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RECOVERY AND REUSE OF ALTERNATIVE WATER RESOURCES IN AGRICULTURE: AN ANALYSIS OF ECO-INNOVATION BETWEEN SOCIAL ACCEPTABILITY AND ECONOMIC-ENVIRONMENTAL SUSTAINABILITY

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Preface

This PhD thesis is part of the Tech4You project, funded under the National Recovery and Resilience Plan (PNRR) within the thematic area *Climate, Energy and Sustainable Mobility*. The project is a strategic initiative aimed at fostering technological and environmental innovation in Italian regions undergoing transition, with the overarching objective of supporting the development of a climate-neutral economic model. This goal is pursued through the design and implementation of integrated strategies for the sustainable valorisation of natural resources and the use of renewable energy sources.

More specifically, this research is carried out within *Spoke 2*, dedicated to *"Technologies to reduce energy consumption and preserve biodiversity – GOAL 2.1 – PP 2.1.1"*. The assigned topic concerns the integrated assessment of the economic, social and environmental sustainability of using end-of-cycle outputs in agriculture.

Within this framework, the study focuses on the potential recovery and integration of properly treated urban wastewater into agricultural production processes, as an innovative solution capable of simultaneously addressing water conservation, environmental protection and the promotion of a circular economy.

Wastewater - defined as water generated by domestic, industrial or agricultural human activities and containing organic and inorganic substances potentially harmful to human health and the environment - once adequately treated, represents a resource that remains underused and largely underestimated in the Italian agricultural context.

From 2023, the entry into force of Regulation (EU) 741/2020 has established minimum quality requirements to ensure that its reuse is fully safe for human health and the environment. This has provided a strong and harmonised European regulatory framework that supports and encourages this practice. Despite this favourable regulatory environment, adoption remains limited due to informational, infrastructural, economic and operational constraints.

The decision to focus on the Basilicata Region is based on substantive reasons. The region has been identified by the PNRR as one of Italy's transition areas requiring innovative proposals and structural change. Moreover, between 2022 and 2024, irrigated agriculture in Basilicata experienced substantial production losses due to increasingly frequent and severe droughts. These events led to the declaration of a state of emergency and highlighted the urgent need for alternative water management solutions. In this context, the agricultural reuse of treated wastewater represents a strategic opportunity to reduce further pressure on natural water resources by introducing new supplies through a recovery-and-recycling approach consistent with circular economy principles and the project's environmental objectives.

Recognising that treated wastewater meets the defining criteria of an eco-innovation - and that many countries worldwide already reuse it for both irrigation and industrial purposes - this thesis aims to examine, from an integrated perspective, the sustainability and social and economic acceptability of wastewater reuse in agriculture. The analysis focuses on four key dimensions:

- the potential and benefits of wastewater use in agriculture;
- the economic, structural and operational barriers to implementation;
- the risks perceived by relevant stakeholders;
- the mechanisms shaping farmers' willingness or reluctance to adopt this resource.

To achieve these objectives, the thesis follows a structured and sequential methodological framework:

1. Chapter 1 outlines the theoretical foundations of innovation, from classical approaches to more recent models that interpret adoption as the combined effect of economic incentives and attitudinal and perceptual factors;
2. Chapter 2 examines the concept of eco-innovation, reflecting the growing focus of research and policy on environmentally oriented innovations, and demonstrates how treated wastewater fully embodies this concept as a solution aligned with current regulatory and environmental goals;
3. Chapter 3 presents an initial empirical study based on a survey of irrigated farmers in the Metapontino Area, aimed at identifying the factors that increase or reduce their propensity to use treated wastewater for irrigation;
4. Chapter 4, building on evidence that risk perception plays a decisive role, presents a second survey investigating perceived risk profiles among farmers in Basilicata and identifying segments characterised by different innovation orientations and risk perceptions;
5. Chapter 5 provides a critical examination of modelling approaches and their ability to represent agricultural systems, analysing how models simplify real-world systems and simulate both current conditions and potential changes. It also highlights how modelling enables analysis beyond the single-farm level, supporting the study of complex systems at broader scales and generating policy-relevant insights that integrate environmental, social and economic dimensions;
6. Chapter 6 reviews the application of optimisation, simulation and Agent-Based models in agriculture for environmental and economic assessments and for analysing interactions among actors. Based on this review, Agent-Based models are identified as the most suitable tools for this context. A preliminary Agent-Based model is therefore developed to analyse the behaviour of monoculture farms in water resource management, examining how adoption propensity and profit vary according to the availability of conventional water and treated wastewater, using data from previous surveys and expert interviews.

Overall, this research contributes to identifying the key conditions that need to be strengthened to enable sustainable practices such as wastewater reuse to be implemented in an economically efficient, socially acceptable and environmentally sound manner. The evidence presented in this thesis provides structured recommendations for the design of policies and measures aimed at preserving natural water resources, particularly in contexts such as the Basilicata Region, which remains in the early stages of sustainable water management development. The impact of this work lies in generating targeted knowledge on a highly relevant topic and in offering practical guidance for strengthening the regulatory, economic, infrastructural and technical support frameworks necessary to encourage the adoption of innovative solutions in the regional agricultural sector.

Chapter 1

Innovation in Economic Development: Theoretical Perspectives and Adoption Dynamics

1. Introduction

Over time, innovation has progressively established itself as a central pillar of evolutionary thought, coming to be interpreted as a key driver of economic, industrial and entrepreneurial development. It is no longer viewed merely as a theoretical construct to be transposed onto productive realities; rather, it has become an essential operational instrument for improving performance and fostering growth at both global and sectoral levels (Malerba, 2000; Kurtz, 2017). The roles attributed to innovation are multiple. At a macro level, it actively shapes competition between national systems, supports the development of countries characterised by conditions of backwardness, and contributes to the emergence of new sectors and technologies as well as to the strengthening of existing firms (Feder & Zilberman, 1985; Freeman, 1994; Gilbert, 2006). While it is crucial to understand the origins of innovation, the processes underlying its creation, and the roles played by the actors and institutions involved, it is equally important to investigate its nature and structural characteristics, together with the factors that determine its adoption and diffusion at the firm level. Innovation does not necessarily coincide with the creation of something *ex novo*. In many cases, it takes the form of a technology or practice whose effects and effectiveness are not yet fully understood and which has never previously been implemented, thus constituting an innovation for the potential adopters to whom it is introduced (Rosenberg, 1982). Moreover, when analysis shifts to a more disaggregated level and focusing on individual decision-making units such as entrepreneurs or firms, additional cognitive, perceptual and behavioural dimensions come into play.

These include learning processes, knowledge generation and interactions among economic actors, all of which collectively shape adoption decisions. This highlights how innovation and its associated processes can vary substantially depending on the scale of observation, whether at the level of large firms, sectoral systems or individual business entities. As a result, the relevant characteristics and dynamics cannot be generalised indiscriminately. Innovations must therefore be properly contextualised, both in terms of their attributes and with reference to the specific features of the sectors and firms concerned (Pavitt, 1984).

To achieve a comprehensive understanding of innovation as it relates to individual firms as decision-making entities and of the processes through which innovation is accepted, adopted and diffused, it is necessary to reconstruct the historical and conceptual trajectory that has led to the identification of the attributes characterising innovation and to the subsequent evolution towards economic and behavioural models capable of capturing the microeconomic determinants of firm-level adoption.

This trajectory begins with insights already present in classical economic theory, develops decisively through the conceptual shift introduced by Schumpeter, and continues with contributions from innovation economics, evolutionary theory and innovation systems. It ultimately converges in diffusion models and more recent socio-economic and behavioural approaches to technology acceptance (Rogers, 1995; Venkatesh et al., 2003; Tey & Brindal, 2012). Through this reconstruction, it becomes possible to grasp not only the evolution of the concept of innovation itself, but also the transformation of analytical perspectives on adoption processes, which have progressively shifted from a predominantly macroeconomic framework towards a micro-behavioural one.

2. Innovation in Economic Thought: The Foundations

Based on the various theoretical contributions that have addressed the creation and diffusion of innovations across contexts over time (Rowe & Boise, 1974; Rogers, 1995; Fischer, 2001), a general definition of innovation refers to "the generation of a new idea and its implementation in a new product, process or service, capable of fostering dynamic growth of the national economy, increasing employment and creating profit for the innovative firm" (Urabe, 1998).

A first element linked to this concept concerns technological change and progress (Solow, 1957; Gilbert, 2006). Among the earliest contributions, Adam Smith, in *The Wealth of Nations* (1776), although he does not explicitly refer to innovation in the strict sense, incorporates this dimension by stressing technological change as an inevitable response to demand and market dynamics. Rising demand and evolving consumer needs lead to new technologies and new outputs. Smith does not emphasise the creation of new technologies as such; rather, he emphasises the need to incorporate technological progress into capital goods and links its effects to labour productivity, specialisation and employment (Malerba, 2000; Kurz, 2017). He identifies technological progress as the innovation required to facilitate and reduce labour, placing workers and operatives at the centre of the process: they both inspire such progress, by seeking concrete solutions to production problems, and benefit from it.

Marx subsequently seeks to explain the role of technological innovation in response to the requirements of modern economies. For Marx, innovation primarily concerns the introduction of new machines and technologies that become integral to production and, as a result, radically transform the technical basis of production (Frison, 1988; Gilbert, 2006). Unlike Smith, Marx frames technological innovation as a structural strategy adopted by the capitalist to increase profits through control of production. In this view, the main subject of innovation is the capitalist individual rather than workers or intellectuals in a broader sense. The capitalist innovates to secure a temporary competitive advantage, which is destined to decline as competitors adopt similar production strategies. Even at this stage, several drivers consistent with modern observations are already evident: higher labour efficiency and productivity, the pursuit of greater profits, and the need to remain competitive in the market.

The phase of invention and the creation of innovation plays an important role in understanding the origins of innovative processes, the motivations sustaining them, the aims pursued and the sectors involved. It is therefore unsurprising that, from Marx onwards, further approaches emerge that interpret technological innovation as an intrinsically social and collective process. In these approaches, innovation is rooted in an economic and institutional context involving diverse actors, and the propensity to innovate depends on market size and the competitive pressure generated by capitalism (Malerba, 2000; Frison, 1988; Kurz, 2017).

Schumpeter (1939; 1942) defines the phases of the innovation process and is among the first to examine systematically and in depth the role of innovation in modern industrial economies. Treating innovation as the main engine of economic development and qualitative social change, he describes it as a "process of industrial mutation that revolutionises the economic structure from within, continuously, progressively destroying the old structure to create a new one". In this perspective, innovation is understood as "creative destruction". Initially, the entrepreneur acquires new competences external to the economic system, securing a position of temporary advantage; this is followed by imitation by other firms, which leads to a restoration of economic equilibrium (Schumpeter, 1939). The innovation process can therefore be divided into three successive phases:

- Invention, a phase centred on scientific research and R&D activities, which Schumpeter considers indispensable especially for large organisations;
- Innovation, the phase in which the invention is concretely applied within production;
- Imitation, a subsequent phase, closely linked to the success of the innovation, in which other firms adopt analogous solutions.

This implies a fundamental distinction between invention and innovation. Invention consists in conceiving, for the first time, a new idea, product or process; it remains essentially scientific in nature and need not be materialised. Innovation, by contrast, is the concrete act of realising "something new". It includes the practical implementation of the invention and its placement on the market in ways that generate profits. In Schumpeter's more mature formulations, however, he clarifies that invention does not necessarily have to precede innovation. Innovation may also take the form of "new combinations of existing resources", the creation of new organisational forms and, more broadly, the opening of new markets and the conquest of new sources of supply in response to the needs of sectors and firms (Schumpeter, 1942).

Within this framework, the protagonist of innovation is the entrepreneur not merely a business manager, but an "agent of change" and a "leader of innovation". The entrepreneur is characterised by traits such as creativity and a revolutionary spirit, which drive the creation of the new rather than the refinement of what already exists (Baussola, 1988).

The incentives to innovate, however, must be sought first in the economic and financial dimension already highlighted by Marx: the pursuit of higher profits and extra rents, obtainable either through prices above those of competitors or through the containment of production costs. Second, competitive pressure and the need for survival push firms to innovate continuously to avoid exclusion from the market. Schumpeter's thought evolves over time, leading him to describe two distinct yet complementary modes of innovation: first as the act of the individual entrepreneur, and later as a function embedded within large organisations.

In his theory of economic development (Becker & Knudsen, 2002), Schumpeter initially focuses on innovative entrepreneurs, viewing innovation as the product of tension between new solutions and social inertia. New entrepreneurs and new firms continually enter the market, introducing novel ideas and products; competition between new and incumbent firms erodes the monopoly rents associated with earlier innovations. However, in the early phase a temporary monopoly is a necessary condition because it provides the fundamental incentive to innovate: without such rents, and under immediate perfect competition, the incentives themselves would weaken. As his thinking develops, Schumpeter acknowledges in *Capitalism, Socialism, and Democracy* (1942) that innovation increasingly becomes the outcome of systematic teamwork within large firms, where the role of the individual entrepreneur is progressively absorbed by the organisation. This entails a loss of individual creative vitality, but it is compensated by greater systematicity and by the availability of resources. A small number of large firms therefore emerges, investing continuously in the search for innovations, both radical and imitative, ranging from basic and applied research to the concrete and sustained development of identified solutions. Moreover, innovation tends to generate further innovation: accumulated knowledge in specific technological domains facilitates the development of additional innovations within the same domain. In this way, large firms, thanks to their knowledge stocks, advanced professional competences and the progressive strengthening of their economic positions, end up obstructing the entry of new small firms.

Schumpeter's vision can thus be transposed to contemporary contexts, where the continuous pursuit of innovation drives economic growth and competitiveness. For firms and organisations today, investing in innovation is not an optional choice but a structural requirement for survival. Now as then, innovating does not only mean "inventing from scratch". It also means recombining existing technologies, organisational models and markets in new and potentially disruptive ways. Moreover, the Schumpeterian innovation process recognises the role of multiple economic actors. It attributes importance not only to those who create and produce innovations, but also to those who adopt them, because it is precisely users' choices, selection and adaptation that make creative destruction operative throughout production chains.

A further lesson, often overlooked, is that innovation emerges in response to specific external conditions and to constraints imposed by relations of political power. Projected into the present, sustainability-oriented regulation can stimulate ecological innovations, just as the challenges posed by climate change can become drivers of new energies and production practices. In this view, constraints should be understood not as obstacles, but as catalysts that can steer innovative efforts towards new combinations. From an evolutionary perspective, innovation has therefore shifted from a rare phenomenon concentrated in individual actors to a continuous, collective and hybrid process, generated through interaction between private initiative and public investment.

3. Theory of innovation and subsequent developments

From an evolutionary perspective, Schumpeter emphasised economic development as an endogenous process of change, driven by innovation and by the entrepreneur and the firm. Building on this view, the debate on innovation evolved through the work of economists who developed more articulated frameworks, highlighting the cumulative, interactive and systemic nature of innovation processes.

Usher (1954) was among the first to introduce a sequential approach to innovation. Unlike Schumpeter, he did not stress the entrepreneur as the main agent of innovation, but viewed innovation as a social and interactive process unfolding over time. He identified four progressive stages: the perception of a problem, the assembly of materials for its solution, insight, and finally the materialisation and refinement of the invention into a functioning model. These stages, he argued, need not be completed by a single actor, nor within the same historical period. Innovation therefore emerges as a cumulative and progressive process involving multiple actors over time. As a result, the figure of a single "innovator" disappears, replaced by a community that gradually refines useful and necessary solutions. Usher also stressed that the development of specific innovations depends on parallel advances across multiple, interconnected technical domains. In doing so, he highlighted the importance of practical and empirical experience in generating innovation, rather than relying solely on purely theoretical research. His contribution thus laid the foundations for the modern view of innovation as a cumulative and interactive process, driven by experience in its various forms.

Rosenberg (1982) reinforced these insights while shifting the focus to the broader economic system. In *Inside the Black Box: Technology and Economics* (Rosenberg,1982), he strongly criticised the neoclassical view of technological change as an exogenous phenomenon, condemning economists' tendency to treat technology as a "black box". In his view, innovation is not driven by forces external to the market, but is strongly shaped by competitive dynamics and concrete production needs.

He therefore expanded the sequential phases of innovation identified by Schumpeter, namely invention, innovation and imitation, arguing that the process is far more complex and articulated, involving multiple stages and actors. Innovation, for Rosenberg, is not a one-off event but a continuous process characterised by incremental improvements and ongoing adaptation to the needs of different sub-markets.

In contrast to the "technology push" model, which sees innovation as mainly driven by scientific research, Rosenberg, like Usher, recognised that many important innovations arise from practical learning, hands-on experience, the capital goods industry, and interactions between producers and users. At the same time, he identified the industrial firm as the central actor, embedded within a complex system of economic relationships. Innovation does not stem from simple strategic decisions aimed at profit maximisation, but from practical needs such as cost reduction, the resolution of production problems (as already emphasised by Usher) and adaptation to real technical constraints. The interaction between capital goods suppliers and user firms is therefore crucial. This relationship remains central in more recent studies, as firms specialising in machinery and equipment provide essential experimental support and facilitate the transfer of practical knowledge within the innovation process.

In later developments of Rosenberg's work, a more pragmatic definition of innovation emerges, described as "a practice or a technology adopted for the first time by a firm, whose effects are still unknown". This clarification is particularly important, as it introduces key elements that underpin more recent definitions of innovation:

1. a practice or technology may already exist on the market, yet still represent an innovation for firms that have not previously adopted it and are unfamiliar with its functioning;
2. innovations do not necessarily have predictable or guaranteed outcomes at the time of adoption, anticipating the role of "uncertainty" and "risk perception", which later become integral to the processes of adoption and diffusion.

Without departing from earlier contributions, Freeman (1987) further expanded the range of actors involved in innovation. Through the concept of the "National Innovation System" (NIS), he fundamentally shifted the focus of analysis. Innovation is no longer an isolated phenomenon attributable to individual firms, as in Schumpeter, but the outcome of complex interactions among heterogeneous actors. These include not only firms and markets, but also universities, public laboratories, financial institutions, public policies, education systems and infrastructures. Freeman placed particular emphasis on the role of institutions and historical-social contexts in shaping national innovative capabilities, showing how public policy, industrial structures, education systems and financial institutions co-evolve to influence innovation performance. From this perspective, innovation occurs at multiple, interconnected levels and scales. Large firms may lead radical innovation in science-intensive sectors; small and medium-sized enterprises, often more specialised, develop innovative solutions for specific niches; universities and research organisations generate shared foundational knowledge.

Innovation therefore resides in the system of relationships, feedback mechanisms and complementarities between institutional components. It is no longer driven by a single entity pursuing a predefined objective, but by a composite and institutionalised subject of innovation.

Freeman also introduced a clear normative dimension, identifying governments as key promoters of innovation, responsible for actively creating and sustaining favourable environments. This perspective anticipates contemporary concerns by highlighting the importance of technology transfer infrastructures, supportive policies and cooperative networks as essential conditions for transforming inventions and scientific results into widely diffused commercial innovations at sectoral or national level.

A fully evolutionary approach to innovation is developed by Nelson and Winter (1985), who propose a more explicitly systemic framework. They reject the neoclassical assumption of optimising rationality and instead identify the firm as the main innovative agent, understood as a collective and heterogeneous organisation operating within a competitive selection environment.

Central to their analysis is the concept of organisational routines, which function as repositories of memory and foundations of firm behaviour. Firms operate under bounded rationality and follow satisficing strategies: when profits remain above a satisfactory threshold, established routines tend to persist; when profits fall below that threshold, firms engage in search processes to develop new routines capable of restoring acceptable performance. This represents a rational response to technological uncertainty and to firms' cognitive limits in considering all possible alternatives (Malerba, 1992; 2000). Through the notion of "technological regimes", Nelson and Winter further show that technologies do not offer uniform opportunities for progress across sectors or production levels. Understanding the nature of innovation and the rules governing technological trajectories is therefore essential to assess whether a given regime favours small firms and start-ups or consolidates the dominance of large incumbents. In regimes characterised by low cumulativeness and high appropriability, small firms can innovate, survive and grow; in regimes with high cumulativeness and low appropriability, economies of scale tend to favour large, established firms (Arrow, 1962). Overall, Nelson and Winter share with earlier authors an evolutionary, cumulative and systemic view of innovation: an endogenous, uncertain and historically path-dependent process emerging from interactions between firms, knowledge, institutions and markets. This framework forms the theoretical basis of contemporary innovation studies.

Although the evolutionary approach to innovation is progressively embraced by Schumpeter and subsequent scholars, important differences remain regarding the motivations behind innovation. For Schumpeter, profit is a necessary but insufficient objective, as entrepreneurs and firms are portrayed as ambitious and creative actors operating within a system shaped by deeper selective forces such as competition and the pursuit of market power. Later authors partially reverse this view, emphasising that innovation stems from concrete needs, practical constraints and feedback from the wider system. Innovation thus appears less as the outcome of ex ante calculated strategic choices, and more as the result of adaptation, problem-solving and learning rooted in real operational contexts. This marks a significant shift from Schumpeter's original framework towards a more complex view in which adoption, diffusion, learning, network structures and institutions play a central role. These are precisely the elements systematised by Everett Rogers (1983) in his general theory of the diffusion of innovations, which places particular emphasis on innovation characteristics, social dynamics and communication channels.

3.1 Neoclassical Innovation vs Evolutionary Innovation

The innovation process has not retained a fixed structure over time. The comparison between the two main schools of thought, neoclassical and evolutionary, with regard to the concept of innovation, its characteristics, the factors driving its implementation and its modes of operation has been clearly articulated by Malerba, drawing on earlier and well-established contributions that highlight substantial differences (Stoneman, 1983; Nelson, 1997; Dosi, 1988; 1997; Ruttan, 1997). In simple and direct terms, the neoclassical approach places the production function at the centre of innovation. Neoclassical economists are oriented towards the achievement of economic equilibrium, assuming that markets tend towards equilibrium configurations through the price mechanism. Firms are described as actors endowed with perfect information, behaving rationally in order to maximise profits, maintain or gain market positions, appropriate innovation rents, often protected by patents, and compete strategically with rival firms. Within this framework, uncertainty does not play a central role, but is mainly addressed through pricing strategies and investments in research and development. As a result, strong emphasis is placed on firm-level strategies.

By contrast, evolutionary economists adopt a dynamic and process-oriented view of innovation, focusing on how firms generate, accumulate and use knowledge through learning processes and interactions with other actors. Knowledge is regarded as a core element, encompassing both codified and tacit components, and is seen as closely linked to past experience, from which new knowledge emerges through local and context-specific learning processes. From this perspective, innovation no longer rests primarily on the production function, but on organisational routines, capabilities and selection processes. This leads to greater interest in economic systems far from equilibrium, which are conceived as being in constant motion and transformation. Firms therefore innovate in order to develop and strengthen their capabilities, respond to competitive pressures and emerging opportunities within their operating environment, and generate new varieties of technologies and organisational solutions rather than merely making marginal improvements. These processes take place through interaction within complex networks of actors. In clear contrast to the neoclassical view, firms are seen as heterogeneous agents characterised by bounded rationality, operating through decision-making routines. Under conditions of uncertainty, they transform themselves by developing new organisational capabilities to cope with unpredictable and discontinuous change.

In conclusion, although both approaches recognise innovation as the main driver of economic change and acknowledge the presence of uncertainty, the evolutionary approach appears more realistic in capturing how innovation processes and economic reality actually function. Herbert Simon (1990) showed that the neoclassical view (based on perfect rationality, profit maximisation and markets systematically tending towards equilibrium) is largely unrealistic, even though it is more easily represented through mathematical models. Firms operating in real-world contexts face limited cognitive capacities, incomplete and imperfectly accessible information and knowledge, and therefore make decisions that are "satisficing" rather than optimal. These elements cannot be overlooked in analyses aimed at understanding the actual functioning of the innovation process.

4. Knowledge as the common thread of the innovation process

Within the evolutionary theory of innovation, knowledge ceases to be seen as a simple exogenous "stock" of technical opportunities and becomes the central explanatory factor of change. It is no longer a neutral input equally available to all, but a historically accumulated dimension, structured through cognitive and institutional arrangements, embedded in routines and practices, and differentiated across sectors and contexts. From this perspective, the contributions of Rosenberg (1982), Nelson and Winter (1985), Dosi (1997) and Malerba (1992; 2000; 2009) can be interpreted as successive stages within a common research trajectory. Although operating at different levels of analysis, these works converge in redefining innovation as a fundamentally knowledge-based and processual phenomenon.

Through the distinction between radical and incremental innovation, Rosenberg showed that the most significant contribution to long-term productivity growth derives not so much from disruptive events themselves, but from the long sequence of incremental improvements, based on existing knowledge, that follows the introduction of a radical innovation. Incremental innovations consist of continuous modifications and refinements applied to an existing technological system. They develop through processes of practical learning, particularly through the repetition of productive activities (*learning by doing*) and through experience gained once products are used in the market (*learning by using*). These processes lead to the gradual refinement of products, production processes and organisational methods.

