irrigated vineyards showed that structural and contextual variables—such as planting density, slope, soil characteristics, vineyard age, and varietal susceptibility—influence indicators related to water scarcity, acidification, and freshwater ecotoxicity. Although the statistical approach identified significant associations, causal interpretation requires caution. Water-related pressures emerge from the interaction between agronomic

practices and territorial conditions, highlighting the need for a clearer and more explicit understanding of the systemic dynamics linking management and impacts.

With respect to the **soil**, the development of the MISQ (Management Impact on Soil Quality) indicator made it possible to integrate multiple dimensions—soil disturbance, organic matter regeneration, nutrient use efficiency, copper ecotoxicological impact, and biodiversity—into a single evaluative tool. Multi-year application confirmed the positive contribution of organic matter inputs and diversified cover crops to improving soil functionality, while also highlighting risks associated with intensive tillage and nutrient excesses. Although MISQ is designed as a replicable tool, its application requires contextual adaptation to different pedoclimatic and management conditions.

For **biodiversity**, research carried out at both farm and territorial scales demonstrated the potential of remote sensing and deep learning for monitoring landscape structure and plant communities. At the territorial scale, the development of the FBS index enabled the assessment of farmland capacity to support biodiversity by integrating cropping systems and semi-natural elements of the landscape. Its application to the Lombardy region revealed marked spatial gradients and emphasized the strategic role of crop diversification and linear ecological infrastructures for the ecological functionality of agricultural landscapes. However, the need to improve data comparability and sample homogeneity remains particularly relevant, especially in relation to dataset limitations. Sample size, acquisition conditions, and territorial specificity can influence the validity and transferability of models, making external validation essential.

Overall, the findings confirm that the transition toward regenerative agricultural systems requires integrated and multidimensional tools capable of linking agronomic practices to environmental impacts and ecosystem service regulation. The methodologies developed in this thesis—synthetic indicators, statistical models, and AI-supported remote sensing tools—represent a relevant operational contribution.

Across the different studies, however, several common limitations emerge: the strong influence of environmental and production context on result interpretation,

the limited comparability of datasets, the variable representativeness of samples, and the need for caution when extending methods to other viticultural systems or geographical settings. Strengthening scientific robustness and transferability will require broader data availability, multi-year and multi-site validation, and refinement of the tools developed to enhance their scalability.

Future research should therefore focus on consolidating cause–effect relationships across natural capital dimensions, improving data comparability for remote sensing applications, and broadening the operational usability of the indicators and models. These steps will be essential to further strengthen the effectiveness and applicability of the proposed tools.

The collaboration with Guido Berlucchi & C. further demonstrated the value of integrating research and business practice. The use of real farm data, combined with monitoring and evaluation methodologies, enabled the development of scalable and applicable solutions. Strengthening data quality, comparability across contexts, and theoretical clarity in interpreting results will be crucial to consolidate the effectiveness of these tools and to support the wine sector in moving toward genuinely regenerative models grounded in the enhancement of natural capital.

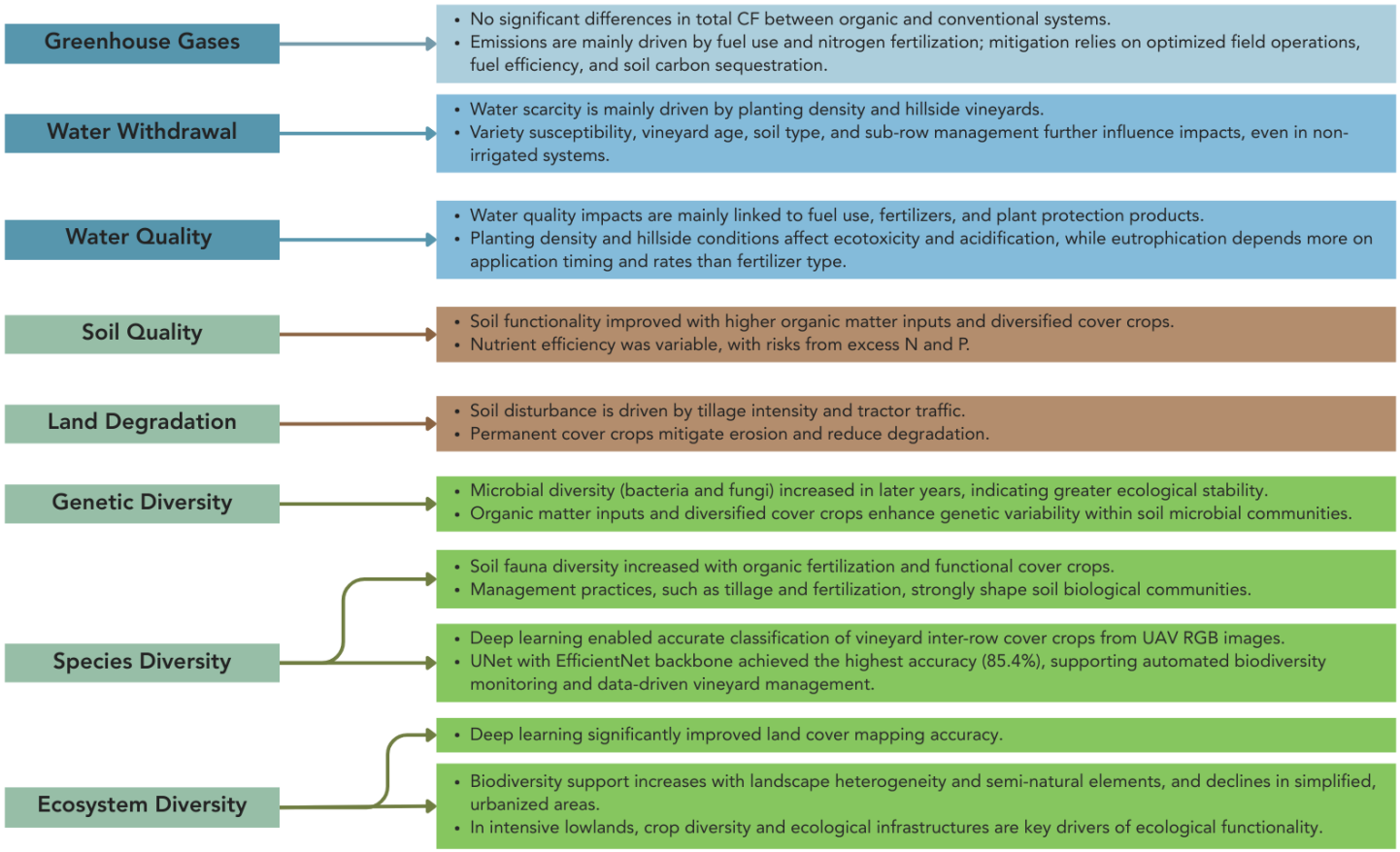


Figure 5 - Schematic synthesis of the main results for each natural capital dimension addressed in the PhD research. The figure links each topic to the corresponding key findings, highlighting the main drivers, management implications, and methodological contributions emerging from the different studies.

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