Radical innovations, by contrast, are characterised by a break with the existing technological framework. They are based on different technical and scientific principles and often aim to open new market segments and new fields of application. However, Rosenberg argues that radical innovations never fully realise their potential without the subsequent accumulation of incremental innovations, which reduce costs, improve reliability, adapt technologies to specific contexts and facilitate their diffusion. In this way, he overturns the traditional hierarchy between radical and incremental innovation: the two are not ordered hierarchically, but represent interdependent moments within a single dynamic process of technological change. Economic growth is therefore rooted less in the rare emergence of major breakthroughs than in the gradual accumulation, diffusion and refinement of technical knowledge through incremental innovation.

Processes of *learning by doing* and *learning by using* generate tacit knowledge that is highly context-specific, difficult to codify and hard to transfer. What is learned through production or use cannot be reproduced simply by consulting manuals. From this perspective, productivity growth depends crucially on the consolidation of repertoires of solutions, procedures and competences that emerge over time through repeated experience and remain largely embedded within organisations and local production contexts. Rosenberg's notion of technological convergence, according which the success of an innovation often depends on parallel developments in complementary technologies, further reinforces the idea of technical knowledge as distributed and interconnected.

Nelson and Winter's evolutionary theory of the firm (1985) operates at a different level of analysis but is conceptually complementary.

While Rosenberg highlights the historical and cumulative nature of knowledge at the level of systems and sectors, Nelson and Winter focus on how knowledge is accumulated, stored and used within firms (Cohen & Levinthal, 1989). Here, the distinction between tacit and codified knowledge becomes central. Tacit knowledge, personal, contextual and embedded in practice, represents the dominant form of organisational knowledge and constitutes the real basis for solving concrete problems. Codified knowledge, formalised in documents, procedures and patents, is more easily transferable but does not exhaust the firm's cognitive resources.

Organisational knowledge is not simply the sum of individual knowledge, but emerges from structured interactions among individuals within specific organisational arrangements.

Within this framework, organisational routines act as the bridge between knowledge and behaviour. Routines define "how things are done" within the firm; they incorporate both tacit and codified knowledge and function as organisational memory.

Following the principle of the "automaticity of skilled behaviour", actors perform complex sequences of practices almost mechanically, as these have been internalised through experience. As a result, a firm's specific history, translated into a particular configuration of routines, determines which competences it possesses, which innovations are "close" in terms of search, and which remain difficult to access. Learning can therefore take multiple forms: *learning by doing* through repetitive production activities, *learning by using* through interaction with users and customers, and *learning by searching* through deliberate problem-solving efforts. In all cases, learning is cumulative, localised and shaped by existing knowledge bases. Firms explore opportunities close to their current competences, rather than within an abstract space of technical possibilities (Ruttan, 1997).

The convergence with Rosenberg is thus clear. Both perspectives recognise the historical and contextual nature of knowledge. With Nelson and Winter, Schumpeter's distinction between invention and innovation, as well as Rosenberg's emphasis on long sequences of incremental innovation, acquire an organisational interpretation. Invention represents only a starting point; effective economic innovation depends on how firms incorporate inventions into their routines and on their ability to transform external knowledge into internal competences.

Dosi further develops this line of reasoning through the concept of the technological paradigm, confirming Rosenberg's insights while introducing an additional level of structure in the relationship between knowledge and innovation. Knowledge is not viewed as an undifferentiated set of ideas, but as a coherent framework of principles, models, relevant problems and performance criteria that guide innovative activity. Firms do not select areas for improvement randomly: the technological paradigm defines the logic through which problems are identified as relevant and solutions are deemed appropriate. In this way, the cumulative nature of knowledge observed by Rosenberg is formalised by Dosi, who shows how paradigms generate well-defined technological trajectories along which innovation unfolds over time.

Malerba (1992) extends the evolutionary perspective further by arguing that paradigms are not universal but sector-specific, since each sector displays distinctive patterns of innovation generation. He therefore emphasises that knowledge relevant to innovation is strongly sectoral: sector-specific knowledge bases exist, and the ways in which knowledge is generated, accumulated and diffused vary significantly across sectors. Taken together, these contributions outline a theory of innovation in which knowledge plays an organising role at multiple levels. At the macro-historical level, technological knowledge evolves as a cumulative social asset, shaped by sequences of *learning by doing* and *learning by using* that fuel incremental progress (Rosenberg, 1982).

At an intermediate level, technological paradigms and sectoral knowledge bases structure the space of possibilities, defining relevant problems, research directions and patterns of interaction among actors (Dosi, 1997; Malerba, 1992; 2009). At the organisational level, knowledge is internalised within routines, practices and capabilities through learning processes that are simultaneously individual and collective, tacit and codified, experiential and reflective (Nelson & Winter, 1985).

This perspective confirms that innovation cannot be understood as the simple outcome of discrete, profit-oriented decisions, but rather as an emergent result of cumulative learning processes, competitive selection and institutional evolution. Table 1 provides a synoptic summary of how the main authors analysing innovation converge or differ with respect to the fundamental components they emphasise.

Table 1. Comparative perspectives on innovation and the nature of knowledge

Authors	Innovating Actor	Motivation for Innovation	Core Innovation Principle	Nature of Knowledge
Schumpeter (1939; 1942)	Entrepreneur / large oligopolistic firm	Appropriation of extra profits and market power through the introduction of "new combinations" that disrupt market equilibrium	Capitalist development as a process of *creative destruction* driven by entrepreneurial innovation	Knowledge treated implicitly; innovation arises from the creative recombination of existing resources
Usher (1954)	Inventors, technicians, and craftsmen over time	Resolution of concrete problems perceived as unsatisfactory	Invention conceptualised as a sequential and cumulative process	Practical and historical knowledge, cumulative in nature and distributed across multiple actors and generations; strong emphasis on experience
Rosenberg (1982)	Industrial firms, capital goods producers, and advanced users	Alleviation of technical bottlenecks and response to production and cost constraints	Innovation as a cumulative and non-linear process, characterised by incremental change and technological convergence	Technical knowledge that is historical, cumulative, largely tacit, and context-specific; generated through learning by doing and using, as well as through interaction
Nelson & Winter (1985)	The firm as a heterogeneous collective organisation	Achievement of satisfactory profit levels (*satisficing*), organisational survival, and performance improvement	Firm behaviour shaped by routines and learning processes	Predominantly tacit knowledge embedded in organisational routines; accumulated through learning by doing, using, and searching
Freeman (1987)	Networks of actors within a National Innovation System	Enhancement of national competitiveness and economic development	Innovation as an outcome of national systems, shaped by institutional interactions, public policy, knowledge infrastructures, and R&D	Scientific, technological, and organisational knowledge mediated by institutions and policy frameworks
Dosi (1997)	Techno-scientific communities and firms	Progress along promising technological trajectories within a paradigm; solution of "relevant" problems as defined by community-specific criteria	Technological paradigms and trajectories guiding innovation through shared cognitive rules defining problems, solutions, and search directions	Knowledge structured within paradigms and characterised by strong selectivity

5. From Innovation as creation to Innovation as adoption and diffusion

Within the evolutionary debate on innovation, the contributions discussed can be read as different yet complementary interpretations of the same phenomenon, progressively analysed through distinct and autonomous perspectives. The analytical focus shifts from the Schumpeterian entrepreneur, conceived as the creator of innovation, to the mechanisms through which real firms learn, imitate, adapt and diffuse innovations over time. This theoretical trajectory makes both possible and necessary the transition from the question "who creates innovation?" to "how does innovation spread, become adopted and get embedded in the behaviour of economic units?", thus paving the way for the formalisation proposed by Rogers (1983).

The first steps in this transition can be found in Usher (1954) and Rosenberg (1982). Usher criticises the idea of invention as an "instantaneous act" and reconstructs it as a cumulative and sequential process, distributed over time and across multiple actors, in which problem perception, accumulation of technical elements, insight and critical revision are intertwined. As a result, the sharp distinction between invention and implementation is weakened: invention itself already incorporates adaptations to technical, organisational and usage constraints. Rosenberg places this reasoning within a historical and cumulative view of technical progress, showing how radical innovation opens up new domains of possibility, while its economic impact unfolds along trajectories of incremental innovation driven by *learning by doing* and *learning by using*, and supported by complementary innovations. Even in the absence of an explicit theory of diffusion, attention thus shifts from the original invention to the process through which a plurality of actors, as producers, users, suppliers and technical institution, learn, adapt and refine technology over time, within a feedback dynamic between those who introduce innovations and those who use them (Kline & Rosenberg, 1986).

With Nelson and Winter (1985), the focus moves to the firm as a learning organisation, structured around routines and subject to competitive selection mechanisms. Under conditions of bounded rationality, firms respond to unsatisfactory performance by initiating processes of localised search and modifying their knowledge base. Innovation emerges as a transformation of routines, while adoption and diffusion become outcomes of the same evolutionary process. Within populations of heterogeneous firms, some experiment, others imitate, and the market selects the most effective configurations. Diffusion is no longer a phase that follows invention, but an emergent result of differences in firms' behaviour and learning trajectories, anticipating Rogers' emphasis on heterogeneous adoption timings and patterns.

Dosi (1997) and Malerba and Orsenigo (1997) further enrich this framework by systematically introducing paradigmatic, institutional and sectoral dimensions. For Dosi, innovation takes place within a technological paradigm that selects relevant problems and meaningful solutions, while technological trajectories represent paths of incremental learning. From this perspective, diffusion concerns not only the number of adopters, but also how firms located at different points along a trajectory selectively integrate innovation into their routines. The literature on technological regimes and sectoral systems of innovation (Malerba & Orsenigo, 1997) further shows that there is no single model of innovation. Sectors differ in terms of technological opportunities, appropriability, cumulativity and knowledge bases. As a result, the emergence, development and diffusion of innovation are strongly shaped by sectoral context. In science-based sectors, public and industrial research and large R&D-intensive firms play a central role; in supplier-dominated sectors, by contrast, user firms adopt innovations generated upstream by input and service suppliers (Malerba & Orsenigo, 1997; Pavitt, 1984).

By developing the first sectoral taxonomy, Pavitt (1984) highlights precisely the existence of supplier-dominated sectors, such as the agri-food sector. In these sectors, most innovations adopted by firms are developed externally, in other industries (agricultural chemistry, mechanical engineering, biotechnology and information technology), and are later transferred to individual firms through channels such as technical intermediaries, input markets and consultancy services. Extending this reasoning to agriculture, and more specifically to the farm or agricultural enterprise, it becomes clear that such units are generally not creators of radical innovation in the Schumpeterian sense, but rather the terminal points of innovation processes initiated elsewhere. This does not imply passivity. On the contrary, adoption processes involve selection, local adaptation, contextual learning and the combination of different types of innovation: technical, organisational and managerial.

The common thread of this analysis inevitably shifts attention from internal innovation generation to the drivers of adoption, the channels of knowledge transfer, and the cognitive, economic and organisational barriers to diffusion. This shift is essential for translating evolutionary theoretical advances and for understanding how the focus has gradually moved from macro-level analysis to more detailed investigations of individual firms within specific sectors. In the case of large high-tech manufacturing firms, internal innovation processes and related activities such as research, development and design are integral to the units being analysed. By contrast, for individual firms embedded within particular sectors, analysis is more theoretically appropriate when it concentrates on how these firms observe, evaluate, adopt or reject innovations developed elsewhere.

The evolutionary and sectoral approach therefore represents the natural bridge towards Rogers' theory (1983). Adoption decisions are not merely responses to profit incentives, but depend on how firms perceive the characteristics of innovations, on the structure of the social and professional networks in which they are embedded, and on the role of technical intermediaries, opinion leaders and support institutions.

From this perspective, it becomes natural to focus on how, when and why specific firms decide whether or not to adopt particular innovations, which factors facilitate or hinder diffusion, and how individual decisions, when aggregated, shape the macro-dynamics of technological change. Finally, returning to the agricultural sector and, more specifically, to the individual farm units that compose it (identified as the central focus of analysis in this thesis) these units represent "privileged analytical units" not because they are "factories of invention", but because they function as terminal nodes within a multi-level network of knowledge production, circulation and incorporation.

6. The diffusion of innovation theory: Rogers as a synthesis of the evolutionary approach and an analytical foundation for firm-level innovation adoption

The theoretical path traced by the authors discussed above inevitably leads to a gradual decentralisation of innovation analysis: away from the central figure of the Schumpeterian entrepreneur and the one-off event of invention, and towards an understanding of the micro-processes through which innovation is adopted, adapted and embedded in concrete organisational practices (Rosenberg, 1982; Usher, 1954; Nelson & Winter, 1982; Freeman, 1987; Dosi, 1982; Malerba & Orsenigo, 1997; Pavitt, 1984).

This shift in focus is crystallised in Everett Rogers' diffusion of innovation theory (1983), which in a sense brings together and systematises the analytical elements developed up to that point from different perspectives. Rogers defines diffusion as the process through which an innovation, understood as an idea, practice or object perceived as new, spreads over time among members of a complex socio-economic system through specific communication channels (Rogers, 1983). The theory is structured around four core elements: the innovation itself, communication channels, time, and the social system. Diffusion is therefore not a random or purely mechanical phenomenon, but the outcome of structured interactions among heterogeneous actors. It is guided by subjective evaluations and conditioned by the perceived characteristics of the innovation.

Rogers' central insight, in direct continuity with evolutionary theorising, is that adoption depends less on the intrinsic technical properties of an innovation than on the perceptions constructed by potential users, their evaluative capacities, the social networks in which they are embedded, and the information channels available to them (Rogers, 1983). This perspective rests on a learning and knowledge-generation process that is not fixed, but relational. Moreover, there is no single, isolated "characteristic" of an innovation that stands alone at the centre of evaluation. Instead, there is a plurality of perceptions shaped by who is evaluating, in which context, and with what prior experience. In this sense, Rogers' theory sits firmly within the evolutionary tradition that stresses the cumulative, contextual and distributed nature of knowledge.

Rogers' classification of adopter categories formalises, in socio-relational terms, the organisational heterogeneity emphasised by Nelson and Winter and the variety of firm behaviours that emerges across different sectoral contexts (Nelson & Winter, 1985; Pavitt, 1984; Rogers, 1983). Following a normal distribution, Rogers identifies five categories: innovators, early adopters, early majority, late majority and laggards. Each category represents not merely a different point in time within the adoption process, but a specific socio-organisational profile, characterised by distinct risk orientations, communication patterns and degrees of integration within local networks.

Innovators introduce the innovation into the system from outside. They have a high propensity to take risks and communication networks that extend beyond local boundaries. Their behaviour, being "unusual" relative to established norms, often means their example is not immediately imitable by others. Early adopters, by contrast, are the true opinion leaders within the local system. Their adoption provides the legitimacy that transforms innovation from a marginal experiment into a trusted practice, catalysing subsequent waves of diffusion. The early majority forms the substantial share of the population and typically requires extensive feedback before deciding; it constitutes the decisive bridge between the initial group of adopters and the late majority. The late majority adopts when the innovation is already established within the system, often yielding to normative pressures and economic necessity. Finally, laggards remain attached to traditional

practices until the alternative becomes economically unsustainable. In this structure, one can recognise an echo of Schumpeter's distinction between the innovative entrepreneur and the imitating mass.
Rogers, however, radicalises it by multiplying the intermediate categories and by stressing that these categories reflect not simple preferences, but structural positions within social networks, different degrees of access to information, and differentiated exposure to mass media and interpersonal relations.
It is important to add that the heterogeneous perceptions characterising this range of adopters tend to cluster around specific attributes of innovation that shape diffusion speed (Rogers, 1983): relative advantage, compatibility, complexity, trialability and observability.
Rogers defines relative advantage as the degree to which an innovation is perceived as superior to the previous solution in terms of functionality, economic efficiency and ease of use.
Compatibility refers to the consistency between the innovation and the organisation's values, prior experiences and established practices.
Complexity concerns the perceived difficulty of understanding and implementing the innovative practice.
The final two attributes are expressed concretely through trialability, defined as the possibility of testing the innovation on a limited scale before full implementation, and observability, understood as the degree to which the results of innovation are visible and communicable to potential adopters.
The combination of these attributes defines the "innovation profile" and the expected rate of diffusion: innovations perceived as having high relative advantage, high compatibility, low complexity, high trialability and strong observability will generally diffuse more quickly (Rogers, 1983).
Figure 1 shows in a synthetic way the aspects considered essential in Rogers' theory.

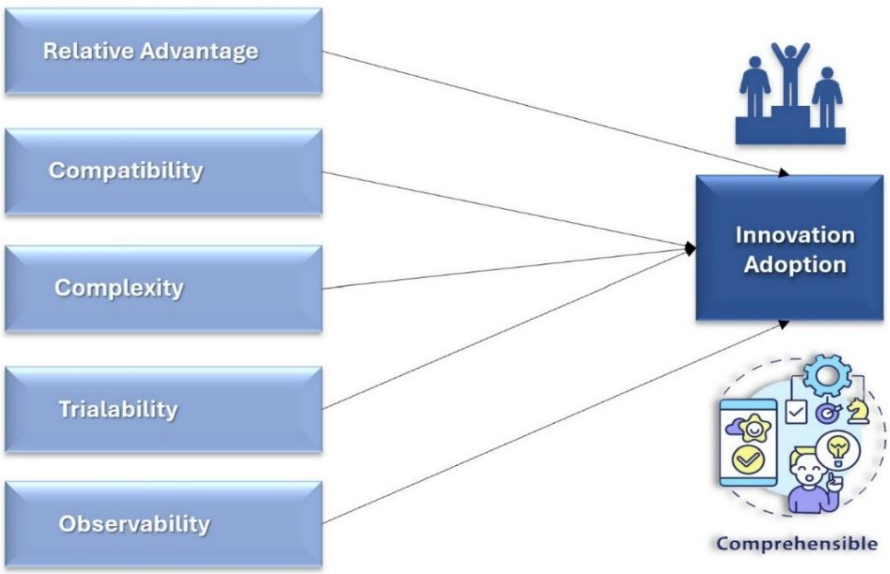

Figure 1. Schematisation of the central attributes in the process of acceptance and diffusion of innovation according to Rogers' theory

However, these attributes are not intrinsic properties of the innovation. They are outcomes of perception and communication processes, and the same technical artefact may be perceived very differently by actors situated in different contexts.

The literature by Sassu (1978) and Wejnert (2002), for example, further emphasises the role of economic advantage in adoption decisions. It highlights that innovations tend to be introduced primarily when economic conditions allow it, and when the calculation emerging from comparing the old and the new technique is favourable. In this view, relative advantage carries for many adopters a primarily economic meaning: profit and cost reduction remain decisive factors, albeit within a broader framework of perceptual evaluation and social pressures (Sassu, 1978; Wejnert, 2002).

Alongside the evaluations guiding adoption choices, the diffusion process also unfolds through a sequence of "knowledge-related" stages that Rogers identifies as knowledge, persuasion, decision, implementation and confirmation (Rogers, 1983). These are not instantaneous steps, but a temporal progression that varies considerably across adopters and depends entirely on the communication modes available.

Diffusion begins when a potential adopter becomes aware of the innovation and understands how it works. An attitude towards it then forms, favourable or unfavourable, which shapes the decision to adopt or reject. Once adopted, the innovation is implemented in concrete practice. The decision is then reinforced through a confirmation phase, in which the adopter seeks support for the choice made.

It is also worth noting that learning and knowledge generation align with evolutionary principles, even though Rogers gives communication channels a central role. Rogers distinguishes between mass media channels, which are particularly effective in spreading general awareness of an innovation, and interpersonal channels, which become decisive during the persuasion phase, when source credibility and reported practical experiences strongly shape attitudes (Rogers, 1983; Wejnert, 2002). Within this communicative dynamic, the figure of the change agent emerges: individuals or organisations acting as external agencies promoting innovation, not merely by disseminating information, but by facilitating the entire learning process and the construction of the knowledge required for adoption (Rogers, 1983). The change agent, while progressively developing perceptions of the need for change, establishes information-exchange relationships, identifies the context's specific problems, creates an intention to change, translates it into concrete action and stabilises adoption. What characterises this role is that it does not impose innovation. Rather, it helps potential adopters understand how innovation works, assess its relevance in relation to their specific constraints and opportunities, test it progressively, and overcome perceived uncertainties and barriers.

How, then, can a change agent be effective? This depends primarily on the ability to identify and work through local opinion leaders, namely those individuals with intrinsic credibility in the system who function as genuine social intermediaries. In this sense, the intermediation mechanism described by Rogers connects directly to the networks of heterogeneous actors that Freeman identifies as central within national systems of innovation (Freeman, 1987), and to Nelson and Winter's emphasis on the distribution of knowledge through structured interactions among organisational actors (Nelson & Winter, 1985).

In summary, diffusion can be understood as the outcome of complex relational and communicative dynamics in which intermediaries, opinion leaders and different channels coordinate in gradually transforming adopters' perceptions and behaviours. This general theoretical framework becomes particularly relevant when applied to the detailed analysis of innovation processes within individual firms and their specific organisational and sectoral contexts. Indeed, it is precisely in this shift from the macro-systemic to the micro-firm level that Rogers' theory displays its strongest explanatory power. The structure Rogers outlines (how adoption decisions form, how social networks facilitate diffusion, and how innovation attributes are perceived differently) provides an indispensable analytical scheme for understanding the behaviour of firms operating in sectors where innovation is not generated endogenously but acquired externally.

Pavitt's sectoral taxonomy (1984), combined with Rogers' theory, provides the interpretative framework needed to understand how firms located within supplier-dominated sectors evaluate, adopt and diffuse externally developed innovations (Pavitt, 1984; Rogers, 1983). For the entities constituting the agri-food sector as well, innovation attributes become the critical factors determining whether a given firm will adopt a new practice, process, technology or managerial method (Rogers, 1983). An innovation that promises a significant reduction in costs or an increase in productivity, that is compatible with existing production and organisational systems, that does not require radically new skills, that can be tested, and whose results are easily observable and communicable, will have a significantly higher probability of adoption. At the same time, adopter categorisation sheds light on the variety of firm behaviours: some entrepreneurs will be innovators who experiment continuously; others will be early adopters whose choices legitimise innovation; others still will belong to later categories, with different decision times and different levels of risk-taking. In the same way, communicating innovation to firms through a combination of channels helps translate technical information into contextual knowledge, facilitates adaptation to firm-specific conditions, and reduces perceived uncertainty and risk (Rogers, 1983).

In conclusion, Rogers' theory encapsulates and formalises the deepest legacy of the evolutionary tradition: the idea that innovation is primarily a process of perceptual evaluation, propagation, incorporation and knowledge transformation within complex and articulated socio-economic systems (Rogers, 1983). It therefore provides the most suitable reference framework for understanding the adoption and diffusion of innovation within firms (such as agricultural enterprise) that operate within a typical supplier-dominated sector.

6.1 Dynamics of Innovation Adoption and Diffusion in the agricultural sector

Analysing innovation processes in the agricultural sector requires a clear departure from the classic Schumpeterian view, historically centred on the entrepreneur as the internal generator of "creative destruction". However, the largely exogenous nature of innovation in agriculture does not imply that adoption is a passive process. On the contrary, as theorised in the induced innovation hypothesis developed by Hayami and Ruttan (1971) and further refined thereafter (Ruttan, 1977), the direction of technical change can be endogenously stimulated by relative factor prices and resource endowments. Farmers are therefore guided by market signals that steer technological development towards saving the relatively scarcer and more expensive factor, typically land or labour, shaping trajectories that influence, upstream, the type of technologies made available for adoption and, downstream, farms' willingness to integrate them (Ruttan, 1977).

Within such a broader framework, acceptance and adoption by individual farmers do not take the form of a simple purchase decision, but rather of a dynamic decision-making problem aimed at maximising expected utility under conditions of uncertainty and risk. Drawing on expected utility models and on the framework proposed by Tang (1974) and empirically applied by Carrillo-Huerta (1977), it becomes clear that adoption decisions result from a careful trade-off between expected income and outcome variability (Carrillo-Huerta, 1977). Farmers thus act as rational decision-makers who assess new technologies through their subjective perception of risk. Seminal studies such as Just and Zilberman (1983), cited in Feder and Umali (1993) and Marra et al. (2003), show that risk aversion, combined with fixed adoption costs, creates significant entry barriers, making innovation processes non-neutral with respect to farm size. Larger farms or those with stronger financial positions can better absorb fixed costs and tolerate early failure risks, while smaller producers are often constrained by credit and liquidity limitations that prevent access to potentially profitable but risky technologies (Ghadim & Pannell, 1999; Feder & Umali, 1993; Marra et al., 2003).

To fully understand how farmers assess and evaluate innovation, it is essential to complement the economic perspective with an analysis of individual perceptions and of the intrinsic characteristics of technologies, in line with Rogers' diffusion of innovation theory (1983).

The first critical attribute considered by farmers is perceived relative advantage. This does not necessarily or exclusively coincide with profit maximisation or cost reduction, but may also include dimensions of security and stability. As shown by Chavas and Nauges (2020), for instance, in production contexts increasingly exposed to climatic and market volatility, farmers may prefer technologies that reduce production risk and the probability of overall failure (such as drought-resistant varieties) over technologies that promise higher average yields but greater variability. Perceived advantage is therefore subjective and closely linked to long-term farm objectives, which may range from expansion to mere economic survival or the preservation of family assets (Ghadim & Pannell, 1999; Chavas & Nauges, 2020).

A second key factor is the compatibility of the innovation with the existing farm system. Agriculture is a systemic activity, where changes in one stage of the production cycle affect others. As highlighted by Feder and Umali (1993), adoption is facilitated when new technologies integrate smoothly with existing agronomic practices, machinery endowments and labour skills. A lack of complementarity may generate hidden adaptation costs that discourage investment. Closely related to this aspect is perceived complexity. Technologies requiring high levels of human capital or radical managerial reorganisation face stronger resistance, particularly in contexts characterised by lower formal education levels or an ageing farming population (Rogers, 1995; Diederen et al., 2003; Rizzo et al., 2024).

Acceptance is also strongly influenced by trialability and observability (Rogers, 1983; Gandasari, 2021). Innovation in agriculture is an active discovery process in which farmers must transform initial uncertainty into manageable risk. The possibility of testing a technology on a small scale, on a single plot or a limited number of livestock units, without committing the entire farm represents a crucial facilitating factor. This gradual approach, consistent with the principle of *learning by doing*, allows farmers to accumulate information and context-specific skills at low cost, reducing the risk of irreversible mistakes (Ghadim & Pannell, 1999). As argued by Marra et al. (2003) and Chavas and Nauges (2020), the value of information acquired over time may be so high that it rationally justifies delaying adoption until uncertainty has been sufficiently reduced (Rogers, 1983; Marra et al., 2003; Chavas & Nauges, 2020).

It is also important to consider the motivations underlying adoption decisions. Alongside the pursuit of economic and productive efficiency, social and competitive pressures play a powerful role. The "technological treadmill" mechanism described by Cochrane (1958) and revisited by Chavas and Nauges (2020) illustrates how adoption often becomes a market-imposed necessity. Early adopters initially enjoy temporary rents, but as the technology diffuses and aggregate supply increases, output prices fall, forcing even late adopters to adopt, not to increase profits, but to remain in the market (Chavas & Nauges, 2020).

Carrillo-Huerta (1977) also highlights the indispensable role of formal credit as an enabling factor. In contexts characterised by imperfect financial markets, access to subsidised loans or in-kind inputs becomes a key driver of acceptance and diffusion, allowing farms to overcome liquidity constraints that would otherwise paralyse innovation among smaller producers (Carrillo-Huerta, 1977).

However, as shown by Rizzo et al. (2024), adoption is not driven solely by economic imperatives. Intrinsic motivational factors linked to farmers' personal values, their attitudes towards environmental sustainability, or their desire for social recognition within the community, play an increasingly important role. The conceptual model proposed by Rizzo et al. (2024), which distinguishes between desirability (the willingness to innovate) and feasibility (the ability to innovate), suggests that adoption occurs only when these two dimensions converge. A farmer may therefore perceive a technology as feasible but not desirable (because it conflicts with personal values), or desirable but not feasible (due to resource constraints), effectively blocking adoption.

Finally, once innovation has been adopted and consolidated at the individual farm level, it is equally important to consider the transition from individual adoption to broader diffusion. This transition is mediated by information channels and by the institutional context. Social learning therefore plays a fundamental role: farmers tend to observe outcomes achieved by neighbours operating under similar conditions and to exchange opinions within professional networks (Ghadim & Pannell, 1999; Rizzo et al., 2024). These processes rely on implicit and self-sought information, allowing farms to reduce search costs and validate the reliability of technologies.

In summary, as reiterated by Ruttan (1977) and confirmed by subsequent studies, successful technological diffusion in agriculture never depends solely on the technical merits of an innovation. It also requires parallel institutional action through effective extension services, cooperatives and support policies, to create favourable conditions that enable farms to fully capture the potential benefits of innovation.

7. From innovation theories to behavioural models of adoption

It is now widely recognised that Rogers' diffusion of innovation theory (1983) represents a foundational contribution to the scientific literature on the transmission of new technologies and practices within social systems. Bakkbulindi (2014) identifies diffusion of innovation theory as the core framework guiding contemporary studies on adoption and diffusion, highlighting several key dimensions that must be analysed in this process: the individual characteristics of adopters, the perceived characteristics of the innovation, and the features of the relevant social and institutional system. Through the attributes of innovation, Rogers explicitly anticipated the importance of perceptual factors in shaping individual decisions. However, despite its conceptual richness, the theory does not provide a fully systematic model capable of capturing all these aspects simultaneously and of empirically assessing the influence of different variables on adoption intentions, thereby limiting its direct applicability.

The core elements of Rogers' framework have been integrated into subsequent theoretical developments, creating a line of conceptual continuity spanning decades of research on economic agents' behaviour (Dissanayake et al., 2022). Venkatraman and Price (1990), for instance, define innovativeness as individuals' propensity to change when exposed to new proposals, emphasising that this propensity translates into specific behavioural responses.

From the 1980s onwards, behavioural research has produced increasingly sophisticated theoretical models, each offering distinct perspectives on the factors influencing technology adoption. These models recognise that the relevance of particular determinants varies substantially depending on the type of innovation under consideration and the category of potential adopters.

Among the behavioural theories developed, the Theory of Reasoned Action (TRA), proposed by Fishbein and Ajzen (1977), represents one of the earliest contributions. TRA conceptualises individual behaviour as the outcome of a deliberate and rational process in which individuals systematically weigh the expected costs and benefits of their actions. According to this framework, behaviour is directly determined by behavioural intention, which arises from the interaction of two main factors: attitude towards the behaviour, defined as an individual's favourable or unfavourable evaluation of the action based on perceived consequences, and subjective norms, understood as perceptions of social expectations and pressures exerted by significant referents. Both factors are generated by underlying beliefs, like behavioural beliefs and normative beliefs, which form the psychological foundations of perceptions (Figure 2).

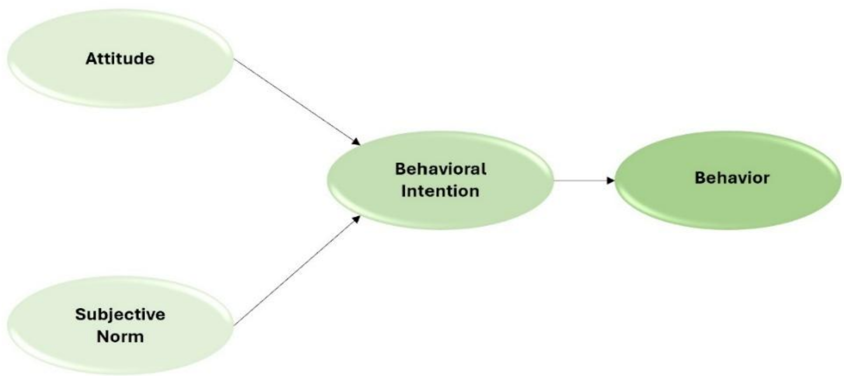

Figure 2. Theoretical outline of Fishbein and Ajzen's (1977) theory of reasoned action

Within this formulation, decisions are not purely rational in the traditional economic sense of utility maximisation, but are mediated by personal perceptions and internalised social pressures. Recognising the limits of TRA in capturing the full complexity of behavioural decision-making, Ajzen (1991) extended the framework by developing the Theory of Planned Behaviour (TPB), introducing a crucial additional construct: perceived behavioural control. This concept emphasises individuals' perceptions of the ease or difficulty of performing a behaviour, based on available resources and perceived constraints within the decision-making context (Figure 3).

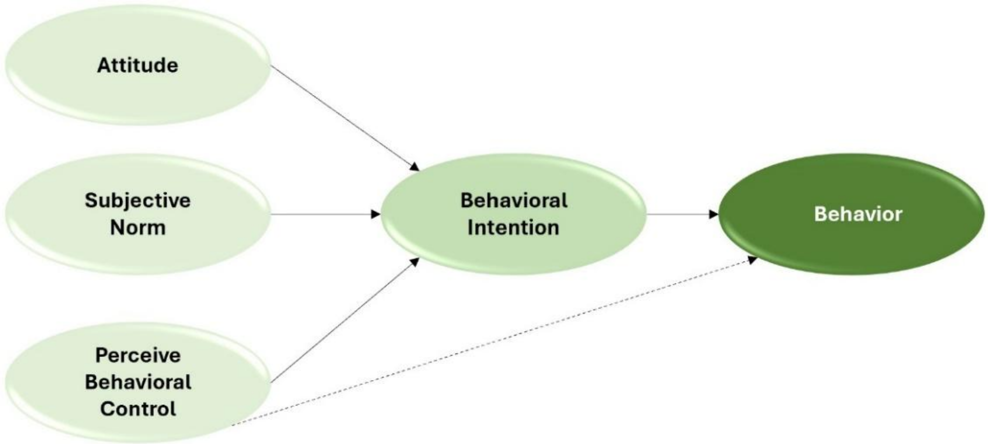

Figure 3. Theoretical framework of Ajzen's theory of planned behaviour (1991)

In parallel with these developments, Davis (1989) pursued a research agenda focused on identifying the key determinants of new technology adoption, introducing a significant shift in analytical focus. Rather than concentrating solely on individual attitudes shaped by perceived constraints and social influences, Davis identified two core constructs that play a decisive role in technology acceptance: perceived usefulness, defined as the degree to which an individual believes that using a particular technology will enhance performance and productivity, and perceived ease of use, understood as the degree to which using the technology is perceived as free of cognitive and operational effort.
These two factors form the pillars of the Technology Acceptance Model (TAM) (Figure 4), originally developed to analyse the acceptance and use of computers and information technologies (Davis, 1989). Within TAM, individual attitude remains an important determinant of behavioural intention, but it is preceded and mediated by the crucial influence of perceived usefulness and ease of use.

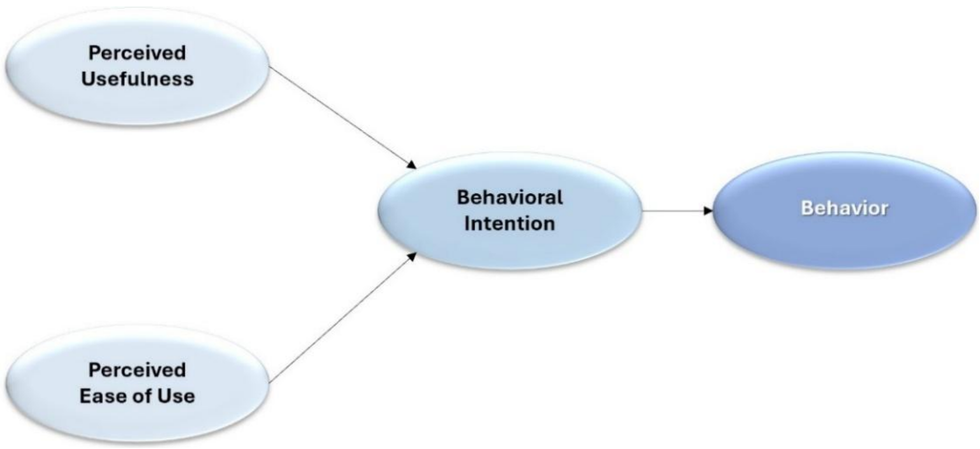

Figure 4. Davis's (1989) Technology Acceptance Model and the Importance of Ease and Perceived Usefulness

Subsequent research produced extensions of the original model, such as TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008), which incorporated additional dimensions considered essential for a more detailed analysis of innovation-related decision-making. These include, for example, perceptions of security and risk (Giovanis et al., 2012), as well as compatibility, trust and self-efficacy (Adrian et al., 2005; Altin Gumussoy et al., 2018).

Venkatesh et al. (2003) later developed the Unified Theory of Acceptance and Use of Technology (UTAUT), representing the culmination of a process of theoretical integration. Rather than rejecting previous assumptions, UTAUT synthesises and reconciles them within a broader framework. Building on Rogers' foundational principles, UTAUT integrates perceptual dimensions and systematically combines the common and distinctive elements of eight earlier theories, including TRA, TPB, TAM and diffusion of innovation theory (IDT), resulting in a particularly robust and comprehensive model.

UTAUT identifies four key determinants influencing the decision to implement a technology or behaviour:

- performance expectancy, referring to the perceived benefits derived from using the technology;
- effort expectancy, related to perceived ease of use and the effort required to master the technology;
- social influence, understood as perceived social pressures and expectations regarding technology use;
- facilitating conditions, defined as the perceived availability of organisational, technical and infrastructural support necessary for use (Figure 5).

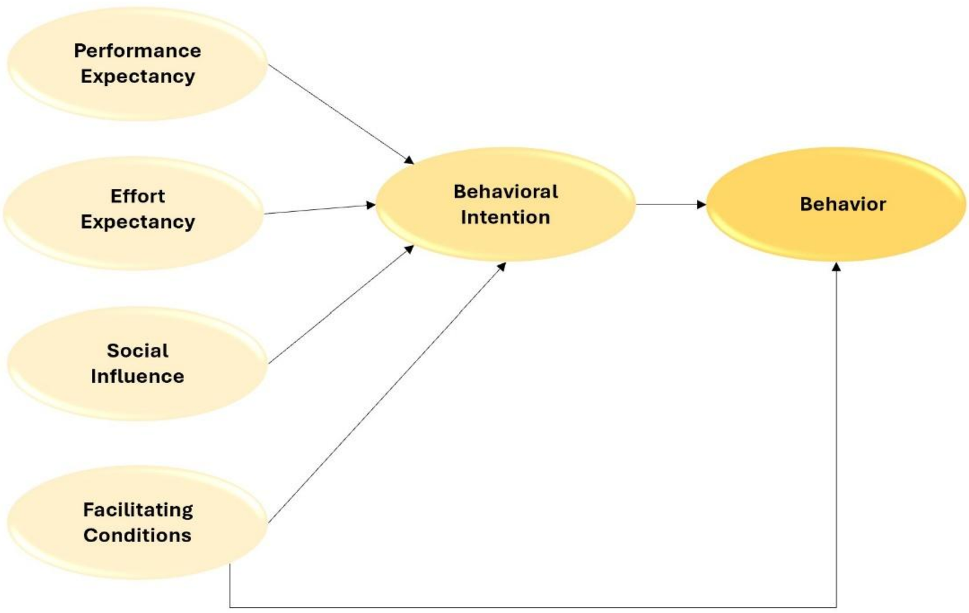

Figure 5. Venkatesh's (2003) UTAUT theory and factors influencing adoption intention and behaviour

A major innovation of UTAUT lies in its explicit recognition that the impact of these determinants varies significantly according to moderating factors related to individual characteristics, such as age, gender, prior experience with similar technologies and the degree of voluntariness in adoption decisions, whether adoption is fully voluntary or partly constrained by external circumstances. This sensitivity allows for a substantial integration of factors central to both economic and behavioural theory (Bagozzi, 2007).

A systematic review of behavioural theories and models makes it possible to clearly identify the main factors shaping innovation adoption. This conceptual consolidation has led to further refinements, such as Yan's (2020) "Basic Model of Human Behaviour with Technologies", which attempts to synthesise the complexity of multiple frameworks within a simplified structure centred on four elements: users, technologies, actions and effects.

This simplification responds more to methodological than to theoretical needs. As noted by Dissanayake et al. (2022), increasing the number of explanatory factors simultaneously raises both analytical complexity and predictive power, highlighting the fundamental trade-off between parsimony and explanatory capacity that characterises behavioural research on technology adoption.

7.1 Applying behavioural theories to agricultural contexts

The analysis of the main behavioural models and theories shows that, within empirical studies aimed at explaining innovative behaviour, some theories have demonstrated greater predictive power than others. With specific reference to agricultural contexts, the Theory of Planned Behaviour (TPB) has proven particularly suitable for interpreting and predicting farmers' intentions and behaviours (Ajzen, 2020). The inclusion of the construct of perceived behavioural control is essential to represent and explain situations in which individual decisions are strongly shaped by external, uncontrollable factors of an environmental, economic, technical or structural nature (Martínez-García et al., 2013; Ajzen, 2020). The presence of objective constraints makes it clear that intention, while necessary, is not sufficient in itself to determine behaviour, revealing a significant gap between what a farmer would like to do and what they consider realistically feasible. The TPB recognises that an individual may have a strong intention to adopt an innovation, driven by positive attitudes and supportive social norms, yet feel hindered by limited financial resources, technical implementation challenges, insufficient specialist knowledge or other objective constraints. In this respect, the TPB provides a more accurate representation of the decision-making tensions that characterise agricultural enterprises and adoption dynamics under conditions of uncertainty and risk. This framework therefore offers a more realistic and applicable perspective for agricultural contexts, where structural factors frequently restrict adoption capacity even in the presence of strong motivation (Badsar et al., 2023).

From a broader perspective, both the Theory of Reasoned Action (TRA) and the TPB offer a useful conceptual framework for interpreting the behaviour of various actors along the agri-food supply chain, highlighting the joint role of attitudes, subjective norms and perceived control in shaping intentions and guiding action. The TRA, for example, has been widely applied in studies on consumer behaviour (Ha, 1998; Simbolon, 2015), the adoption of sustainable practices (Marshall et al., 2010), organisational change (Martínez-García et al., 2013) and corporate behaviour (Octasylva et al., 2021). The combination of attitudes and subjective norms makes it possible to capture both the individual dimension of choices and the influence exerted by the social context and reference networks. Similarly, the TPB has been applied to the study of alternative consumption behaviour (Alam & Sayuti, 2011; Verma & Chandra, 2018; Alam et al., 2024), entrepreneurial behaviour (Kautonen et al., 2013; Al-Mamary & Alraja, 2022) and agricultural business management (Senger et al., 2017), showing that including perceived control helps explain why individuals with favourable attitudes may nevertheless display markedly different behavioural outcomes. However, both Fishbein and Ajzen's theories remain primarily focused on individual behaviour, and are sometimes less suitable for describing the adoption of complex organisational innovations, as they do not fully incorporate factors such as the availability of technical resources or environmental constraints that shape business decisions (Haryanti & Subriadi, 2020). To address these limitations, the scientific literature has sought to extend the original theoretical framework by incorporating more specific constructs, such as knowledge of innovations or perceptions of climate risks (Tama et al., 2021), in order to explain, for instance, how awareness of climate change impacts and perceptions of business vulnerability influence intentions to adopt adaptive practices or resilient technologies. In this way, the TRA and TPB become flexible frameworks into which agriculture-specific variables can be embedded, preserving the core structure of the models while enhancing their ability to capture sectoral and territorial particularities.

Continuing along this analytical line, the Technology Acceptance Model (TAM) provides a particularly suitable perspective for describing how agricultural entrepreneurs evaluate technologies that promise to transform production and organisational processes, shifting attention directly to perceived benefits and ease of use. The literature has confirmed its effectiveness in studying the acceptance of precision agriculture technologies (Adrian et al., 2005) as well as innovations and organisational and structural changes (Ndubisi, 2007; Suhartanto & Leo, 2018; Dai & Cheng, 2022). In these cases, perceived usefulness captures how farmers assess the contribution of a new technology to productivity, cost reduction or quality improvement, while perceived ease of use reflects the extent to which the technology is considered compatible with available skills, existing infrastructure and established management routines within the business.

As previously discussed, the Unified Theory of Acceptance and Use of Technology (UTAUT) represents the natural evolution of these approaches (Venkatesh et al., 2003), as it integrates contributions from earlier models into a unified theoretical framework. It is particularly well suited to analysing adoption processes in complex agricultural contexts, where innovation is also shaped by networks of actors, institutions and infrastructural conditions. Numerous studies have applied the UTAUT to examine the introduction of precision agriculture technologies (Shi et al., 2022; Wiliam et al., 2021; Nguyen et al., 2023; Cahyani et al., 2024; Sabbagh & Gutierrez, 2023) and structural and process innovations (Nejadrezaei et al., 2018; Xie et al., 2022). The four core constructs of the model allow the simultaneous assessment of the role of economic and productivity expectations, operational challenges, social pressures and infrastructural support in shaping adoption intentions and behaviour. Extended versions of the model have also confirmed the importance of incorporating perceptions of risk and environmental uncertainty, which are often crucial in agricultural decision-making (Bagozzi, 2007). Although widely recognised as one of the most comprehensive theories for explaining technology adoption, the UTAUT is not universally applicable without contextual adjustments. As noted by Venkatesh et al. (2003), the influence of social pressure tends to weaken in contexts where innovation adoption is entirely voluntary and not driven by institutional initiatives or binding policy measures, suggesting the need to calibrate the model's constructs to the specific characteristics of the sector and agricultural context under consideration.

Overall, the progressive evolution and empirical application of these models highlight that the analysis of agricultural innovation cannot rely on a single dimension, but must instead adopt an integrated perspective that simultaneously considers the technological implications of innovation, its economic viability, the psychological mechanisms that drive its acceptance, the social dynamics that facilitate or hinder its diffusion, and the impacts resulting from its implementation (Figure 6). Only through such a scientifically robust approach is it possible to explain why certain innovations spread rapidly and sustainably within business systems while others encounter significant and persistent resistance, and to formulate policy recommendations grounded in solid theoretical foundations so that agricultural innovation processes become simultaneously sustainable, equitable and widely shared.

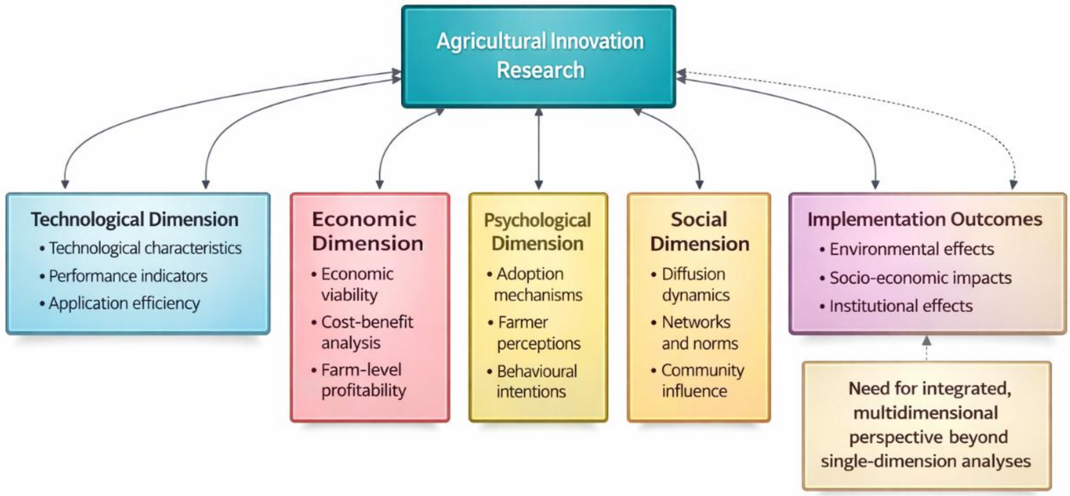

Figure 6. An integrated view of agricultural innovation: the interaction between technological, economic, psychological, and social dimensions, to fully understand the processes of adoption and diffusion.

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Chapter 2

From Treatment to the Field: Irrigation with Treated Wastewater as an Eco-Innovation

1. Introduction

Eco-innovation is an economic and systemic phenomenon of growing relevance in the contemporary context, marked by increasing global environmental pressures and the urgent need for a deep transition towards sustainable production and consumption models (Durán-Romero & Urraca-Ruiz, 2015). Unlike conventional innovation, which is neutral regarding the direction of change and primarily oriented towards profit and market competitiveness, eco-innovation explicitly incorporates environmental sustainability constraints and objectives as essential components of its definition and measurement (Rennings, 2000). The apparent clarity of this conceptual distinction conceals significant theoretical, methodological and empirical complexity, since eco-innovation cannot be reduced solely to market-driven "green" technological innovations, but rather constitutes an articulated socio-technical phenomenon encompassing technological, organisational, social and institutional transformations (Kemp & Pearson, 2007; Rennings, 2000).

Understanding the multidimensional nature of eco-innovation, the theoretical mechanisms underpinning it, the factors that encourage its adoption by organisations and firms, and the ways in which it can be translated into concrete and effective solutions, is therefore a matter of primary strategic importance, both for advancing research and for designing and implementing sustainable development policies.

2. The Use of Treated Wastewater for Irrigation as an Eco-Innovation

2.2 What Is an Eco-Innovation?

The first appearance of the term *eco-innovation* in academic literature dates back to 1996, when Claude Fussler and Peter James published *Driving Eco-Innovation: A Breakthrough Discipline for Innovation and Sustainability*, a work that became a key point of convergence between environmental engineering, management and innovation economics (Fussler & James, 1996). This contribution offered an initial, albeit preliminary, operational definition, identifying eco-innovation as the set of "new products and processes that create value for customers and firms while significantly reducing environmental impacts".

Although this early formulation captured the core of the challenge, namely, reconciling economic and environmental imperatives, it required further conceptual refinement and more rigorous methodological systematisation. In particular, it did not explicitly address key issues such as how to measure impact reductions, the time horizon over which environmental effects should be assessed, or how to treat innovations not primarily motivated by ecological objectives but still capable of generating substantial environmental benefits.

A more rigorous systematisation of the concept was developed through the *Measuring Eco-Innovation (MEI)* project, promoted by the European Commission in 2007 (Kemp & Pearson, 2007). This research effort produced the first formal and empirically applicable definition of eco-innovation. According to Kemp and Pearson, eco-innovation consists of the "production, assimilation or exploitation of a product, production process, service, or management or business method that is new to the organisation (developed or adopted) and that, over its entire life cycle, reduces environmental risks, pollution and other negative impacts associated with resource use compared with relevant alternatives".

This definition incorporates several conceptually and methodologically more complex choices. First, it grounds the defining criterion of eco-innovation in actual environmental performance, namely, observable reductions in impacts, rather than in the motivations or intentions of

innovators. This represents a crucial distinction: for example, a firm may develop a technology aimed at lowering operating costs by improving energy efficiency, driven primarily by economic incentives. However, if that innovation produces a verifiable reduction in environmental impacts, it qualifies as an eco-innovation regardless of whether its original motivation was ecological (Porter & van der Linde, 1995). This classification choice has important theoretical implications, acknowledging that innovation motivations are complex, multidimensional and often hybrid, and that eco-innovation status should not depend on the presumed "purity" of intent.
Second, the definition requires assessment from a life-cycle perspective (*life cycle thinking*), compelling analysts and policymakers to consider all stages of production and consumption, thereby avoiding local optimisations that could ultimately worsen overall environmental sustainability (Kemp & Pearson, 2007). This requirement prevents the phenomenon known as *environmental burden shifting*, whereby reducing impacts at one life-cycle stage (for instance, during production) may be offset by increased impacts at other stages (such as transport or end-of-life), undermining the validity of the overall evaluation.
Third, the principle of comparison with "relevant alternatives" is explicitly introduced: an innovation qualifies as an eco-innovation insofar as it generates lower environmental impacts than the technology, process or practice that represents the prevailing sectoral standard or the most advanced available technological state. This principle recognises the dynamic nature of evaluation benchmarks, whereby what constitutes a radical eco-innovation in a given historical context may later become standard practice.
Alongside Kemp and Pearson's contribution, Rennings (2000) developed a broad theoretical framework that extended the concept of eco-innovation well beyond the strictly technological domain. He articulated the concept across three possible dimensions of transformation towards sustainable development:
• technological innovation;
• social innovation;
• institutional innovation.
This distinction stemmed from a targeted critique of traditional economic research, specifically its tendency to focus policy analysis and intervention solely on technological solutions while neglecting the need for changes in consumption patterns, organisational structures and governance systems (Norgaard, 1994). Rennings further highlighted that, although the adoption of end-of-pipe technologies aimed at reducing downstream pollution can formally qualify as eco-innovation, such measures are insufficient to produce genuinely sustainable transformations unless accompanied by broader changes, ranging from environmental management systems and consumer preferences for less polluting products to new regulatory frameworks capable of internalising environmental costs (Klemmer et al., 1999).
On this basis, Rennings identified three structural features that fundamentally distinguish eco-innovation from conventional innovation, framing it as a specific class of economic phenomena requiring dedicated theories and policy instruments.
The first feature concerns the problem of the *double externality* (Rennings, 2000). When a firm introduces an eco-innovation, it generates two benefits that it cannot fully appropriate through the market. On the one hand, the knowledge produced tends to spill over to competitors, who benefit without bearing the associated costs. On the other hand, environmental benefits take the form of public goods, accessible to all regardless of their contribution to financing the innovation. Because firms do not capture revenues proportional to the total social value created, private incentives to

invest in eco-innovation fall below the socially optimal level (Jaffe & Palmer, 1997; Rennings, 2000). As a result, the market, left to itself, tends to under-provide eco-innovation, making coordinated public intervention necessary to stimulate an adequate level of "green innovation" (Jaffe & Palmer, 1997).

The second feature is the *regulatory push/pull effect* (Rennings, 2000). In the case of eco-innovation, alongside the availability of new knowledge and market demand as traditional drivers of innovation (Pavitt, 1984), environmental regulation plays a central role (Kemp, 1997). Environmental rules act simultaneously as a pressure factor, requiring firms to comply with increasingly stringent standards, and as an enabling factor, creating opportunities for the introduction of innovative solutions (Rennings, 2000). In practice, eco-innovations rarely emerge spontaneously in the market without adequate regulatory support (Green et al., 1994; Porter & van der Linde, 1995). Regulation is therefore far from marginal; it becomes decisive in shaping the type, pace and direction of eco-innovation processes over time.

Finally, the importance of social and institutional innovation is reaffirmed (Rennings, 2000). Environmental sustainability cannot be achieved through technical progress alone. The three identified dimensions do not evolve independently but through co-evolutionary processes that require the joint development of technologically eco-compatible, socially acceptable and institutionally supported innovations. Change in one dimension generates pressures and opportunities in the others, and progress towards sustainability demands synchronised advances across all three fronts (Freeman, 1992; Norgaard, 1994). A clean technology, for instance, remains marginal if consumers continue to prefer high-impact products and if public institutions fail to introduce incentives or obligations that encourage its adoption. Sustainability thus emerges as a project of systemic transformation involving technology, behaviour and institutions simultaneously.

2.3 Eco-Innovation and the Circular Economy

Eco-innovation plays a catalytic role in the practical implementation of the circular economy. A meaningful transition towards circular models is not feasible without the development and diffusion of eco-innovations capable of enabling, at both technical and organisational levels, the closure of material loops and the valorisation of waste and by-product streams (Bao & Ha, 2023). Conversely, the circular economy and its principles provide eco-innovation with a systemic framework that gives it a clear strategic direction and ambitions for structural transformation. The circular economy is, in fact, configured as an alternative economic paradigm to the traditional linear model, proposing a system in which material flows are organised according to closed and regenerative cycles (Kirchherr et al., 2017).

Within this perspective, by-products and production waste are no longer interpreted as residues destined for disposal, but rather as potential inputs for other processes, generating economic and environmental synergies simultaneously (MacArthur, 2015).

As a result, the foundational assumptions of the circular economy constitute a natural context for the emergence and application of eco-innovations of various kinds. In this sense, the *cradle-to-cradle* approach, also known as the regenerative approach, represents a concrete manifestation of the co-evolution between eco-innovation and the circular economy: product and process design is required, from the earliest development stages, to incorporate the intention to maximise residual value at end of life, facilitate the selective recovery of components and materials, and continuously feed new production cycles through recovered resource flows (McDonough & Braungart, 2002). Within this interpretative framework, eco-innovation is not an auxiliary or secondary instrument for achieving the circular economy, but rather its operational expression at technological and organisational levels, representing the means through which the transition to circular models takes tangible form (Bao & Ha, 2023).

2.4 Characteristics, Dimensions and Drivers of Eco-Innovation

What are the characteristics that distinguish eco-innovation from conventional innovation, defining its nature and shaping the ways in which organisations and firms adopt it?

First, as already noted, an eco-innovation must generate a verifiable and measurable reduction in environmental impacts compared with established sectoral alternatives. This does not imply the pursuit of an absolute optimum or a "zero-emissions" ideal, but rather a relative and context-dependent improvement (Kemp & Pearson, 2007). It is also essential to reiterate that eco-innovation presupposes an element of novelty, even if relative and context-specific: an agricultural enterprise that adopts locally a practice already widespread internationally still introduces an innovation within its specific context (OECD, 2005).

Moreover, eco-innovation must ensure eco-efficiency, understood as the ratio between economic outputs, such as income or productivity, and environmental inputs, such as resource consumption and emissions. From this perspective, eco-efficiency expresses the ability to avoid decoupling economic growth from improvements in environmental performance, configuring a relationship in which profitability and sustainability reinforce one another rather than coming into conflict (OECD, 2009; Porter & van der Linde, 1995).

Finally, eco-innovations are intrinsically multidimensional. A single solution may simultaneously involve product, process, organisational and, potentially, institutional innovations, thereby amplifying its overall environmental effect (OECD, 2009). In this regard, the OECD has systematically structured the analysis of eco-innovations along three critical dimensions: targets (products, processes, organisational structures, institutions), mechanisms (the ways in which change is introduced) and impacts (the environmental effects actually achieved) (Kemp, 1997; OECD, 2009). Figure 1 briefly shows the characteristics that characterizes wastewater as an eco-innovation.

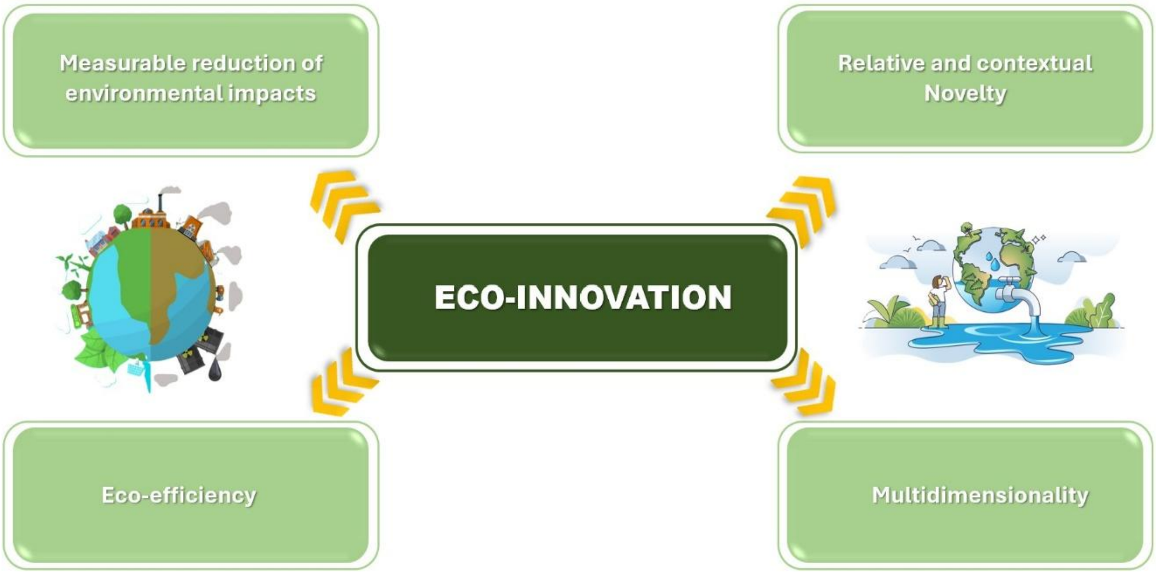

Figure 1. Aspects that overall define an innovation as "eco-innovation"

Beyond identifying the characteristics that qualify an innovation as an “eco-innovation”, it is equally important to understand the factors that promote its adoption, a key issue for designing effective policies and assessing its diffusion potential. The literature identifies two main categories of determinants: external factors and internal factors, the latter largely controllable by the firms involved (Bossle et al., 2016).

Among external factors, regulatory pressure emerges as the most significant driver: environmental regulations operate simultaneously as a constraint and as an opportunity for innovation (Rennings, 2000). However, the predominance of regulatory motivation suggests that many eco-innovations still take the form of largely reactive responses rather than proactive strategic choices (Chen et al., 2012).

Beyond formal regulation, traditional market pressures from customers, competitors, suppliers and certification bodies also play an important role. Through mechanisms of imitation and organisational conformity, these actors push firms to replicate the behaviour of other sectoral players in order to align with prevailing standards (DiMaggio & Powell, 1983; Bossle et al., 2016).

Another critical external factor is cooperation among firms, universities and research centres, since eco-innovation often requires competences, knowledge and technologies distributed across multiple actors. Collaborative processes enable resource sharing, the transfer of tacit knowledge and the distribution of risks associated with innovative investments (Cainelli et al., 2012; Bossle et al., 2016).

Finally, government support through public funding, subsidies, research programmes and, more broadly, the sectoral technological environment, significantly influences both the likelihood and the scale of eco-innovation adoption (OECD, 2009).

With regard to internal factors, operational efficiency and cost savings represent central drivers. Eco-innovations can generate substantial cost reductions, consistent with the hypothesis that stringent environmental regulations can stimulate innovations capable of simultaneously improving environmental performance and economic efficiency (Porter & van der Linde, 1995; Green et al., 1994; Bossle et al., 2016).

Furthermore, eco-innovation adoption is facilitated by the development of specific internal organisational capabilities. In particular, this includes *environmental capabilities*, meaning competences that enable firms to monitor, manage and reduce environmental impacts. For example, companies that implement environmental management systems and obtain dedicated certifications tend to innovate more frequently, as such systems encourage them to quantify critical issues, set targets and engage in continuous learning (Demirel & Kesidou, 2011; Bossle et al., 2016). Another relevant factor is internal environmental culture. When organisational members perceive sustainability as an intrinsic and strategic value for the firm, rather than merely as an external constraint, eco-innovation tends to become a natural component of corporate identity, moving beyond a compliance-driven logic (Verghese & Lewis, 2007; Bossle et al., 2016). This is complemented by the role of qualified human capital: firms that invest in environmental training and the acquisition of specialised skills are more actively involved in sustainable innovation processes (Bossle et al., 2016).

In summary, the adoption of eco-innovation requires a coherent integration of internal capabilities and external pressures, in order to define a guiding strategy that steers organisations along a path of sustainable transition and transformation.

2.5 The Reuse of Treated Wastewater in Agriculture as an Eco-Innovation

The reuse of treated wastewater for agricultural irrigation constitutes an emblematic case of eco-innovation. It simultaneously incorporates multiple innovative dimensions, activating technological, organisational and institutional factors, and generating articulated environmental, economic and social benefits. From this perspective, wastewater reuse also represents a concrete application of circular economy logic (Michetti et al., 2019), responding to the growing need for Integrated Urban Water Management (IUWM) aimed at supporting the transition towards more sustainable water use and the closure of material cycles (Ansari et al., 2024).

With reference to the target dimension in the OECD (2005) framework, the reuse of treated water for irrigation can simultaneously be understood as:

- a product innovation, as it introduces and makes available a "new" water resource that was previously inaccessible as a commercial and functional option;
- a process innovation, since it entails significant changes in agricultural water supply methods, partially replacing abstraction from surface or groundwater sources with the use of treated wastewater;
- an organisational innovation, as it requires the creation of new governance, monitoring and coordination arrangements between wastewater treatment plant operators and farmers, integrating sectors that have traditionally operated separately;
- an institutional innovation, through the development of new regulatory frameworks, concession agreements and tariff systems governing the flow and quality of water intended for agricultural use (Michetti et al., 2019; Ociepa-Kubicka & Pachura, 2017).

Regarding the mechanism dimension, the treated wastewater reuse model combines elements of re-design, understood as a radical rethinking of agricultural water supply and wastewater management, shifting from a linear "treatment and discharge" model to a circular "treatment and recovery" model, with elements of alternative innovation, as it provides a functionally substitutable water resource compared with conventional sources (Michetti et al., 2019). This combination places the phenomenon at an intermediate-to-high level of radicality, with significant potential to generate substantial environmental benefits (Ociepa-Kubicka & Pachura, 2017).

From an environmental impact perspective, reuse delivers a plurality of verifiable and measurable benefits. First, it reduces pressure on conventional water sources, contributing to the conservation of river and lake ecosystems and to mitigating the problem of over-allocation of water abstraction rights relative to actual availability, a critical issue in arid and semi-arid basins. Second, it lowers pollution in receiving water bodies by preventing wastewater discharge into aquatic ecosystems and preserving their biotic integrity. Third, it enables a reduction in the use of synthetic chemical fertilisers, as treated wastewater retains significant nitrogen and phosphorus content, thereby decreasing dependence on chemical inputs and the greenhouse gas emissions associated with their production and transport (Michetti et al., 2019; Ansari et al., 2024). Finally, it provides a relatively reliable water supply that is less dependent on seasonal climate variability, contributing to food production stability and climate resilience in contexts of increasing water scarcity (Ansari et al., 2024).

From a circular economy standpoint, the reuse of treated wastewater represents, as already noted, a paradigmatic application of the principle of closing material cycles. It implements a recursive loop in which water, after domestic and civil use, is treated to restore specific quality standards and subsequently reused for agricultural irrigation, which generally requires lower quality levels than potable uses (Ociepa-Kubicka & Pachura, 2017; Michetti et al., 2019). This "functional cascading" of uses constitutes an operational expression of the concepts of water footprint reduction and circular water management, translating the cradle-to-cradle paradigm into the water cycle (Ansari et al., 2024).

Over time, evidence has progressively accumulated showing that the need to introduce treated wastewater reuse for irrigation has emerged simultaneously across diverse countries and geographical contexts, as the result of converging exogenous and endogenous forces (Reference).

At a broader scale, the main exogenous pressure is linked to the intensification of water scarcity, driven by climate change, increased precipitation variability and rising water demand for domestic, agricultural and industrial uses. Empirical literature shows that agriculture accounts for the largest share of water withdrawals in most world regions, representing approximately 70% of global abstraction (Michetti et al., 2019), while accelerated urbanisation further concentrates pressure on limited water resources, particularly in arid and semi-arid areas (Ansari et al., 2024). At the same time, climate change is altering rainfall patterns and increasing the frequency and intensity of drought events, especially in Southern Europe and the Mediterranean region (Michetti et al., 2019; Manganiello et al., 2024).

This context is compounded by growing regulatory pressure at the international level, for instance following the adoption of the European Water Framework Directive 2000/60/EC and the United Nations Sustainable Development Goals, which impose increasingly stringent standards in terms of water efficiency and environmental sustainability. This environment generates a genuine *regulatory push,* encouraging states and organisations to orient themselves towards alternative water supply solutions (Ociepa-Kubicka & Pachura, 2017; Michetti et al., 2019). The uptake of treated wastewater reuse has also been facilitated by the progressive maturation of treatment technologies. Although around 80% of global wastewater is still untreated, scientific research has extensively demonstrated the technical feasibility and environmental benefits of reuse, particularly in contexts where the adoption of advanced treatment processes (such as sand filtration, chemical oxidation with hydrogen peroxide and UV irradiation) enables the achievement of quality standards compatible with agricultural use (Michetti et al., 2019).

Finally, from an eco-innovation perspective, wastewater reuse for irrigation can be interpreted as a systemic response to traditional environmental market failures, as well as to regulatory pressures and market pull factors that drive eco-innovation adoption (Ociepa-Kubicka & Pachura, 2017). The scarcity of freshwater from conventional sources generates negative externalities that are not fully internalised in market prices, creating conditions under which reuse becomes particularly advantageous from an environmental standpoint (Michetti et al., 2019).

Ultimately, the need to implement water reuse solutions reflects growing awareness of the necessity to transition towards integrated water management models and circular economy practices, in response both to regulatory pressures and to a market demand increasingly oriented towards sustainable practices (Ociepa-Kubicka & Pachura, 2017).

3. The Regulatory Framework at European and National Level

In a European and Mediterranean context marked by the intensification and increasing frequency of drought events, reference to the European Union's regulatory framework is essential to understanding the development trajectories of treated wastewater reuse as a structural response to water scarcity. The regulatory dimension represents one of the most significant drivers in the adoption of treated wastewater reuse, operating simultaneously as an exogenous pressure that constrains and guides stakeholder behaviour and as an enabling factor that creates favourable conditions for innovation.

At European level, Directive 91/271/EEC constituted the first major intervention, introducing fundamental requirements for the collection, treatment and monitoring of urban wastewater prior to discharge into receiving water bodies. Subsequently, the Water Framework Directive (2000/60/EC) established an integrated framework for the protection and management of water resources, laying the conceptual and operational foundations for future reuse-oriented policies.

With specific regard to the agricultural use of treated wastewater, the decisive turning point came with the adoption of Regulation (EU) 2020/741, which entered into force in 2023 and introduced harmonised minimum requirements for the reuse of urban wastewater for irrigation.

Regulation 2020/741 classifies so-called "reclaimed water" into four quality categories (A, B, C and D), differentiated according to crop types and irrigation methods, thereby providing a common reference framework for Member States and reducing prior regulatory fragmentation. More recently, Directive (EU) 2024/3019 has represented a substantial recast of the legislative framework, introducing significant innovations, including the removal of stringent nitrogen and phosphorus limits where their use aligns with crop nutrient requirements, and the strengthened application of the "polluter pays" principle, which mandates differentiated obligations for advanced quaternary treatment in large urban agglomerations (≥150,000 population equivalents).

Overall, the evolution of EU legislation signals a gradual shift from a predominantly emergency-driven approach towards a strategic vision focused on circularity and sustainable water resource management, consistent with Sustainable Development Goal 6.4 of the 2030 Agenda and with circular economy principles (Michetti et al., 2019).

In Italy, the regulatory framework has developed in a broadly parallel manner. Ministerial Decree 185/2003 represented the first comprehensive regulation governing wastewater reuse for irrigation, industrial and civil purposes, establishing specific chemical-physical and microbiological parameters. This framework was subsequently incorporated and consolidated within the broader legal architecture of the Environmental Code (Legislative Decree 152/2006), which regulates water protection. More recently, the so-called *Drought Decree* (Decree Law 39/2023) introduced additional constraints for sensitive areas and mandated the preparation of Risk Management Plans aligned with European guidelines.

Despite the existence of a national legal framework, the implementation of water reuse remains highly uneven across Italian regions. This is largely due to the fact that national legislation delegates responsibility for defining specific criteria and implementation modalities to regional authorities. Several regions (such as Emilia-Romagna, Veneto, Lombardy, Apulia, Tuscany, Liguria and Sardinia) have already adopted dedicated decrees and territorial plans (Iren, 2021; Mantovi et al., 2019; Antonelli et al., 2020; Farabegoli, 2023), whereas in other areas reuse remains largely experimental and lacks a structured regulatory framework (Mininni et al., 2024).

This fragmentation reflects the complexity of multi-level governance and the absence of a coherent national planning strategy, factors that Michetti et al. (2019) identify as critical constraints on the diffusion of innovation in water management systems.

Beyond technical and regulatory aspects, the economic dimension of legislation plays a central role in determining the feasibility of reuse. Ministerial Decree 185/2003 establishes that treatment costs are borne by users of the Integrated Water Service, while distribution costs for treated water fall on final users. ARERA Resolution 580/2019/R/IDR, which defines the Water Tariff Method for the period 2020–2023, allows operators to retain 75% of the profits generated from reuse activities, allocating the remaining 25% to limiting tariff increases (Peruzzi, 2020). With regard to cost allocation, Regulation (EU) 2020/741 provides no explicit guidance, leaving a degree of uncertainty around the investments required to develop advanced treatment infrastructure. In response, several Italian regions are experimenting with alternative tariff models, including dynamic pricing schemes that differentiate water prices according to treatment level, taking into account both operational costs and infrastructure investments (Hernández-Chover et al., 2022). The coexistence of heterogeneous approaches reflects the absence of a nationally harmonised pricing framework and constitutes one of the main financial barriers to reuse implementation, particularly in regions with more limited economic capacity.

At present, Italy treats approximately 6.7 billion cubic metres of wastewater per year, a volume exceeding by 43% the total amount of potable water supplied nationwide. However, only a limited share of this resource is actually reused for irrigation, highlighting the existence of substantial untapped potential (Istat, 2024). The most recent European directives adopted in 2024 outline an especially ambitious roadmap, requiring that by 2035 all urban wastewater undergo at least secondary treatment and that, by 2045, large-scale treatment plants mandatorily adopt quaternary treatment. The introduction of the principle of Extended Producer Responsibility (EPR), which obliges pharmaceutical and chemical producers to contribute to the costs of advanced treatment, represents an additional incentive mechanism supporting more sustainable management models aligned with environmental protection and circular economy objectives.

3.1 Challenges and Barriers to the adoption of wastewater reuse

Although the reuse of treated wastewater in agriculture is generally presented in the literature as a promising solution to address water scarcity and enhance the resilience of agricultural systems, its adoption cannot be understood in exclusively positive or linear terms. Alongside its potential benefits, a number of obstacles, risks and barriers emerge that shape both its acceptance and its actual implementation. These challenges concern, on the one hand, structural and institutional aspects, such as initial investment costs, inadequate infrastructure, weak regulatory frameworks and limited public support in terms of technical assistance, monitoring and incentives (Antwi-Agyei et al., 2016; Maina et al., 2020). On the other hand, the literature highlights the importance of perceptual, psychological and socio-cultural factors, including disgust associated with the origin of the water, mistrust of its quality, health and environmental concerns and, more broadly, the difficulty of overcoming negative social representations of reuse (Chfadi et al., 2021; Karimi and Ataei, 2023; Alsa'di et al., 2024). Added to this is the possible misalignment between immediately perceived economic benefits and less visible long-term risks, such as those related to soil and crop contamination, which may make the adoption process ambivalent and far from contradiction-free (Khanpae et al., 2020). From this perspective, wastewater reuse appears not only as a technical issue, but as a complex process whose sustainability depends on the interaction between material conditions, institutional arrangements and social dynamics.

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Chapter 3

Intention to use wastewater in agriculture: Incentives and behavioural determinants driving farmers' decisions

Preamble: Economic theory and objective determinants of innovation adoption in agriculture

Economic theory provides a fundamental analytical framework for understanding how farmers approach innovative choices, generally favouring behaviours that maximise expected utility (Adesina & Zinnah, 1993; Zongo et al., 2015; Shang et al., 2021; Ruzzante et al., 2021; Adnan et al., 2019). However, this perspective remains incomplete unless it also considers how individual, structural and organisational factors shape entrepreneurs' actual economic decisions. Morris (1991) highlighted that human capital quality, economic status, and social and political contexts are crucial determinants of the adoption and diffusion of innovations (Wejnert, 2002).

The scientific literature identifies a hierarchy of key factors that operate simultaneously within the decision-making process:

• Socio-demographic and socio-economic characteristics such as age, educational attainment and experience (Knowler & Bradshaw, 2007; Ruzzante et al., 2021);

• Technical and structural farm-level factors, including firm size and income (Daberkow & McBride, 1998; Tey & Brindal, 2012);

• Institutional and informational factors, including access to credit, public subsidies, information sources and advisory services (Adnan et al., 2019; Guo et al., 2020).

Equally important is the role of social networks and membership in collective organisations in encouraging innovative participation (Araque-Padilla & Montero-Simo, 2022).

Recognising that the effects of these multiple factors are highly heterogeneous and context-specific, strongly dependent on the type of innovation considered and the characteristics of the originating context (Ruzzante et al., 2021; Dissanayake et al., 2022), it becomes essential to incorporate perceptual dimensions into this analytical framework.

In particular, based on extensions of behavioural theories empirically applied in the existing literature, risk perception emerges as one of the central constructs in the process of innovation acceptance and adoption (Giovanis et al., 2012; Venkatesh & Bala, 2008; Tama et al., 2021). Extensions of the UTAUT theory applied to various agricultural evaluation contexts (Venkatesh et al., 2003; Sabbagh & Gutierrez, 2023; Xie et al., 2022) and of the TAM model (Davis, 1989; Venkatesh & Bala, 2008; Giovanis et al., 2012) have, for example, demonstrated the need to integrate this dimension, as it enables a deeper understanding of perceptions and emotional responses that can implicitly alter the propensity to accept or reject an innovation.

Moreover, Venkatesh et al. (2003) emphasise that perceptual aspects may themselves be influenced by individual characteristics such as age, education level, income and experience, highlighting the need to jointly consider both human capital quality and the perceptual dimension in the adoption process.

Within this integrated theoretical framework, where structural factors and perceptual aspects interact with individual and farm-level preconditions, this chapter presents an empirical investigation into farmers' propensity to adopt treated wastewater for irrigation. This practice is examined as an emerging and often underestimated eco-innovation that may represent a viable alternative for sustaining agricultural production, particularly in light of the recurrent drought scenarios increasingly affecting the Mediterranean regions. The study simultaneously examines the role of key determinants such as age, educational attainment, experience, farm size, income, water supply sources, and access to institutional and informational resources, while also analysing how the perception of risks potentially associated with using this resource further influences farmers' innovation-related decisions.

An Analysis of Farmers’ Propensity to Use Reclaimed Wastewater in Agriculture

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Abstract

In the Mediterranean Basin, increasing water scarcity, exacerbated by climate change, necessitates the use of alternative water resources in agriculture. This study analyses farmers' propensity to use reclaimed wastewater for irrigation in Basilicata, a region in Southern Italy. Through a survey of 167 farms and the application of a logit model, this work evaluates the role of the main factors influencing farmers' propensity to use this new resource. The results show that a higher level of education, adequate knowledge of regulations, and participation in Producers’ Organisations significantly increase the likelihood of adoption. In contrast, concerns related to product quality, worker health, and groundwater pollution represent significant barriers. The findings underscore the need for integrated interventions that enhance farmers' awareness and knowledge of the characteristics and impacts of new practices, thereby fostering innovative and sustainable management of water resources.

1. Introduction

Water scarcity is affecting many geographical areas, particularly the Mediterranean Basin. In this area, climate change, characterised by prolonged periods of drought, reduced annual rainfall, and heatwaves, is expected to intensify in the following years compared to the global average, with significant consequences for water and food availability and the population's well-being (Ali et al., 2022). In Europe, the estimated economic losses due to droughts are around EUR 9 billion/year, of which EUR 1.4 billion concerns Italy (Cammalleri et al., 2020; Villani et al., 2022). A rise in average temperatures of 2°C by 2050 is expected to increase these losses by more than 70% (Cammalleri et al., 2020). In the Mediterranean region, 60% of drought-related damage is concentrated in agriculture, and projections to 2100 estimate that the value of agricultural losses will double (Cammalleri et al., 2020). Indeed, agriculture is the production sector with the highest water consumption (Ryder, 2017).

Globally, irrigation accounts for 70% of water use. The growth of the world's population, changing consumption patterns in emerging countries, and the resulting rise in food demand suggest that irrigated areas are expected to expand considerably in the coming years. This will lead to increased irrigation requirements for many autumn-winter and spring crops, when water needs are not fully met, putting additional pressure on natural water reserves, and raising costs for farmers (Ali et al., 2022; Michetti et al., 2019). To effectively address droughts and water scarcity, it is essential to adopt a proactive approach and implement specific measures, as purely emergency interventions are technically and economically ineffective. The use of reclaimed wastewater is an economically, politically, and environmentally beneficial solution, as it meets agricultural water demand and reduces pressure on natural water resources (Deh-Haghi et al., 2020; Michetti et al., 2019). It aligns with the principles of the circular economy, focusing on reduction, reuse, and recycling, thereby facilitating an effective transition from waste to resource (Morales and Belmonte-Ureña, 2021). The use of wastewater for irrigation, properly treated and controlled to ensure microbiological and physicochemical quality, is already a common practice in some areas experiencing water shortages and provides benefits for both the water supply and the recovery and utilisation of the nutrients within it (Amann et al., 2018).

With Regulation (EU) 2020/741, the European Union has established minimum water quality requirements for the reuse of reclaimed urban wastewater in agriculture, aiming to facilitate and economically encourage this practice while protecting public health and the environment. In recent years, in Italy, the recycling and reuse of urban wastewater for agricultural purposes have been permitted in some regions (Manganiello et al., 2024; Michetti et al., 2019). However, despite the considerable advantages, there are still barriers to its acceptance and related investments. They include the absence of specific regulations, a lack of incentives for implementation, health and production quality issues, infrastructure deficiencies (Michetti et al., 2019), aspects related to social norms (Dolnicar et al., 2011), and risk perception (Dobbie and Brown, 2014). The social acceptance of urban wastewater recycling and reuse practices is widely discussed in the literature (Deh-Haghi et al., 2020; Khanpae et al., 2020; Ricart et al., 2019).

The acceptance and propensity to adopt these practices relate to perceptions of the risks associated with the quality of the products obtained, market difficulties and the effects on the health of producers and consumers (Dobbie and Brown, 2014; Michetti et al., 2019; Mukherjee et al., 2013; Ndunda and Mungatana, 2013). Risk perceptions can differ considerably among individuals and, along with environmental concerns (Ndunda and Mungatana, 2013; Ricart et al., 2019) and the availability of clear and sufficient information (Dobbie and Brown, 2014; Michetti et al., 2019), can greatly influence the likelihood of using reclaimed wastewater for irrigation. Understanding how and to what extent these different factors influence farmers' behaviour is a crucial topic. The decision to use alternative water resources for irrigation depends on farmers. Recognising the key aspects behind farmers' attitudes can help improve current wastewater management systems and guide specific actions for their future implementation. This study aims to examine farmers' likelihood of using reclaimed wastewater for irrigation through a field survey conducted on a sample of irrigated farms in Basilicata. Basilicata is a southern Italian region heavily impacted by climate-related emergencies and drought, where a specific regulatory framework for wastewater use and an appropriate risk management plan are still lacking.

Analysing the factors that can promote or hinder the use of this resource in Basilicata's agricultural systems is crucial for developing policies aimed at encouraging wastewater reuse. Furthermore, the results of this analysis help address the existing knowledge gap concerning perceptions of potential benefits from a change in production processes and the farms' capacity to adapt to changing contexts, which are vital for agricultural competitiveness (Xie et al., 2019). Wastewater reuse for irrigation can be regarded as a genuine eco-innovation in terms of process, as the effects related to technical aspects, such as treatment, transport, and distribution operations, are still being investigated, and there is no comprehensive understanding of the benefits and hazards associated with its practice. Furthermore, the adoption of reclaimed wastewater irrigation remains limited to a few countries, and the quality and safety requirements for its optimal and responsible use depend heavily on the development of current legislation, with specific adaptations for different nations (Michetti et al., 2019). After a review of the factors influencing the adoption of innovative agriculture practices (Section 2), sections 3 and 4 describe the methodology used in the work and the results obtained. Discussion and concluding remarks are presented in Section 5.

2. Factors affecting the adoption and diffusion of innovations in agriculture

Innovation drives long-term economic growth and increases the firms' competitiveness (Aghion and Festré, 2017). In agriculture, innovation takes the form of new factors and/or practices that improve products or production performance. It involves implementing innovative modifications and changes involving products or production processes, new technologies or farming practices, and acquiring specific knowledge (Läpple et al., 2015). Matunhu (2011) emphasises the variety of agricultural innovations, ranging from new hybrids and fertilisers to technical means and advanced management practices. Stock et al. (2015) provided an overview of existing innovations and their applications, identifying the main motivational factors related to their direct and indirect effects. Other research strands have delved into the adoption of innovative agri-environmental technologies, analysing the probability of adoption by farmers, including both adopters and potential users (Baumgart-Getz et al., 2012; Lastra-Bravo et al., 2015; Unay-Gailhard and Bojnec, 2016). Stemming from Rogers' work in 1995, literature on innovation has explored several factors influencing the adoption and diffusion of innovations. They include socio-demographic, economic, structural characteristics, information and risk perception.

2.1 The socio-demographic factors

Among socio-demographic factors, age is the first factor of interest, even if there are conflicting views on its contribution to the propensity to innovate. Indeed, in the agricultural domain, several studies have shown that age inversely affects the adoption of innovations, with younger farmers being more likely to promote and implement agricultural innovations (Giovanopoulou et al., 2011; Serebrennikov et al., 2020). This is attributed to their longer planning horizons and lower risk perceptions compared to older farmers. In contrast, other authors consider age as a factor directly related to experience in the field and skills acquired over time, identifying a favourable and significant association with the adoption of innovations (Azam and Banumathi, 2015; García-Cortijo et al., 2019).

Indeed, experience in the sector is a factor that could positively or negatively influence the propensity to adopt and use innovations (Rizzo et al., 2024). In the agricultural sector, experience can incentivise the adoption of innovation, as more experienced farmers are more likely to adopt innovations due to the considerable knowledge they gain over time (Liu and Brouwer, 2022; Medhi et al., 2020; Singh and Maharjan, 2017). On the other hand, greater agricultural experience is associated with well-established management techniques, making transitioning to new farm organisations and production processes more complex (Sapbamrer and Thammachai, 2021).

Education is another significant factor in the decision to innovate (Rizzo et al., 2024). A low level of education is often identified as a barrier to adopting innovations (Lindblom et al., 2017). In the agricultural sector, more educated farmers have a higher ability to understand the pros and cons of innovative investments (Abdulai et al., 2011; Azam and Banumathi, 2015; Sapbamrer and Thammachai, 2021). According to this view, education would allow for easier acquisition of information and skills from several sources, a quick association of benefits with new practices and technologies, and a significant reduction of associated risk perception (Chatzimichael et al., 2014; Dolnicar et al., 2011; Rizzo et al., 2024). Thus, a higher level of education is linked to a greater willingness and ability to obtain information and skills, generates confidence in the proposed innovations, and contributes significantly to their acceptability (Liu and Brouwer, 2022; Michetti et al., 2019; Siegrist and Cvetkovich, 2000).

Gender is a factor that has been the subject of vast discussion due to its controversial effects on the propensity to adopt innovations. Different effects stem from the contexts in which innovation is proposed and the type of innovation (Aznar-Sànchez et al., 2020; Fadeyi et al., 2022). In the agricultural sector of less developed countries, many women having the role of farm manager showed a significantly higher propensity to adopt technical and management innovations, even though some revealed limited skills in the field compared to men (Druschke and Secchi, 2014).

In other development contexts, such positive attitudes of women towards innovation have been attributed to a strong propensity for inter-firm collaboration (Aznar-Sànchez et al., 2020) and a greater concern with unsustainable practices, including their long-term effects (Sodjinou et al., 2015). However, other studies have denied the existence of a significant relationship between gender and technology adoption, as men and women may be actively involved in agriculture but with different roles and responsibilities (Fisher et al., 2015; Mariano et al., 2012; Serote et al., 2021).

2.2 Economic and structural factors

Farm income is a key determinant for adopting innovations (Fadey et al., 2022; Rizzo et al., 2024). Innovative practices and techniques often entail high operational costs, especially in the initial stages of implementation, making the most productive farms the only ones able to bear the related economic burden (García-Cortijo et al., 2019; Lasch et al., 2007; Schimmelpfennig, 2016). In addition, higher income levels enable firms to face prolonged periods of economic recovery related to innovative investments (Barnes et al., 2019). Thus, the profile of innovative farms is often associated with higher incomes, which, in turn, are also linked to a larger size (García-Cortijo et al., 2019). A different view emerges in other studies, which found that farm income can have a negative effect on the adoption of innovations, mainly justified by the associated high-risk perception (Zeweld et al., 2018).

A relevant issue for the innovation adoption is the relationship between on-farm and off-farm income. Indeed, farmers who receive additional income from off-farm sources are more likely to adopt innovative practices and technologies due to their greater economic security, which incentivises them to be less risk adverse (Sriwichailamphan and Sucharidtham, 2014).

In parallel, farm size also plays a crucial role in the acceptance and adoption of innovation (Piñeiro et al., 2020; Rizzo et al., 2024). This role is theoretically controversial and is not exclusively related to income level. Some studies have highlighted how smaller farms can implement technical and management innovations more quickly, as they are more flexible and can consequently more easily adjust their activities to remain competitive in the market (Bonney et al., 2007; Dalla Corte et al., 2015; Läpple and Van Rensburg, 2011). On the other hand, larger farms can face greater difficulties in implementing innovations. These difficulties stem from the need to extend cultivation, technical input, and process changes to the entire farm, which would be complex and costly (Liu et al., 2019). On the contrary, other authors have argued that larger farms have more economic resources to

invest and can reorganise better and convert business activities, as they demonstrate a high awareness of existing problems and the solutions that innovations entail (Baumgart-Getz et al., 2012; Chatzmichael et al., 2014; Sapbamrer and Thammachai, 2021; Serebrennikov et al., 2020).
According to this perspective, small farms would have fewer economic resources, more significant difficulties in accessing credit and need more incentives to implement innovations (Liu et al., 2018; Sapbamrer and Thammachai, 2021).

2.4 The role of information and knowledge factors

Several studies have demonstrated how knowledge of innovation's characteristics, working mechanisms, and impact influences its adoption process (Chuang et al., 2020; Michetti et al., 2019; Rogers, 1995).
Within the agricultural sector, the level of knowledge, operationalised by the degree of education and vocational training, was found to be positively correlated with the adoption of new technologies (Micheels and Nolan, 2016; Moura et al., 2019). Chuang et al. (2020) showed that the availability of well-structured training courses can encourage farmers' adoption of new technologies, while low levels of adoption can be attributed to inadequate information, resulting in a lack of innovation-specific knowledge.
Alongside in-house knowledge and expertise, the flow of information from outside the company and the possibility of exchange and interaction with other parties, through participation in producer networks or connection with consulting services or research institutions, is relevant in the process of disseminating innovations (Bjerke and Johansson, 2022; Matuschke et al., 2007; Pannell et al., 2006; Rogers, 1995). Collaboration and knowledge transfer networks, training programs, and interaction with extension agents help improve knowledge and skills about a specific innovation and contribute to increasing the likelihood of its adoption (Abdulai et al., 2011; Chatzimichael et al., 2014; Dhraief et al., 2019; Derwisch et al., 2016; Khalid et al., 2017; Sodjinou et al., 2015). Communication and information sharing are key to improving farmers' ultimate knowledge, which is indispensable in decision-making.

2.5 The risk perception

In recent years, several studies have examined the role of psychological and attitudinal factors in determining the adoption of innovations. Among these factors is the perception of risk associated with innovation. Perceived risks are related to uncertainty and a lack of confidence in the new (Mankad et al., 2012). The extent of perceived risk in relation to a specific innovation may depend on factors such as access to information, strength of knowledge and experience in the field (Egri, 1999; Dolnicar et al., 2009; Ghadim et al., 2005). The availability of accurate information and greater knowledge of the pros and cons of innovation translates into higher levels of acceptance of innovations, as there is a greater understanding of the benefits associated with their use, which results in lower perceptions of risks or greater tolerance of them (Siegrist and Cvetkovich, 2000).
Perceptions will differ depending on the type of risk, the individual's attitudes, and the social context (Siegrist and Árvai, 2020). In agriculture, the perception of risk associated with new products, processes and production techniques has been studied with reference to financial, environmental and health risks (Deh-Haghi et al., 2020; Mariano et al., 2012; Sabbagh and Gutierrez, 2023). The high upfront costs of acquiring new technologies generate concerns about not recouping the investment, deterring farmers from implementing them (Sabbagh and Gutierrez,

2023). Deh-Haghi et al. (2020) showed how farmers' perceptions of health risks are hindering factors in the adoption of innovations. The fear of contamination and disease associated with the use of reclaimed wastewater for irrigation generates negative perceptions of this resource and limits the adoption of such techniques (Keraita et al., 2008; Srinivasan et al., 2009; Woldetsadik et al., 2018).

Risk perception is also related to the individual's attitude toward risk. The higher the risk aversion, the more farmers will opt for traditional production systems and the lower the propensity for complex innovations, characterised by high maintenance costs and unpredictable market demands (Xie et al., 2015), thus leading to their late adoption (Liu et al., 2013). Table 1A in the Appendix summarises the factors discussed in the literature that can significantly influence the process of adopting innovations, specifying the type of relationship observed and the analytical models used.

3. Data and Methods

3.1 The study area

The present study was conducted in Basilicata, one of the regions in Southern Italy highly affected by climatic alterations and frequent drought phenomena. According to rainfall data for the last decade from the Ministry of Agriculture, Food Sovereignty and Forestry (MASAF), the average rainfall in Basilicata is around 650 millimetres per year, mainly concentrated in the autumn and winter months. However, due to climatic anomalies and exceptional weather events, these data appear unstable and vary considerably from one period to another and from one area to another. Basilicata is a region with a strong agricultural vocation and boasts a wide range of irrigated crops. According to the 2020 Census by the National Institute of Statistics (ISTAT, 2021), there are 8,842 irrigated farms in the region. The most productive areas in the region are in Matera province, where there are 22,800 irrigated hectares, accounting for 76% of the regional irrigated area. This study focused on farms located in this province (Figure 1). These areas are the region's main arid and semi-arid areas and are more sensitive to water scarcity challenges.

Figure 1. The study area

3.2 The sample

A field survey was carried out to collect primary data and information on farmers' propensity to use reclaimed wastewater for crop irrigation and the factors that may influence its use. A questionnaire was administered to 167 farmers through face-to-face interviews. Participation in the survey was voluntary and motivated by a strong interest in the subject among farmers. The survey was conducted from April to August 2024. Therefore, the analysis is based on a convenience and non-probability sample, but it can give useful insights into the propensity of farmers to use unconventional water and reorganise traditional irrigation management to ensure environmental sustainability and agricultural productivity. The questionnaire was divided into four sections. The first section aimed to collect farmers' socio-demographic information, such as age, experience in the sector, level of education, agricultural training, and on-farm and off-farm income. The second section aimed to collect data on farm characteristics, including production yields and the destination of outputs. An entire subsection was devoted to irrigation, water use and consumption. The third section included questions to identify farmers' primary sources of information and their level of knowledge of wastewater and current regulations. Specific questions were asked to detect the propensity and willingness of farmers to use reclaimed wastewater on their farms.

The final section explored motivational aspects, such as farmers' perceived advantages and disadvantages that may influence their propensity to use wastewater and farmers' risk perceptions regarding issues and/or hazards to human health, the environment, production quality, and product marketing. The sample accounts for a total Utilised Agricultural Area (UAA) of 6,765.7 hectares, and 5,472.7 hectares of irrigated land (81% of UAA and 24% of the province's irrigated land).

Fruit (35% of UAA) and horticultural crops (17.8% of UAA) are the prevailing crops, followed by intensive crops such as kiwi (7.6%) and strawberry (6%).

Most farmers simultaneously cultivate several crops, trying to limit monoculture and apply diversification strategies. For 87% of the interviewed farmers, farm activity is the primary source of income, and 43.7% of the respondents declared an income of over € 50,000, followed by a further 31.7% of farmers with incomes between € 28,000 and € 50,000.

Moreover, 90% of respondents use the drip irrigation system, as it ensures optimal and efficient water delivery, thereby limiting waste and runoff losses. In addition, 32% of the sample confirmed using advisory services on irrigation systems.

Water is mainly from the Irrigation Consortium (about 86% of farmers). Nevertheless, about 83% of the respondents stated that they have encountered several utilisation problems, including water scarcity and inefficiency of distribution systems. Most farms use meters to monitor irrigation water consumption (72.5%). On average, water consumption accounts for 3,870 m^3, varying according to the crops. Horticultural crops, strawberry and kiwi have the highest seasonal water requirements (around 4,250 m^3 per hectare on average), followed by fruit crops (3,778 m^3). Table 1 and 2 synthesise the main characteristics of the sample.

Table 1. Main characteristics of the sample (descriptive statistics)

Variable	*Mean*	*Standard Deviation*
Age (years)	52.3	17.3
Experience in the sector (years)	23.0	16.3
Utilized Agricultural Area (UAA)	40.5	43.0
Irrigated UAA	32.7	34.2
Total Agricultura Area	46.8	48.8
Water cost (euro/mc)	0.70	0.07
Water consumption (mc)	3,870.0	1,256.5

Table 2. Main characteristics of the sample (frequencies)

Variable	*% of the sample*
Education level	
Higher education (Upper secondary and tertiary education level)	57
Lower education (Primary and middle school)	43
Agricultural education (Specific training in agriculture)	
Yes	44
No	56
Income class	
Up to 28.000 €	24.6
28.000 € - 50.000 €	31.7
50.000 € and more	43.7
Irrigation System	
Microirrigation	90
Other systems	10
Origin of Water	
Irrigation consortium	86
Other Source	14
Use of consulting services	
Yes	32
No	68
Participation to Producers' Organisations	
Yes	50
No	50

3.3 Methods

The empirical analysis was divided into two steps.

In the first phase, through an exploratory and descriptive analysis, we examined the relationship between farmers' propensity to use wastewater for irrigation and various socio-demographic, economic, and motivational factors. Parametric and nonparametric statistical tests were used, according to the type of variables, to obtain information on data distribution and understand which variables might have some relationship with the propensity to use wastewater.

In the second step, a logit model was used to estimate the influence of some selected independent variables on the likelihood of using reclaimed wastewater.

In the binary logit model, the dependent variable *y* can assume only two values (0 or 1) and the conditioned probability of *y* is given by (Greene, 1997):

$$Prob(y = 1|x) = \Lambda(\beta' x)$$

Where:

- Λ is the logistic cumulative distribution function
- x is the vector of explanatory factors
- β is a vector of coefficients associated with the explanatory factors.

The marginal effects of changes in the explanatory variables on the probability of y are estimated by:

$$\frac{\partial Prob(y = 1|x)}{\partial x} = \frac{e^{\beta' x}}{1 + e^{\beta' x}}$$

In our model, the dependent variable y =1 if the farmer stated to be propense to use reclaimed wastewater for irrigation; y=0 otherwise, and the vector of independent variables includes:

1) The farm size in terms of Utilised Agricultural Area (continuous variable: hectares)
2) the Education level: 0= primary or middle school level of education; 1= upper secondary level and tertiary education level
3) the knowledge of legislation on wastewater: 0= no knowledge; 1= some level of Knowledge
4) use of irrigation consulting service: 0= no use of consulting service; 1= use of consulting service
5) the participation in Producers' Organisations (0=NO; 1= YES)
6) Perception of possible risks deriving from wastewater use, such as:
    - worsening of product quality (0=NO; 1= YES)
    - danger to the health of farmers (0=NO; 1= YES)
    - danger of groundwater pollution (0=NO; 1= YES)

4. Results

4.1 Farm's and Farmer's characteristics and propensity to use reclaimed wastewater

Most farmers (60.5% of the sample) state they favour using reclaimed wastewater to irrigate crops. The propensity to use alternative water sources is related to their more extensive availability than conventional water (for 65% of farmers who are propense to use reclaimed wastewater), the possibility of reducing fertilisers due to the possible presence of organic residues in the recycled water (for about 48.5%), and the lack of other water sources (for about 42.6%).

About 70% of sample believe that adopting this resource requires adapting traditional irrigation systems and 64% think that using wastewater for irrigation can be dangerous. They think wastewater irrigation can be dangerous due to the possibility of accumulation of undesirable substances in the productions (63% of the sub-sample) and the deterioration of the quality of the products (44%). In addition, about 30% think using this water source may harm natural habitats and contribute to groundwater contamination.

The relationship between specific farms' and farmers' characteristics and the propensity to use wastewater for irrigation was verified through parametric tests: t-test and chi-square, according to the continuous/categorical variables. Tables 3 and 4 show the main results.

No significant differences exist in propensity of using wastewater in relation with the farm's size, the irrigated area, the seasonal water consumption, while propensity highly differ according to the age and the experience of the farmers. Pearson's Chi-Square (χ^2) and Cramers'V tests revealed a statistically significant association between education level and propensity to use wastewater. Farmers with a higher level of education and agricultural vocational training are more likely to use wastewater for irrigation if allowed by regional regulations (Table 4).

Moreover, the propensity to use wastewater was found to be significantly associated with the use of irrigation advisory services and the knowledge of current regulations on wastewater use. Further aspects refer to farmers' perceived concerns and issues regarding the quality of products irrigated with wastewater, the health of workers directly involved in the use of this water source and environmental impacts on the farm agroecosystem. Concerns about the deterioration of product quality resulting from wastewater use and the perception of environmental and health risks were found to be significantly (and inversely) associated with the propensity to use this resource.

Table 3. Analysis of mean differences by wastewater use propensity group: results of t-tests

Variable	*t-test Value*	*p-value*
Age (years)	11.001	<.001
Experience in the sector (years)	10.803	<.001
Utilized Agricultural Area (UAA)	-0.690	0.246
Irrigated UAA	-1.399	0.082
Water consumption (mc)	-0.330	0.371

Table 4. Analysis of the relationship between main discrete factors and wastewater use propensity: results of chi-square tests

Variable	χ^2	*p-value*	*Cramers' V*	*p-value*
Knowledge of legislation (No/Yes)	42.655	<0.001	0.505	<0.001
Income class (up to 28,000€ /28,000-50,000€ /more than 50,000 €)	8.746	0.013	0.229	0.013
Education level (higher/lower level)	77.502	<0.001	0.681	<0.001
Agricultural training (No/Yes)	37.603	<0.001	0.475	<0.001
Use of consulting services (No/Yes)	23.550	<0.001	0.376	<0.001
Participation to Producers' Organisations (No/Yes)	20.200	<0.001	0.348	<0.001
Products quality concern (No/Yes)	24.077	<0.001	-0.380	<0.001
Groundwater pollution concern (No/Yes)	17.336	<0.001	-0.322	<0.001
Workers' health concern (No/Yes)	38.507	<0.001	-0.480	<0.001

4.2 Factors affecting the propensity to use wastewater

The logit model estimates the impacts of selected variables on the propensity to use wastewater for irrigation. The results of the model are presented in Table 5. The value of the likelihood ratio chi-square is 40.62 and indicates the model's goodness of fit. The accuracy of the model was further supported by the area under the ROC curve, which was equal to 0.9499, suggesting a high discriminatory power in distinguishing between the positive and negative classes. The classification matrix employed to evaluate the model's performance indicated an overall accuracy of 86.2%, with a sensitivity of 89.1% and a specificity of 81.8%. These results highlight a well-balanced classification performance, demonstrating the model's considerable precision in correctly predicting both the propensity and the non-propensity to use treated wastewater.

As expected, the level of education, knowledge of the legislation, and participation in Producers' Organisations are found to affect farmers' propensity to use wastewater positively. On the contrary, the likelihood of using wastewater decreases if farmers are concerned about the quality of products, the workers' health, and groundwater pollution, and the larger the farm's size. As already underlined, the effects of firms' size are rather controversial, and this factor can favour or hinder the adoption of new practices/products according to the innovation characteristics and the action of other motivational or socio-economic factors. In our study the farm's size has a negative effect. This finding aligns with previous studies such as Läpple and Van Rensburg (2011) and Khaledi et al. (2010), suggesting that smaller farms may have more flexibility to implement new practices and organisational and managerial changes can be more complex when the size increases.

The odds ratios provide information on how much significant variables affect the propensity to use alternative water sources. A higher level of education leads to more than a 9-fold increase in the likelihood of wastewater use. That confirms the relevance of formal education as a promoter of innovation adoption, which is consistent with previous studies (Abdulai et al., 2011; Azam and Banumathi, 2015; Siegrist and Cvetkovich, 2000). The degree of information and knowledge of reclaimed water regulations also showed a significant influence on the propensity to use wastewater. The knowledge of the regulation increases the likelihood of farmers to use wastewater by a factor of 3.5. Very relevant is the effect of participation in the Producers' Organisation, which increases the likelihood of wastewater use by about 5-fold. These findings underline how the integration of knowledge and the actions of specialised organisations and agents (Chatzimichael et al., 2014; Derwisch et al., 2016) encourage individuals to adopt new practices and technologies.

On the contrary, the current use of advisory services does not significantly affect the probability of adopting wastewater irrigation. Lastly, the signs of the coefficients related to concerns of market risks or health and pollution dangers are consistent with the relationships underlined in the literature (Sapbamrer and Thammachai, 2021; Woldetsadik et al., 2018). When farmers are concerned about the quality of products, workers' health or environmental issues, the propensity to use wastewater decreases by 76%, 90% and 87%, respectively. That highlights how such negative perceptions constitute significant barriers to adoption.

Table 5. Results of the logit model

Variables	**Coeff.**	**Std. error**	***p* value**	**[95% Conf. Interval]**		**Odds Ratio**
Utilised Agricultural Area	-0.122	0.004	0.024	-0.228	-0.001	0.987
Education level	2.286	0.605	0.000	1.099	3.472	9.835
Knowledge of legislation	1.272	0.511	0.013	0.269	2.275	3.568
Use consulting services	0.958	0.754	0.204	-0.523	2.437	2.606
Participation to Producers' Organisations	1.600	0.536	0.003	0.548	2.652	4.955
Products quality concern	-1.396	0.571	0.014	-2.515	-0.278	0.247
Workers' health concern	-2.304	0.599	0.000	-3.479	-1.130	0.099
Groundwater pollution	-2.028	0.685	0.003	-3.373	-0.682	0.131
Log likelihood	-47.291					
LR chi-square	40.62 ***					
Average VIF value	1.27					

***$p < 0.01$

5. Discussion and Conclusions

The propensity of farmers to adopt new practices and/or new resources appears to be closely conditioned by several factors, whose combination is decisive for innovative choices and behaviour (Woldetsadik et al., 2018).

The logit model results highlight two main factors influencing farmers' propensity to use reclaimed wastewater as an irrigation resource.

The first group relates to the human and social capital. The awareness of the applicability of innovations and understanding of their characteristics influence farmers' propensity to apply new practices. This awareness depends on the ability to utilise information and is related to accumulated prior knowledge and absorptive capacity (Cohen and Levinthal, 1990). Human capital characteristics play a relevant role in this ability. Our results indicate that farmers with higher levels of education are more likely to utilise alternative water resources. This finding aligns with previous studies, which suggest that more educated farmers are better able to perceive the advantages associated with a specific innovation and can evaluate its convenience from multiple perspectives (Azam and Banumathi, 2015; Chams and García-Blandón, 2019). Moreover, an accurate knowledge of the legislation on wastewater reuse and its potential field of application positively impacts farmers' propensity. These factors play a significant and connected role. A higher level of education creates the conditions for farmers to feel the need to constantly update and inform themselves, positively influencing their attitudes towards proposed innovations (Abdulai et al., 2011; Siegrist and Cvetkovich, 2000). Similarly, the adoption of innovation is a function of the information flow from external sources and social networks. In line with previous studies (Abdulai et al., 2011; Micheels and Nolan, 2016), participation in networks, such as Producers' Organisations, can facilitate the transfer of information and knowledge and enhance the adoption of new practices.

Our study did not find any significant effect of current advisory services and technical support on the likelihood of using wastewater. This result seemingly contradicts previous literature, which indicates that support services are effective channels for information transfer and sharing (Matuschke et al., 2007; Pannell et al., 2006), and promote the adoption of innovative and/or unfamiliar practices and products (Chuang et al., 2020; Métouolé Méda et al., 2018). Indeed, the role of technical support warrants further investigation to understand the proper functions the consultancy system actually plays for farms, the types and objectives of services it offers, and the intensity of interactions.

A second key factor in adopting innovative practices is the risk that farmers associate with implementing new methods. Depending on the specific characteristics of the innovation, the risks can concern multiple areas (market, health, and the environment) (Garcia et al., 2024). When there is no complete understanding of how new practices impact these areas, farmers' decisions are primarily based on their beliefs. Consequently, risk perceptions can act as significant barriers to using alternative water resources. Our results indicate that concerns about product quality, workers' health, and groundwater contamination negatively affect the willingness to use wastewater. This finding is consistent with previous studies (Deh-Haghi et al., 2020; Keraita et al., 2008; Woldetsadik et al., 2018). Human and social capital, as well as risk perception, are closely linked, and risk perception depends on access to information and innovation-specific knowledge (Dolnicar et al., 2009; Egri, 1999; Vignola et al., 2013). Higher levels of acceptance of innovations come from a greater understanding of their benefits, which reduces the perceived risk and increases trust in the new (Mankad et al., 2012; Siegrist and Cvetkovich, 2000; Yanakittkul and Aungvaravong, 2020).

Consistent with the findings of Rizzo et al. (2023), the adoption of innovative agricultural practices is driven by education and training. Indeed, this factor serves as the starting point for implementing changes in production practices and management, enabling farmers to gain in-depth knowledge of the practices in question and their effects. Simultaneously, this increases confidence in the innovation and significantly reduces the perception of associated risks (Dolnicar et al., 2011). Moreover, technical support can be important and indispensable in reducing the uncertainty associated with new practices, enhancing expertise, and ensuring their proper implementation.

Therefore, this study emphasises the need for an integrated approach. It should combine information and technical training interventions to raise farmers' awareness of the impacts and potential uses of alternative water sources and to help overcome their perceived barriers. The adoption of wastewater reuse practices demands more efficient information channels that provide accurate and current knowledge of the local context, national and European regulations, quality standards for reusing purified water, and the policy measures in effect at the regional level. Further research is needed to explore how targeted training programmes and communication strategies can minimise barriers linked to risk perception, thereby aiding farmers' adoption of innovative practices.

In conclusion, this paper offers a comprehensive overview of the factors influencing the adoption of innovative irrigation practices in the agricultural setting of Basilicata. Although this study focuses on a limited geographical area, it offers some valuable insights into aspects that need to be strengthened to ensure the effective and safe use of reclaimed wastewater, thereby promoting the sustainable use of water resources. Two main limitations of the work can be underlined. First, it does not address the issue of the tariff system and its effects on farmers' propensity to use different water resources. Secondly, the analysis was focused on the propensity to introduce wastewater irrigation, regardless of necessity issues. Indeed, factors affecting the likelihood of using unconventional waters could be different if the farmer has to use reclaimed wastewater due to drought and a lack of freshwater or because of the expected effects.

APPENDIX A

Table 1A. Factors from literature influencing innovation adoption

Factor	Authors	Influence on innovation adoption	Empirical model employed
Age	Al-Shenaifi et al., 2017	YES	Spearman's Correlation.
	Giovanopoulou et al., 2011	YES	Regression and Heckman's Specification.
	Métouolé Méda et al., 2018	YES	Multinomial Logit.
	Chatzimichael et al., 2014	YES	Probit.
	Azam & Banumathi, 2015	YES	Logit.
	García-Cortijo et al., 2019	YES	Linear Regression.
Experience	Ullah et al., 2020	NO	Multinomial Logit.
	Muema et al., 2018	YES	Probit – Heckman's Specification.
Education Level	Azam & Banumathi, 2015	YES	Logit.
	Pradhan et al., 2017	YES	Linear Correlation and PCA.
	Dolnicar et al., 2011	YES	Regression.
	Chatzimichael et al., 2014	YES	Probit.
	Siegrist & Cvetkovich, 2000	YES	Correlation Analysis.
	Michetti et al., 2019	YES	Non-Parametric Analysis - CHAID.
	Deh-Haghi et al., 2020	YES	Probit.
	Kazeem et al., 2017	YES	Probit.
Gender	Ward et al., 2016	YES	Logit.
	Druschke & Secchi, 2014	YES	Spearman's Correlation.
	Sodjinou et al., 2015	YES	Probit.
	Shange, 2015	NO	Logit.
	Serote et al., 2021	YES	Probit.
	Neway & Zegeye, 2022	YES	Logit.
Income	Lasch et al., 2007	YES	Multiple Regression.
	García-Cortijo et al., 2019	YES	Linear Regression.
	Barnes et al., 2019	YES	Multinomial Logit (MLN).
	Grabowski et al., 2016	YES	Multinomial Logit.
	Zeweld et al., 2018	YES	Multivariate Probit.
	Sriwichailamphan & Sucharidtham, 2014	YES	Logit.
Farm Size	Läpple & Van Rensburg, 2011	YES	Multinomial Logit.
	Dalla Corte et al., 2015	YES	Logit.
	Liu et al., 2019	YES	Multinomial Logit.
	Pradhan et al., 2017	YES	Linear Correlation and PCA.
	Chatzmichael et al., 2014	YES	Probit.
	Haghjou et al., 2014	YES	Logit.
Information and Knowledge	Micheels & Nolan, 2016	YES	PCA and Poisson Regression.
	Matuschke et al., 2007	YES	Probit.
	Bjerke & Johansson, 2022	YES	Logit.
	Chuang et al., 2020	YES	Multiple Regression.
	Dhraief et al., 2019	YES	Logit.
Risk Perception	Ndunda & & Mungatana, 2013	YES	Logit.
	Dolnicar et al., 2011	YES	Regression.
	Mariano et al., 2012	YES	Binary Logit and Poisson Regression.
	Viesi et al., 2017	YES	PCA.
	Liu, 2013	YES	Regression.
	Yanakittkul & Aungvaravong, 2020	YES	PLS-SEM.
	Sabbagh & Gutierrez, 2023	YES	PLS-SEM.

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Chapter 4

When water returns to the field: Perceived risks in the agricultural reuse of wastewater

Preamble: Risk perception as a determinant of wastewater adoption in agriculture

The reuse of reclaimed wastewater in agriculture represents an eco-innovation of growing relevance in the contemporary global context, marked by increasing water scarcity exacerbated by climate change and the rising frequency and intensity of extreme weather events. Although technical research and applied advances primarily focus on technological, infrastructural and regulatory feasibility, more recent literature recognises that adoption of this practice depends to a significant extent on economic, perceptual, informational and institutional factors operating at both individual and collective levels. As highlighted in Chapter 3, the first empirical study conducted on a sample of farmers in Basilicata showed the crucial role of risk perception as one of the main determinants of willingness to adopt treated wastewater for irrigation. In particular, it emerged that the perception of specific risks, such as those related to human health, environmental pollution and the deterioration of agricultural product quality, significantly reduces farmers' willingness to implement this practice, even under objectively critical conditions of water scarcity.

This finding reflects a broader pattern confirmed by the international literature: risk perception has frequently been incorporated into behavioural studies in the agricultural sector, both as an integrated component of existing theoretical models (Venkatesh & Balia, 2008; Giovanis et al., 2012; Karimi & Ataei, 2023; Savari et al., 2025) and as an independent factor (Antwi-Agyei et al., 2016; Deh-Haghi et al., 2020), examined in relation to specific innovations and practices. However, the literature still shows significant gaps in understanding the multidimensional structure of risk perception associated with wastewater reuse, as well as the mechanisms through which it influences farmers' actual behaviour. Chfadi et al. (2021) stressed the importance of distinguishing between the perception of contamination risk (more rational in nature, linked to concerns about pathogens or chemical substances) and other perceptual dimensions rooted in psychological reactions, such as feelings of disgust and deeper cultural considerations. These authors observed that such dimensions may vary significantly in response to different informational stimuli. Alsa'di et al. (2024) confirm the complexity of this issue, identifying the multidimensional nature of risk perception as a strong barrier to the acceptance and use of wastewater.

Further research addresses risks related to the quality and safety of wastewater used for irrigation: Deh-Haghi et al. (2020) demonstrated that acceptance keeping it high only when quality and safety are perceived as adequate, whereas willingness to use wastewater declines sharply otherwise, showing that economic benefits are subordinate to perceived safety. Dona et al. (2023) likewise highlighted the heterogeneity of risk perception, showing that it varies significantly according to crop type and proximity to direct human consumption: ornamental and fodder crops face less resistance than food crops, following a perceptual gradient whereby lower perceived contact with water corresponds to lower perceived risk. Maina et al. (2020), however, found that adoption may occur even in the presence of high perceived risks, suggesting that the relationship between risk perception and behaviour is not linear but mediated by factors such as the availability of alternatives and economic pressure. Conversely, Karimi and Ataei (2023) emphasised that the lack of models explicitly and systematically linking social risk perception (health-related, environmental and ethical, as analysed in their study) to farmers' actual behaviour represents a critical gap in the literature.

Overall, these studies indicate that risk perception has a complex and multidimensional structure that is still addressed in a fragmented manner. This chapter aims to fill this gap through a structured analysis of the multiple dimensions of risk perception associated with wastewater as an eco-innovation. The study identifies and synthesises the different risk perceptions emerging from the data, and then constructs homogeneous segments of adult adopting farmers characterised by distinct profiles in terms of risk perception, socio-demographic characteristics and orientation towards innovation. This approach makes it possible both to describe perceptual heterogeneity within a sample of the agricultural population of Basilicata and to identify which combinations of perceived risk dimensions, farm characteristics and individual attitudes generate the profiles most receptive or, conversely, most resistant to adoption of the practice.

From Risk to Resource: Understanding Farmers' Perceptions of Wastewater Reuse

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Abstract

The use of treated wastewater in agriculture represents an innovative and sustainable strategy to addressing the growing issue of water scarcity. This study examines farmers' perceptions of risk associated with the reuse of this resource in a context of limited water availability and climate change. The work was based on a field survey of a sample of farmers in Southern Italy. Collected data on socioeconomic characteristics and information on farmers' experiences and attitudes toward the use of wastewater in irrigation were analysed using multivariate techniques. Through principal component analysis (PCA), three main dimensions of perceived risk have been highlighted, related to environmental, market and health concerns. Based on these dimensions, cluster analysis has identified five distinct farmer profiles, differentiated by the level and nature of risk perception, degree of regulatory knowledge, and farmers' openness to innovation. The findings indicate that risk perception is associated with demographic factors, including age and level of education, and is positively influenced by knowledge and training. The study emphasises the importance of targeted and differentiated information and training strategies in overcoming reluctance and promoting broader and more informed adoption of wastewater reuse in agriculture, thereby contributing to more resilient and sustainable agricultural production.

1. Introduction

Although the use of treated wastewater has already been tested in various agricultural contexts in Europe and developing countries (Minhas et al. 2018; Colella et al. 2021), its large-scale adoption is still limited by multiple factors (Tariq et al. 2023; Younas et al. 2021).

Firstly, its use is restricted by the regulatory framework, which varies significantly from one country to another depending on water emergency conditions and the availability of conventional water resources (Ortega-Pozo et al. 2022). More recently, Directive (EU) 2024/3019 introduced further technical specifications for wastewater treatment, identifying stringent safety standards and defining the responsibilities for the costs of treatment. Secondly, where the use of treated wastewater is guaranteed, farmers' perception of risk plays a decisive role in its diffusion (Karimi and Ataei 2023; Garin et al. 2021; Ahmmadi et al. 2021). The benefits associated with the use of this resource have been confirmed by numerous studies (Poustie et al. 2020; Drechsel et al. 2022). They include contributions to productivity, nutrient supply, and the consequent savings on fertilisers, as well as reduced freshwater use. Nevertheless, several critical issues may hinder its adoption by farmers. Concerns persist regarding health and safety, the quality of agricultural products produced with wastewater, and the potential accumulation of contaminants in soil and groundwater (Ofori et al. 2021; Mishra et al. 2023). Indeed, despite current regulations imposing strict quality requirements for the reuse of water in agriculture, the health risks for agricultural producers and consumers can be significant (Scott et al. 2009; Dickin et al. 2016; Natasha et al. 2023) and the potential presence of pathogens and heavy metals can compromise the quality and safety of agricultural products (Jiang et al. 2022; Drechsel et al. 2022; Trotta et al. 2024), limiting their marketability and causing potential damage to ecosystems (Daughton and Ternes 1999; Mishra et al. 2023; Wang et al. 2021), alterations to natural habitats and soil contamination (De-Los-Ríos-Mérida et al. 2021; Poustie et al. 2020).

Moreover, socioeconomic and psychological factors can also act as barriers to the adoption of wastewater reuse (Msaki et al. 2022; Karimi and Ataei 2023). Several studies have highlighted how risk perception varies according to age, level of education, and work experience among farmers (Msaki et al. 2022; Serote et al. 2021; Sánchez-Cañizares et al. 2022). Younger farmers with a higher level of education tend to be more open to innovations and the use of new water management techniques (Serote et al. 2021; Sánchez-Cañizares et al. 2022). Similarly, greater environmental awareness is associated with a greater propensity to experiment with sustainable solutions (Msaki et al. 2022; Karimi and Ataei 2023), including the reuse of treated wastewater.

The primary objective of our research is to determine whether and how farmers' perception of environmental, health, and market risks influences their propensity to use treated wastewater for irrigation purposes. Although the literature already offers relevant contributions on the topic of risk perception related to the use of unconventional water resources (Karimi and Ataei 2023; Garin et al. 2021; Ahmmadi et al. 2021; Ofori et al. 2021; Manganiello et al. 2024; Sohail et al. 2021), systematic analyses exploring the correlation between subjective perceptions and the socio-demographic and attitudinal characteristics of farmers are still limited and the identification of different farmers' profiles based on human capital characteristics and behavioural aspects is still poorly explored in the literature (Hyland et al. 2016; Kropf et al. 2024). In-depth analysis of these dimensions is crucial to support the development of public strategies that effectively promote the widespread and informed adoption of innovative agricultural practices.

The present work is based on a survey of a sample of farmers in Basilicata, a Southern Italian region that is particularly vulnerable to the effects of drought. In recent years, water scarcity has exacerbated the difficulties faced by the agricultural sector in this region, raising concerns about water availability and the sustainability of irrigation practices. The study aims to address two main questions:

1) How does risk perception affect farmers' decisions to use treated wastewater?

1) Can we relate the perception of risk and the propensity for innovation to specific farmers' profiles?

Answering these questions can provide valuable insights for developing more effective and targeted water resource management policies.

The work is articulated as follows. After a literature review on risk perception (Section 2), Section 3 describes the data and methods used in the study, and Section 4 presents the results. Section 5 presents the main conclusions of the work and their implications for strategies to implement sustainable water management.

2. Innovation in agriculture and risk

Innovations in the agricultural sector encompass the introduction of new products and production process (Montes de Oca Munguia et al. 2021). They can include the use of advanced inputs, such as fertilisers with innovative formulations (Avane et al. 2022) and genetically improved cultivars (Abdul-Rahaman et al. 2021), as well as the use of alternative resources, including unconventional water sources (Elmahdi 2024). Moreover, over the last few years, there has been a gradual shift from conventional agronomic practices to highly efficient and more environmentally sustainable techniques (Zheng et al. 2022), with a particular focus on cultivation operations and irrigation methods (Karunathilake et al. 2023; Narayanamoorthy and Jothi 2019).

The adoption of such innovations is not always immediate or widespread. In agriculture, the main barriers to adoption lie, on the one hand, in the high costs of acquisition, management and maintenance (Sandberg and Aarikka-Stenroos 2014; Sidibé et al. 2021) and, on the other hand, in the lack of knowledge about all the direct and indirect effects of their use (Chen et al. 2022; Ahsan et al. 2022). It is widely recognised that farmers tend to adopt an innovation only when it is perceived as necessary and beneficial from both economic and operational perspectives (Rogers 2003; Kaine and Wright 2022). It is therefore essential that the innovation offers concrete benefits compared to the solutions currently in use, benefits that can be derived from reliable scientific evidence and/or positive experiences with previous innovations, whether their own or those of others (Lubell et al. 2011; Thompson et al. 2019; Kaine and Wright 2022). In this regard, the attributes of observability and understandability outlined by Rogers (2003) in his Diffusion of Innovations Theory also play a crucial role in determining the behaviour of acceptance and adoption of an innovation.

The ability to observe the results of an innovation facilitates a more informed assessment of its advantages and disadvantages (HuiJts et al. 2019). Similarly, a greater understanding of the functioning and mechanisms underlying an innovation increases its accessibility and likelihood of future adoption (Scovell et al. 2022). Kang and Park (2011) highlighted how the combination of awareness and knowledge increases perceptions of an innovation's performance and, consequently, increases its acceptance.

Conversely, a deficit in these attributes can generate uncertainty or amplify perceptions of possible risks associated with innovations (Slovic 1987; Huijts et al. 2019; Scovell et al. 2022). As in other sectors, risk and uncertainty are key determinants in decision-making and directly affect the rate of innovation adoption in agriculture (Feder 1980; Shapiro et al. 1992). It has been highlighted that the combined action of individual risk perception and the farmer's attitude towards risk plays a crucial role in defining the propensity to adopt (Ghadim et al. 2005; Li et al. 2021). About risk perception, Slovic (1987) emphasised its multiple determinants by developing the so-called psychometric paradigm: cognitive factors, emotional factors, utilitarian assessments and shared

values all play a role in defining individual perceptions of risk, contributing in a significant and differentiated way (Ghadim et al. 2005; Hellerstein et al. 2015).
According to Rogers (1975), perceived risk is the subjective cognitive assessment of two dimensions: the severity of the risk and individual susceptibility. Perceived severity expresses the level of seriousness attributed to a given event, while perceived susceptibility represents the degree to which individuals consider themselves exposed or vulnerable to that event. Further studies have analysed risk perception as applied to the adoption of innovations, confirming that this concept is highly subjective and complex, shaped by predominantly intuitive and emotional cognitive processes rather than rational and conscious (Greiner et al. 2009; Dessart et al. 2019). Moreover, risk perception is not a static element, but rather varies according to the socioeconomic and cultural context, as well as the type of innovation being considered (Eitzinger et al. 2018; Fahad and Wang 2018; Dessart et al. 2019). Therefore, the decision-making process in conditions of actual or potential risk is dynamic: before actual use, farmers form preconceptions about the economic and productive effects of innovation (Greiner and Gregg 2011), but practical experience allows for a gradual reworking of initial beliefs thanks to the integration of specific and contextualised knowledge (Ghadim et al. 2005; Alam et al. 2024). In this context, learning and the possibility of gradual experimentation would play a central role in reducing uncertainty and redefining perceived risk (De Buck et al. 2001; Greiner et al. 2009; Pfeiffer et al. 2021).
Caswell and Zilberman (1986) found that the availability of reliable information and targeted training programmes are key factors in reducing risk perception, as they improve skills related to the use of innovation, clarify expected performance and help reduce perceived complexity (Kumar et al. 2018; Pfeiffer et al. 2021). Several empirical studies have shed light on the role of different perceived risks in the adoption of innovative agricultural practices. They highlighted how socioeconomic, motivational and contextual factors lead the decision to invest in those innovations.
Some of these studies are reported in Table 1B in the Appendix, which summarises, for each analysed innovation domain, the dimensions of perceived risks considered and the factors that can facilitate or inhibit their adoption. Risk perception, combined with an individual's risk attitude, determines the propensity to adopt an innovation. The concept of risk attitude integrates several aspects relating to psychology, neuroscience and behavioural economics. It is related to individual preferences and personality traits, reflecting the extent to which individuals find perceived risk attractive or unattractive and consequently prefer to face or avoid it (Figner and Weber 2015). According to the psychological approach, risk attitude is the result of individual characteristics, such as age, education, gender, but also the domain and the cultural and economic contexts in which decision making applies (Frey et al. 2023; Raftery et al. 2001; Antle 1987).
Frey et al. (2023) distinguish between two components of risk preference: a general and a domain-specific (e.g., health, finance) dimensions, referring to a general and multiple narrow traits. The domain-specific traits can be related to different risks and benefits people perceive in each domain. Cultural values, such as individualism and collectivism, can shape risk attitudes; however, the patterns can vary by context and measurement approaches, and opposite hypotheses can support the relationship between values and risk preferences (Rieger et al. 2015).
Moreover, Rieger et al. (2015) found significant cross-country differences in risk aversion levels, influenced by economic conditions and cultural factors such as individualism and uncertainty avoidance. Social norms exert powerful effects in modulating risk-taking behaviour, often amplifying or attenuating risk preferences depending on cultural context, gender, socioeconomic

status, and situational factors such as group presence or social comparison. Studying the process of technology adoption by cassava farmers in Ghana, Dadzie et al. (2022) found that social networks significantly influence the risk attitudes. Specifically, social interactions, along with a high degree of trust among farmers in their social networks, tend to reduce risk aversion and affect risk attitude, either because farmers respond to social stimuli or because networks act as information sources, thus reducing uncertainty.

3. Data and Methods

3.1 Study area and data

Data were collected through a field survey on a sample of irrigated farms located in the Basilicata region, specifically in the Metapontino area (Figure 1), the centre of the region's intensive irrigated agriculture. Since 2022, in line with the climatic trends observed in Southern Italy, in Basilicata, the frequency and intensity of extreme drought events have increased significantly (Bentivenga and Piccarreta 2023; Istat 2025), with substantial repercussions on agricultural production (Istat 2024). According to ISTAT data (2024), in 2022, the agricultural sector suffered a 0.7% decrease in production volume, associated with reductions in cultivated land and labour inputs. The combination of water scarcity and infrastructure inefficiencies (e.g. leakages in distribution networks) is a critical factor for crop yield stability, exacerbating the vulnerability of farms in areas that are already structurally disadvantaged (Ingrao et al. 2023). A substantial weight of irrigated agriculture characterises the Metapontino area and, therefore, is particularly exposed to these critical issues. Although local farmers have adopted mitigation strategies – such as the construction of wells and tanks for rainwater collection, the implementation of micro-irrigation systems and the adoption of advanced water management technologies (Massari et al. 2021) – these interventions, while effective in the short term, do not guarantee systemic resilience in the medium to long term. Therefore, exploring alternative solutions such as the reuse of treated wastewater is a viable option for the sustainability of the regional agricultural sector.

Figure 1. Study Area - Basilicata Region and Metapontino Area

A semi-structured questionnaire was administered to a sample of farmers in Basilicata who own irrigated farms. The survey was conducted between July and December 2024, through direct interviews carried out in collaboration with Producer Organisations (POs) active in the area, or via digital administration using the Google Forms platform. The final sample included 200 farms. The questionnaire was divided into four thematic sections, designed to cover the aspects relevant to the analysis comprehensively:

- Human capital: Socio-demographic variables (age, level of education, agricultural training) and information on the farm's income.
- Farm characteristics and water management: Structural data (area, crop patterns, infrastructure) and information on irrigation practices, with a focus on the motivations behind the adoption of innovative technologies.
- Knowledge: Farmers' level of knowledge and awareness of wastewater reuse regulations (e.g. EU Regulation 2020/741) and water quality requirements for the irrigation of food crops.
- Perception of risks associated with wastewater reuse: Farmers' concerns about the use of treated wastewater, including the accumulation of contaminants in soils, the risk of clogging of equipment, the potential compromise of product quality, and impacts on human and environmental health. This last section of the questionnaire was also aimed at collecting information on farmers' attitudes toward innovation.

Tables 1 and 2 report the main socioeconomic characteristics of the sample. The sample accounts for 7,308 hectares of total Utilised Agricultural Area, 80% of which is irrigated. The average farm size is 36.5 hectares, but there is significant variability, with farms ranging from 2 to 350 hectares. Approximately 50% of farms are under 25 hectares. The average annual water consumption for irrigation is 3,760 m³ per hectare, with variability depending on the crops and their respective water requirements. Almost all farms (98%) are specialised in fruit and vegetable production, and only a small proportion of the sample is oriented towards the cultivation of other species, such as maise, sunflowers and sorghum.

Table 1: Descriptive statistics of the sample

Variables	**Mean**	**Standard deviation**
Utilised Agricultural Area (hectares)	36.5	40.6
Agricultural irrigated area (hectares)	29.2	32.5
Age (years)	51.4	17.0
Irrigation water quantity (m^3/ha)	3,758.5	1,251.6
Farm management experience (years)	21.8	15.7

Table 2: Frequency distributions of main socio-economic characteristics of the sample

Variable	Frequency
Educational level	Primary = 17% Lower secondary school = 25% Higher secondary school = 33.5% [illegible]
Professional training during last 3 years	No = 56% Yes = 44%
Income level	Up to 15,000 euro = 6.5% From 15,000 to 28,000 euro = 18.5% From 28,000 to 50,000 euro = 33% More than 50,000 euro = 42%
The farm is the main source of income	No = 16.5% Yes = 83.5%
Farmer is full time employed on farm	No = 33% Yes = 67%

A widespread concern among farmers is the future availability of water resources: 83% of the sample state they are alarmed by the effects of climate change and the increasing frequency of droughts, predicting a progressive reduction in available water resources. In response to these critical issues, 87% of respondents have adopted drip irrigation systems with the aim of optimising water use efficiency and reducing consumption. However, structural issues persist regarding the efficiency of local water sources. The primary source of water is from irrigation consortia, and 83% of the water consortia users had problems related to limited water availability and inefficiencies in its distribution. That makes 61% of the sample in favour of using wastewater for irrigation, mainly because it provides access to greater volumes of water than conventional sources and offers potential agronomic benefits linked to reduced fertiliser use.

The last section of the questionnaire was dedicated to identifying the risks that farmers associate with the use of treated wastewater and their attitudes towards innovation. A higher percentage of farmers perceive the accumulation of undesirable substances and market difficulties for products irrigated with wastewater as relevant risks (Table 3). Just over a third of farmers fear damage to irrigation systems. The least perceived risks are groundwater pollution (18% of farmers surveyed) and increased soil salinity (21% of the sample). As far as innovativeness is concerned, the attitude of farmers towards innovation was investigated by adapting Rogers' definition of innovators, early adopters, early majority, late majority, and laggards. Therefore, farmers were asked how they feel about innovation, whether they are attracted to new technologies and are prompt to invest to be at the forefront or only decide to adopt a new technology when it is already established and widespread. The sample's distribution by the innovation attitude is reported in Table 4. Only 10% of the sample can be classified as "innovators", but about one-third of the surveyed farmers feel themselves as "early adopters".

Table 3: Frequency distribution of risk perception items

Perceived Risks	Frequency No	Yes
Damages to irrigation system	65%	35%
Unwanted substances accumulation	61%	39%
Market difficulties for wastewater irrigated products	61.5%	38.5%
Worsening of product quality	71%	29%
Alteration of natural habitats	79.5%	20.5%
Groundwater pollution	82%	18%
Increase in soil salinity	79%	21%
Consumers' health risks	72%	28%
Workers' health risks	77.5%	22.5%

Table 4: Frequency distribution of surveyed farmers by innovation attitude

Attitude toward innovation	*Frequency*
I am attracted to new technologies, I am willing to invest more to be at the forefront, and I am also willing to accept when an innovation proves to be a failure (innovators)	10%
I am interested in new technologies if I think they can bring real advantages or benefits (early adopters)	32%
I am interested in new technologies, but I prefer to make sure that the innovation has real benefits or advantages before investing in it (early majority)	23.5%
I am wary of adopting a new technology. I only adopt a new technology when other people have already adopted it (late majority)	23.5%
I only decide to adopt a new technology when it is already established and widespread (laggards)	11%

3.2 Methods

The analysis of the collected data was divided into three steps. In the first phase, items related to the perceived risks associated with using wastewater for irrigation were analysed using a polychoric Principal Component Analysis. This approach enables the information from the initial variables to be summarised into a small number of components, allowing the latent structure of the data to be identified. The suitability of the data for this type of analysis was verified using the Kaiser-Meyer-Olkin (KMO) index, Bartlett's Sphericity Test and the variable-specific measure of sampling adequacy (MSA). To improve the interpretability of the components, a Varimax orthogonal rotation was applied. The second phase of the work involved conducting an exploratory analysis to investigate any relationships between components related to perceived risks, socioeconomic characteristics, attitudes towards innovation, and levels of knowledge on wastewater for irrigation. To this end, parametric and non-parametric statistical tests (t-tests, ANOVA, chi-square tests, and the Kruskal-Wallis test) were employed, depending on the nature of the variables. The third phase of the analysis aimed to identify different profiles of farmers based on their perception of risk. Therefore, the factor scores derived from PCA were used in a hierarchical cluster analysis applying the Ward's method. The choice of the number of clusters is derived from the analysis of the dendrogram and the ratio of variance between and within clusters. The characterisation of the groups was based on the centroid values and was further specified by examining the relationships between the groups and variables such as the level of knowledge of regulations, attitude towards innovation, and propensity to use wastewater for irrigation. Principal component analysis was conducted using the Psych package of the R software. All other analyses were carried out using IBM SPSS Statistics Version 30.0.

4. Results

4.1 Farmers' risk perception of wastewater uses for irrigation

By applying PCA on risk perception items, three components were extracted that explain 76.7% of the total variance. The meaning of the components can be derived from the matrix of factor loadings (Table 5), which reports the correlation between each original variable and each component, with higher values indicating a greater contribution to the component's explanation. The three components can be interpreted as different dimensions of the perceived risk associated with the use of wastewater in agriculture: perceived risk related to the accumulation of undesirable substances and the quality of the final products (Component 1); perceived environmental risk, related to the contamination of soil and natural ecosystems (Component 2); risk for the health of agricultural workers and consumers (Component 3).

Table 5. Factor loadings matrix

Perceived risk items	Component 1	Component 2	Component 3
Unwanted substances accumulation	0.826		0.413
Damages to irrigation system	0.829	0.242	0.154
Groundwater pollution	0.470	0.695	
Increase in soil salinity		0.728	0.290
Alteration of natural habitats	0.107	0.780	0.244
Worsening of product quality	0.546	0.544	0.251
Consumers' health risks	0.224	0.327	0.889
Workers' health risks	0.298	0.200	0.883
Explained variance	25.5%	26.5%	24.6%

KMO = 0.75; Bartlett's test = 20.366, p-value = 0.004832

Risk perception increases with age, with statistically significant differences between age groups. More specifically, farmers over the age of 55 have significantly higher levels of risk perception for all three risk dimensions considered. Furthermore, information and knowledge play an important role. In all three risk areas, farmers who are not informed about the regulations on wastewater use report significantly higher levels of risk perception than farmers who have some or full knowledge. Similar results emerged in relation to level of education and participation in professional agricultural training courses, suggesting that access to information and formal education reduces levels of risk perception.

Risk perception is closely linked to openness to innovation. More specifically, farmers with more innovative attitudes (innovators and early adopters) tend to perceive risks to a lesser extent than those with less innovative attitudes (Table 6). A comparison of the distributions of component values across different categories of innovators reveals statistically significant differences in relation to all three dimensions of perceived risk (Table 7). Pairwise comparisons better specify these relationships. The values of perceived accumulation risk vary significantly across categories of innovativeness. The differences are less pronounced when environmental and health risks are considered. They are significant only when comparing extreme groups of innovativeness, while in the intermediate categories differences are mostly not statistically significant (Table 8).

Finally, the same three risk components were related to farmers' propensity to use wastewater for irrigation. Farmers who are in favour of using wastewater demonstrate a significantly lower perception of risk than those who do not declare themselves willing to use it (Table 9). These findings are consistent with those reported in the literature (Dessart et al., 2019).

Table 6. Descriptive statistics of components values by innovativeness category

Perceived Risk	Innovativeness category	Mean	Std. Deviation
Accumulation Risk (Component 1)	Innovators	-0.6098	0.3424
	Early adopters	-0.3184	0.8126
	Early majority	-0.1539	0.9129
	Late majority	0.5441	1.0652
	Laggards	0.6470	1.1228
Environmental Risk (Component 2)	Innovators	-0.4739	0.3351
	Early adopters	-0.3902	0.6290
	Early majority	0.2074	1.1374
	Late majority	0.2823	1.2110
	Laggards	0.5199	0.9514
Health Risks (Component 3)	Innovators	-0.3706	0.3837
	Early adopters	-0.3822	0.4453
	Early majority	-0.1127	0.9224
	Late majority	0.6758	1.3089
	Laggards	0.2460	1.2007

Table 7. Kruskall-Wallis test on differences of perceived risks' components by farmers' innovation attitude

	Kruskall-Wallis Statistic	p-value
Component 1: Accumulation Risk	36.572	<0.001
Component 2: Environmental Risk	20.523	<0.001
Component 3: Health Risk	20.133	<0.001

Table 8. Pairwise comparison of perceived risks' components by farmers' innovation attitude categories

Sample 1-Sample 2 Comparison	Component 1: Accumulation Risk		Component 2: Environmental Risk		Component 2: Health Risk	
	Statistic test	Mod. Sig.[a]	Statistic test	Mod. Sig.[a]	Statistic test	Mod. Sig.[a]
Innovators-Early adopters	-0.996	1.000	-0.073	1.000	0.424	1.000
Innovators-Early majority	-1.657	0.974	-1.797	0.724	-1.244	1.000
Innovators-Late majority	-4.229	**0.000**	-2.209	0.272	-2.222	0.263
Innovators-Laggards	-3.834	**0.001**	-3.032	**0.024**	-4.210	**0.000**
Early adopters -Early majority	-0.975	1.000	-2.400	0.164	-0.488	1.000
Early adopters -Late majority	-4.549	**0.000**	-2.972	**0.030**	-1.426	1.000
Early adopters -Laggards	-3.760	**0.002**	-3.715	**0.002**	-2.622	0.087
Early majority-Late majority	-3.328	**0.009**	-0.533	1.000	-1.200	1.000
Early majority-Laggards	-2.872	**0.041**	-1.770	0.768	-2.762	**0.058**
Late adopters - Laggards	-0.215	1.000	-1.344	1.000	1.005	1.000

Table 9. Descriptive statistics of components values by willingness to use wastewater for irrigation and Mann-Whitney test on differences results

Would you use treated wastewater for irrigation?	Accumulation Risk	Environmental Risk	Health Risk
No	0.513	0.422	0.494
Yes	-0.735	-0.269	-0.315
Mann-Whitney test	2590.5	3052.5	3016.5
Sig.	<0.001	<0.001	<0.001

Risk perception and farmers' profiles

Five groups were identified through the cluster analysis based on factor scores of the three dimensions of perceived risk. Table 10 shows the average values of the three components for each group. The box plots (Figure 2) illustrate the internal distribution of each cluster and help to characterise it better.

Table 10. Mean of Perceived Risk components by clusters

	Accumulation Risk	Environmental Risk	Health Risk	Number of cases
Cluster 1	-0.719	-0.370	-0.475	89
Cluster 2	1.206	-0.325	-0.692	38
Cluster 3	0.834	-0.742	1.564	25
Cluster 4	-0.138	2.258	-0.616	17
Cluster 5	-0.012	0.822	1.289	31

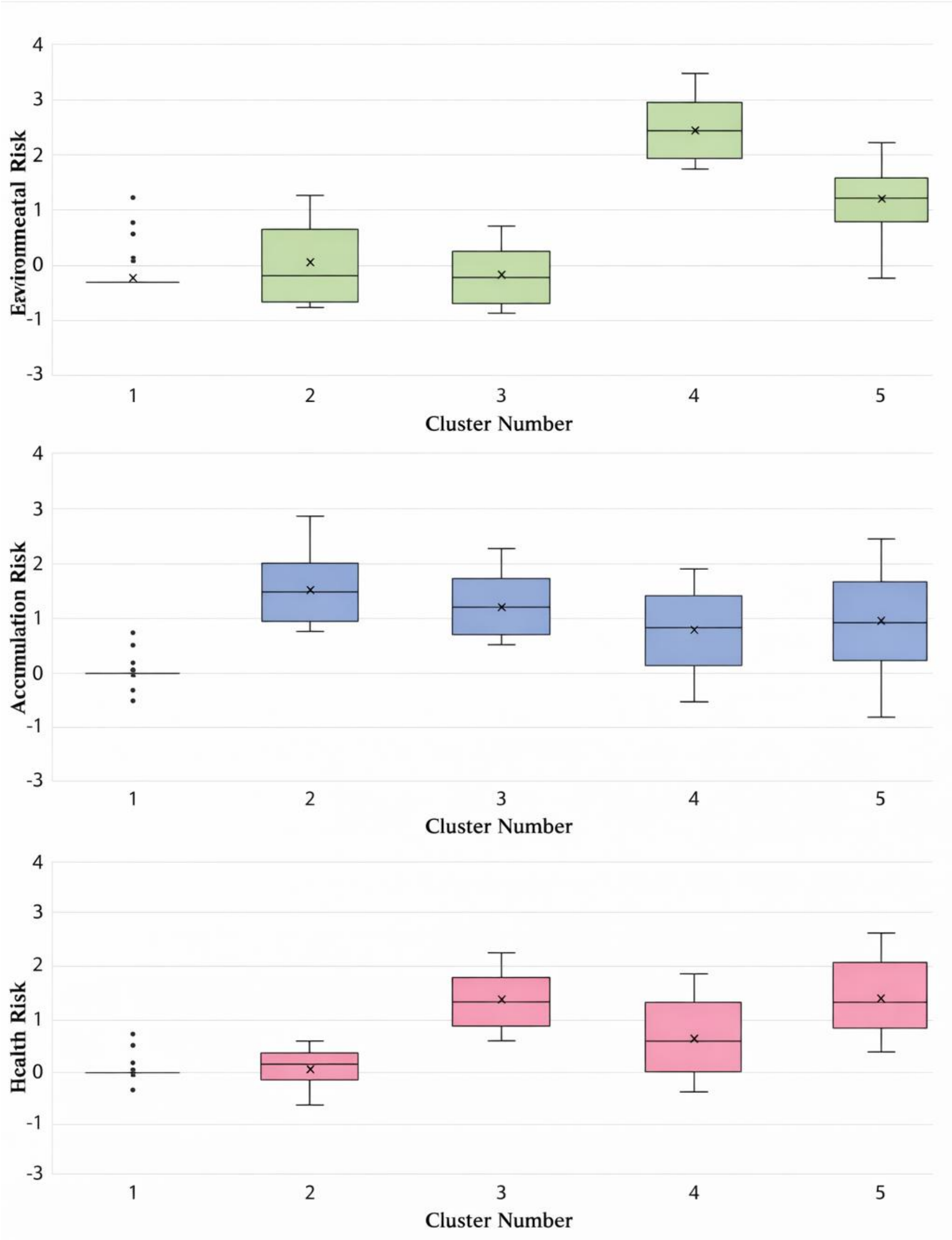
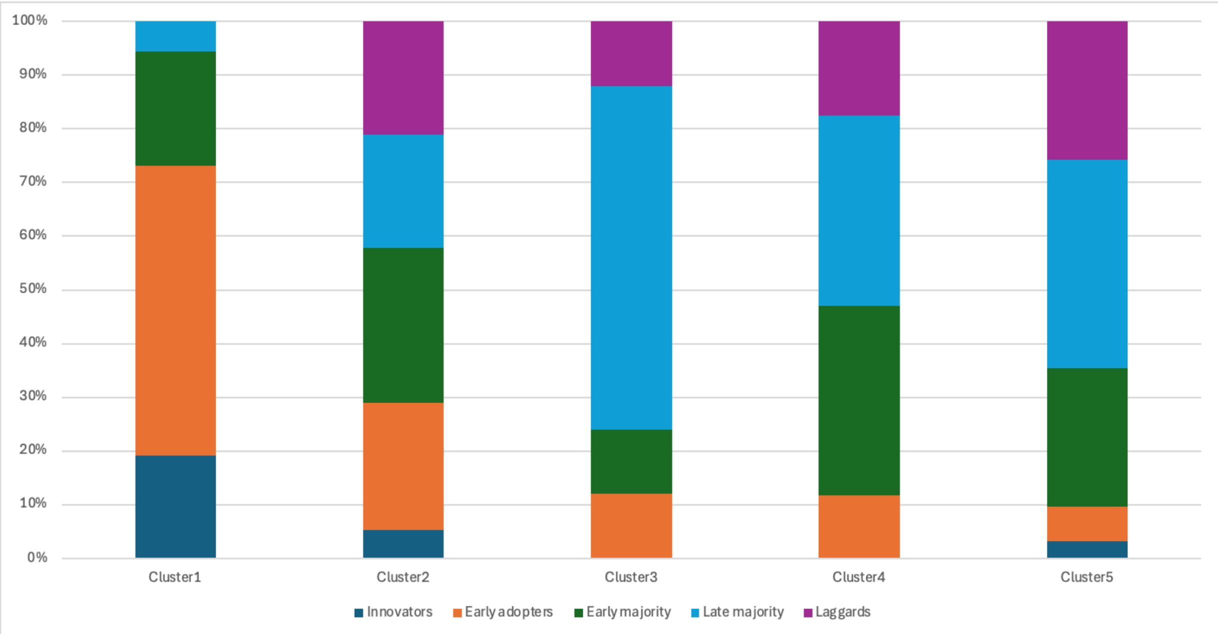


Figure 2. Distributions of risk perception components by clusters

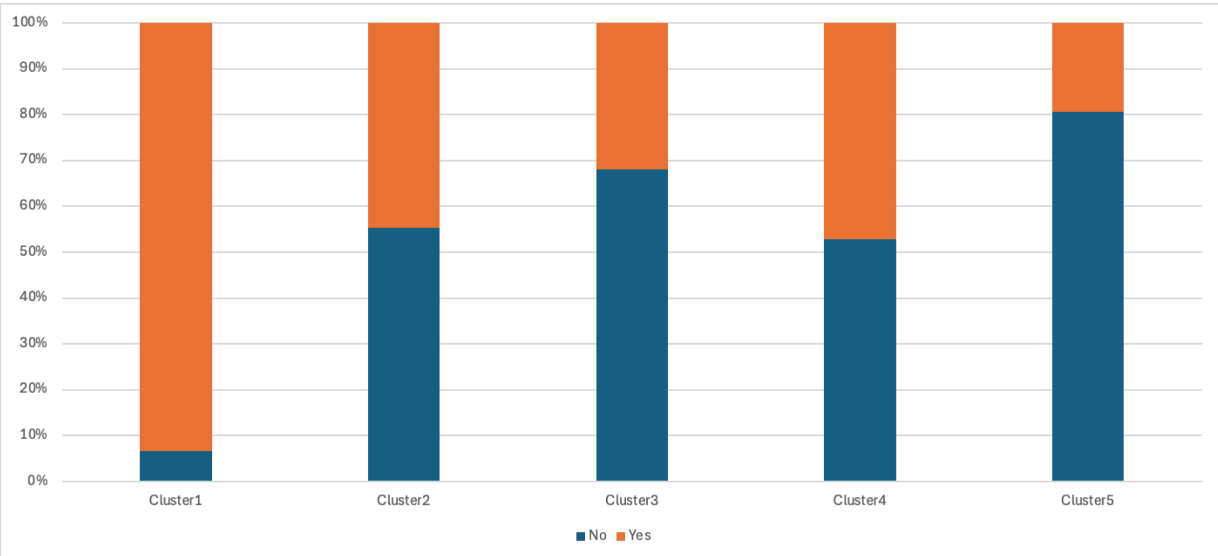
Cluster 1, which represents the largest group (44.5% of respondents), is characterised by a substantial internal homogeneity and a level of risk perception below the sample average for all dimensions analysed. Cluster 2 (19.0% of the sample) exhibits similar characteristics to those of Group 1 in terms of environmental and health risk perception. However, it differs from Group 1 in that it has a very high perception of accumulation risk, the highest value observed among all groups. This profile suggests a specific sensitivity to the accumulation of pollutants, compared to a less marked assessment of the other two risks. Cluster 3 (12.5% of cases) is characterised by a high perception of health risk, the highest among all clusters. Concern about the accumulation of unwanted substances is also high, while the value for environmental risk is negative. That could reflect greater attention to the direct consequences that the accumulation of unwanted substances can have on health, rather than environmental aspects. Environmental risk is particularly felt in Cluster 4, which represents the smallest group in terms of numbers (8.5% of respondents). It is generally associated with a low perception of health risk. This last aspect distinguishes it from Cluster 5 (15.5% of the sample), in which both environmental and health risks are particularly relevant. In contrast, the perception of accumulation risk is very differentiated within the group.

Regarding the attitude toward innovation and willingness to use treated wastewater for irrigation, Graphs 1 and 2 show the distribution of the farmers by group and clearly illustrate the differences between groups. More specifically, Group 1 comprises farmers who are more open to innovation and are also more willing to utilise wastewater. In contrast, groups 3 and 5 exhibit a lower propensity to innovate and are also more cautious in the use of wastewater. In general, there is a statistically significant relationship between group membership and these two elements (Attitude toward innovation by groups: $\chi^2 = 96.689$, $P < .001$; Cramer's $V = 0.348$, $P < .001$. Willingness to use wastewater by groups: $\chi^2 = 75.980$, $P < .001$; Cramer's $V = 0.616$, $P < .001$).

Graph 1. Distribution of clusters by attitude of farmers toward innovation



Graph 2. Distribution of clusters by willingness to use treated wastewater for irrigation



By analysing the socio-demographic and attitudinal characteristics of the different groups, it is possible to define more accurate farmer profiles that can help identify strategies and tools to increase the use of unconventional resources.

Cluster 1: The Experimenters
The experimenters demonstrate a significantly low perception of the risks associated with using treated wastewater for irrigation purposes. Contrary to what one might assume, the reduced perception of risk does not stem from a lack of awareness of opportunities and threats related to this resource, but rather from a high degree of knowledge of current regulations on wastewater use. That suggests that knowledge of regulations and safety guidelines contributes to rationalising risk assessment, orienting it towards a perspective of management and mitigation rather than alarmism (Ghadim et al. 2005; Kang and Park 2011; Kumar et al. 2018; Pfeiffer et al. 2021). From a socio-demographic perspective, members of this group are distinguished by a higher level of education and a lower average age, indicating a clear correlation between the quality of human capital, the degree of regulatory knowledge and learning, and the perception of risk. Similarly, as highlighted in the literature, these factors correlate with the adoption of innovative practices (Eitzinger et al. 2018; Dessart et al. 2019; Fahad and Wang 2018). The positive attitude of this group of farmers towards innovation is related to a strong acceptance of wastewater use: 93% of farms are in favour of this practice. In line with this orientation, about 73% of the Experimenters self-identify as "innovators" and "early adopters" in agricultural innovation contexts, highlighting a proactive propensity towards the adoption of new technologies. In essence, this first cluster represents a segment of highly informed, educated and young farmers, whose high level of knowledge and constant professional development translate into a moderate perception of risk and a marked openness to alternative sustainable practices.

Cluster 2: Product concerned
The members of this group show a very low perception of the risks to human health (for agricultural workers and consumers) and environmental risk associated with the use of treated wastewater. That suggests that farmers from this group consider these aspects to be negligible or effectively mitigated. On the contrary, their primary concern is focused on the risk of accumulation of undesirable substances and the quality of agricultural products. This concern is intrinsically linked to potential damage to irrigation systems and, more significantly, to the negative economic implications of reduced product quality. The possible reduction in market price and increase in production costs suggest that this group is highly sensitive to factors that directly affect profitability and commercial competitiveness (Joffre et al. 2019; Greiner et al. 2009; Regan 2019). Unlike Experimenters, Product Guarantors do not show specific characteristics with respect to age, education or knowledge of the regulation. That implies that these factors do not primarily shape their perceptions of risk and priorities. A distinctive feature of this group is their marked tendency to allocate a large portion of their production to direct sales on the market and to associations (on average, 37% of production, higher than for other groups). This commercial strategy reinforces the hypothesis that product quality and its perception by the market, as well as by the end consumer, are priorities (Jiang et al. 2022; Alsa'di et al. 2024), justifying their selective concern about risks that could compromise this quality and, consequently, their ability to sell and retain customers. Therefore, farmers in this group can be described as pragmatic and strongly market-oriented, with a risk assessment that favours the protection of the quality and economic value of agricultural

products over other environmental or health considerations, which are perceived as less immediate or relevant to their operations and sales strategy.

Cluster 3: Health Concerned

This profile of farmers has a high perception and prioritisation of risks to human health, both for consumers and agricultural producers, associated with the use of wastewater. This concern is predominant and associated with considerable apprehension about the accumulation of undesirable substances in agricultural products. That suggests a strong emphasis on direct implications for health and food safety (Tinh et al. 2021; Ekane et al. 2021). Approximately 60% of these farmers are unaware of the regulations governing wastewater use, and 72% have a low level of education. These data suggest a potential correlation between information/education deficits and a greater perception of risk, particularly in complex and unexplored areas, such as the use of unconventional water resources. Consistent with these observations, 68% of this group is not inclined to use wastewater, stating clear reluctance to adopt this practice. Knowledge is a key factor in overcoming concerns about using wastewater, and 76% of the group deem it necessary to receive adequate training for the correct and safe use of wastewater.

Age is also a distinctive and significant factor for this cluster, as 64% of its members are over 65 years of age. Belonging to an older age group may result in a lower propensity to keep up to date with new regulations and technologies, and in greater caution or risk aversion (Msaki et al. 2022; Serote et al. 2021). This picture is further supported by their self-identification as "late majority" or "laggards" in innovation contexts. That suggests a general tendency to preserve traditional practices and a greater hesitation in adopting new agricultural methods.

Cluster 4: Environment Concerned

Comprising a small number of farmers, this group's primary concern is the environmental risks associated with wastewater use. This strong focus on ecological impacts is associated with a perception of the risk to human health (of workers and consumers) significantly low, suggesting a differentiated assessment of potential hazards. A key element characterising this cluster is the information gap: 56% of farmers are unaware of the regulations governing the use of wastewater and its practical implications prior to use. This lack of information on regulations and quality requirements for this resource may contribute to their greater concern for the environment, as the absence of clear guidelines or a poor understanding of safety measures can amplify apprehensions about potential ecological damage (HuiJts et al. 2019; Scovell et al. 2022). This consideration determines that only 53% of farmers in this cluster are willing to use wastewater for irrigation.

In terms of innovation adoption, this cluster ranks predominantly between the "early majority" and the "late majority". This implies that farmers belonging to this group may be willing to adopt new practices, such as wastewater use, but only after observing the adoption and success of others. Their propensity for innovation is therefore evidence-based, requiring validation by other actors before implementation proceeds (Scovell et al. 2022).

Cluster 5: The Cautious

The last cluster shows a high perception of risk regarding the environmental and health impacts of wastewater use, while there is a significant variability in terms of accumulation risk. Demographically, the group is similar to group 3: on average farmers are 64 years old and, crucially, they have a low level of education (77% of the group has a primary level of education). Additionally, 78% of these farmers are not informed about the legislation and regulations governing the use of wastewater. The combination of factors, such as age, low level of education, and, above all, a lack of specific information and knowledge, proves to be decisive. It suggests that these farmers' uncertainty and resistance to innovation do not stem from a conscious assessment of risks and benefits, but rather from a cognitive and regulatory gap that prevents a complete understanding of practices and safety guarantees (Slovic 1987; Shapiro et al. 1992; Greiner et al. 2009; Scovell et al. 2022; Alam et al. 2024). Consistent with these aspects, an overwhelming majority of farmers belonging to this group (81%) are not inclined to use wastewater for irrigation. This high percentage of reluctance cannot be attributed to a rational assessment but is likely the result of a perception of risk amplified by negligence of existing safety measures and regulations, complemented by a general aversion to risk common among older and less educated age groups (Li et al. 2021). All that translates into marked resistance to the adoption of innovative practices such as wastewater irrigation, highlighting the need for interventions aimed at bridging the information gap and promoting training and regulatory learning.

5. Discussion and Conclusions

The use of treated wastewater for irrigation is emerging as a viable strategy to address the pressing challenges of climate change and the increased demand for water resources (Manganiello et al. 2024; Singh 2021; Karimi and Ataei 2023; Soller et al. 2017). Nonetheless, the widespread implementation of this practice is significantly impeded by farmers' perceptions of risk, which are profoundly shaped by individual variables and the context in which they operate (Mishra et al. 2023; Karimi and Ataei 2023; Tariq et al. 2023; Younas et al. 2021; Garin et al. 2021; Ahmmadi et al. 2021).

Our research highlighted that farmers' risk perceptions are related to various factors, including their awareness of regulations, educational level, age, and attitudes toward innovation. We identified five distinct farmer profiles, each characterised by their own concerns, levels of resistance and openness to the application of wastewater.

The analysis of these profiles provides critical insights into the underlying factors influencing the adoption of this practice, aiding in the formulation of more effective promotional strategies. The findings reveal a strong association between risk perception and the inclination toward innovation, indicating that as risk perception intensifies, there is a notable decline in the intention to adopt innovative solutions (Karimi and Ataei 2023; Greiner et al. 2009; Pfeiffer et al. 2021). These results confirm the findings of previous studies, which posit that perceptions of various risk types can catalyse innovative behaviours, thereby influencing individual decision-making processes (Sohail et al. 2021; Ismail et al. 2012). The outcomes of this study identify two pivotal factors that influence risk perception: technical and regulatory knowledge, on the one hand, and attributes related to the quality of human capital, on the other. For instance, the group identified as Experimenters exhibited a markedly low perception of risk, which correlates with their comprehensive understanding of regulations and safety protocols.

In contrast, groups such as the Health Concerned and the Cautious, who possess limited familiarity with this resource and the relevant regulations, tend to overestimate risks, particularly those associated with health and product quality. These findings align with previous research in the domain. Indeed, the significance of information in alleviating risk perception is extensively documented in the literature (Caswell and Zilberman 1986; Kumar et al. 2018; Pfeiffer et al. 2021; Sabbagh and Gutierrez 2022; Ahmed et al. 2024). The results suggest that transparent and

accessible communication regarding legal requirements and wastewater treatment procedures could substantially mitigate resistance and promote the utilisation of this unconventional resource (Kang and Park 2011; Slovic 1987; De Buck et al. 2001; Greiner et al. 2009; Joffre et al. 2019).
At the same time, factors such as age, education, and professional training serve a pivotal role in shaping an individual's openness to novel practices. Younger farmers with higher levels of education, such as the group of Experimenters, exhibit a heightened propensity to perceive the reuse of wastewater as an opportunity rather than a potential hazard. In contrast, older farmers with lower educational backgrounds tend to adopt a more cautious stance, frequently attributable to a scarcity of information or a general aversion to risk (Msaki et al. 2022; Serote et al. 2021; Sánchez-Cañizares et al. 2022). Indeed, age and education function as moderating variables regarding risk perception and attitude, thereby influencing farmers' openness to innovation. This suggests the need to implement targeted informational campaigns that employ appropriate communication strategies to effectively reach different farmer profiles (Regan 2019; Joffre et al. 2019; Hu et al. 2022; Li et al. 2022; Gardezi et al. 2022). A more innovation-oriented attitude correlates with an increased likelihood of utilising wastewater for irrigation. These findings are supported by existing literature: farmers characterised by a more innovative profile, as delineated by Rogers (2003), display a greater inclination to adopt alternative solutions, particularly if they have previously engaged with complex technical innovations (Li et al. 2022; Li et al. 2021; Ahmed et al. 2024; Lubell et al. 2011; Thompson et al. 2019; Kaine and Wright 2022). Consequently, addressing factors that can influence farmers' innovative attitudes is essential for enhancing the adoption of new practices. Peer influence and social networks have the potential to affect farmers' willingness to adopt innovations (Rogers 2003). That highlights the significance of fostering strong social connections and facilitating information dissemination to encourage more innovative behavioural patterns (Ren et al. 2022).
Farmers do not assess diverse risks in the same way. Product Concerned farmers are primarily concerned with product outcomes and focus on the potential economic repercussions of wastewater use, given that a worsening in product quality could adversely affect their market competitiveness (Daughton and Ternes 1999; Drechsel et al. 2022). Environmental, on the other hand, direct their attention towards environmental implications, but display a certain willingness to adopt new practices if their benefits are demonstrated. These differences indicate that, to promote the adoption of wastewater, it is necessary to employ tailored messages. For some farmers, emphasising the economic advantages (Poustie et al. 2020; Drechsel et al. 2022) and microbiological safety (Gashaye 2020; Khan et al. 2022) may prove more effective. For others, highlighting the environmental sustainability of wastewater use could yield more persuasive outcomes (Poustie et al. 2020; Trotta et al. 2024; Tella et al. 2025). Therefore, it is clear that a single strategy is insufficient for incentivising the use of wastewater in agriculture. To effectively promote the adoption of this practice, it is crucial to develop multi-faceted strategies that encompass:
1. Training and information campaigns, including outreach on regulations and safety protocols, aimed at mitigating the substantial knowledge gaps prevalent among older and less educated farmers.
2. Evidence-based demonstrations, through pilot projects or case studies, that can show the concrete advantages of using wastewater, thereby alleviating uncertainties among the most hesitant farmers and fostering networks of pioneering farmers who can act as credible testimonials.
3. Specific economic incentives designed to reassure farmers, such as Product Concerned farmers, who harbour concerns regarding potential impacts on crop quality and market valuation.

In summary, while the use of wastewater in agriculture represents a concrete approach to contemporary water scarcity, its efficacy will hinge on the capacity to translate technical data into comprehensible messages, enhance the confidence of potential users through concrete evidence, and tailor communication strategies to the distinct needs and concerns of various farmers' groups. Our study underscores the significance of investing across multiple dimensions in a joint and differentiated manner. That can help transform this practice, still perceived as risky by many farmers, into a collective opportunity for a more resilient and sustainable agriculture.

APPENDIX B

Table 1B. Innovative agricultural practices: Risk perceptions and influencing factors

Authors	Innovation	Perceived Risk	Reducing (-) or Intensifying (+) Factors
Greiner et al., 2009	Best Management Practices (BMPs)	Sever Drought Risk Market/Economic Risk Institutional Risk Production Risk	**(-)** External consultancy **(-)** Experience of conservative practices **(-)** Motivation: Maximising productivity **(-)** Improving individual knowledge **(-)** Governance assistance
Joffre et al., 2019	Aquaculture Practices	Market Risk	**(-)** Interactions public and private sector actors **(-)** Information/Knowledge diversification **(-)** Collective actions/institutional arrangements
Regan, 2019	Smart Farming Innovations	Financial Risk Negative consumer perceptions Risk Ethical/Privacy Risk Exclusion Risk	**(+)** Complexity of innovations **(+)** High costs **(-)** Consultancy and information support
Sabbagh and Gutierrez, 2022	Microirrigation System	Financial Risk Specific technology Risk	**(-)** Political incentives **(-)** Assurances from farmers' associations **(-)** Education and professional training **(+)** Complexity of system use
Tinh et al., 2021	Chemical Pesticides on Rice	Farmers health Risk Environmental contamination Risk	**(-)** Economic benefits perception **(-)** Chemical accessibility **(-)** Education and professional training **(+)** Moral norms **(+)** Efficient information channels
Ahmed et al., 2024	Precision Dairy Tools (PDT)	Physical Animal stress Risk Privacy Risk Financial Risk	**(-)** Technology-based social networks **(-)** Targeted professional information and training **(-)** Individual confidence in the user's ability **(+)** Social confinement
Hu et al., 2022	Green Control Techniques	Crop Pest and Disease Risks	**(-)** Performance expectancies **(-)** Facilitating conditions **(-)** Technical education **(-)** Agricultural subsidy policies **(+)** Low effect observability
Li et al., 2021	New Soil and Water Management Technologies	Financial Risk Infestation Risk Uncertainty long-term benefits Risk	**(-)** Targeted government grants **(-)** High perceived efficiency **(-)** Non-company employment **(-)** Age **(-)** Past memory and experience **(+)** Low income **(+)** Low technical training level **(+)** Complexity **(+)** Structural constraints
Li et al., 2022	Agricultural Green Production practices (AGP)	Environmental Risk Economic Risk Temporal Risk Social Risk	**(-)** Environmental regulation **(-)** Environmental contractual agreements **(-)** Professional training **(-)** Technical demostration/testability **(-)** Perceived efficacy **(+)** Unavailability government financial incentives
Ekane et al., 2021	Sewage Sludge	Environmental Contamination Risk Chemical Risk Social Rejection Risk Technical Risk	**(-)** Quality certifications **(-)** Scientific evidences **(-)** Economic benefits **(-)** Environmental benefits **(+)** Restrictive usage policies **(+)** Social/public alarmism **(+)** Reduced transparency about resource origin **(+)** Reduced trust in the resource
Gardezi et al., 2022	Decision Support Systems for Precision Agriculture (DSS)	Privacy/Loss of data control Risk Economic Risk Social/Company work Risk Reduced trust Risk	**(-)**Inclusive activities **(-)** Training and technical support **(-)** Observed benefits **(+)** Reduced regulatory transparency **(+)** High power concentration in corporations **(+)** Economic disparities between companies

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Chapter 5

Modelling as Decision Support in Agriculture

1. Introduction

The adoption by farms of practices described as efficient, resilient, or sustainable is not, in itself, sufficient to define an agricultural system as "sustainable" in its actual functioning. An effective representation of the complexity of agricultural systems and the practices that characterise them requires a holistic approach capable of integrating the multiple dimensions that determine system performance (Therond et al., 2017). This is particularly relevant in light of the profound transformation agriculture has undergone since the mid-twentieth century: pre–Green Revolution systems tended to maintain a closer balance with natural ecosystems, valuing closed biogeochemical cycles and conservation-oriented practices (Tahakik et al., 2024).

With the advent of the Green Revolution, the primary objective progressively shifted towards increasing crop yields (Green et al., 2005; Tahakik et al., 2024), pursued through intensification based on synthetic fertilisers, pesticides, and other external inputs designed to sustain or protect production (Goulding et al., 2007; Savary, 2014; Arizpe et al., 2011). Although these strategies contributed to a substantial rise in agricultural productivity, they have also generated long-term side effects that have become increasingly evident at the environmental scale (Foley et al., 2005; Ulla et al., 2024).

In this context, growing attention has been directed towards systems capable of combining productivity and sustainability, reducing reliance on approaches focused solely on maximising yields and profits, and instead enhancing a broader range of ecosystem services (Foley et al., 2005; Bhagat et al., 2024). The relationship between agriculture and the environment, however, remains highly complex. Although governed by different dynamics, these two domains can be reconciled through management practices that align production goals with the conservation of natural capital (Bhagat et al., 2024).

Recent literature highlights promising perspectives centred on improving the efficiency of chemical and water input use, strengthening internal material recycling processes within agricultural systems, and adopting digital and intelligent technologies to enable site-specific agronomic management (Georgopoulou et al., 2021; Kuisma et al., 2012; Rains et al., 2011).

To analyse these dynamics rigorously, the definition and study of agricultural systems require appropriate conceptual and methodological tools. The complexity of interactions among agronomic practices, economic outcomes, and environmental impacts makes it necessary to employ approaches capable of representing and assessing multiple system dimensions simultaneously.

Modelling, in its various forms, constitutes a key instrument in this respect: it enables the formal description of how agricultural systems operate, the quantification of their processes, and the simulation of alternative management or structural change scenarios (Ewert et al., 2011). Over time, agricultural modelling has evolved and diversified to address specific objectives and contexts (Ascough & Ahuja, 2019), offering increasingly accurate representations of a highly complex reality in which ecological, technical, and social dimensions interact according to dynamic rules. Indeed, agricultural systems are complex socio-ecological systems whose functioning emerges from the interaction between natural processes and human decisions accumulated over time. The evolution of farming practices and the introduction of mechanical and managerial technologies have enabled substantial productivity gains and major changes in farm management, but have also increased the need for targeted adaptive decisions capable of balancing productive, economic, and environmental sustainability objectives (Borges et al., 2019).

For these reasons, models applied in agriculture, and more specifically at the farm level, must simultaneously address the need for accurate representation of biophysical processes, on the one hand, and management variables linked to human capital, on the other (Ascough & Ahuja, 2019).
In this chapter, after examining the key factors underlying the need to integrate ecological and social components in system analysis, the main types of models applicable to agricultural systems will be reviewed. Their theoretical foundations, practical applications, and operational limitations will be discussed, with the aim of clarifying the role of modelling in understanding and transforming agricultural practices towards more sustainable and resilient forms.

2. Integrating Environmental and Social Aspects into Decision Models

2.1 The Importance of the Ecological Component

The ecological component now represents an indispensable element in modelling applied to agricultural systems. The close interconnection between agriculture and the environment, grounded in reciprocal relationships, requires an integrated assessment of production processes and their impacts on ecosystems (Grazelak et al., 2022).
Despite its significance, the environmental component was for a long time marginal in economic models, which often focused exclusively on productive efficiency or economic optimisation (Singh & Panda, 2012). Only in recent decades, alongside growing public awareness of climate change and sustainability, has the need to account for the ecological implications of agricultural practices become firmly established. Agricultural activities, particularly in highly developed countries, exert multiple environmental pressures: greenhouse gas emissions and pollutant releases, contamination of soil and water matrices, accumulation of chemical residues along trophic chains, biodiversity loss, and fragmentation of natural habitats (Cotter et al., 2014; Semaan et al., 2007; Alary et al., 2016; Li et al., 2020).
These effects, often cumulative, have made it essential to define policies and instruments capable of steering agriculture towards a more sustainable balance between production and conservation.
Ex ante assessment of the environmental impacts of agricultural practices has become a crucial stage in the design and implementation of sectoral policies (Kelly et al., 2023). It enables the prior identification of the potential consequences of specific management measures and supports the design of corrective interventions aligned with sustainability objectives. Experience has shown that development policies based solely on intensification or productive efficiency do not always yield outcomes compatible with environmental protection (Erickson, 1994; Mosnier et al., 2009; Kleftodimos et al., 2021). In some cases, incrementi in economic and productive efficiency may coincide with significant environmental impacts, creating tensions between profitability goals and the conservation of natural resources (Mosnier et al., 2009).
This awareness has driven a gradual evolution in agricultural system modelling towards approaches that integrate the ecological dimension in a more comprehensive manner. Several models developed to support the ex ante evaluation of the environmental effects of specific policies or management practices have enabled more precise analysis of impacts on key components of agroecosystems, combining economic benefits with potential ecological externalities associated with each intervention.
From this perspective, a thorough understanding of the ecological dynamics governing agroecosystems is an essential prerequisite for developing reliable models. Identifying relationships between biotic and abiotic factors, understanding the resilience mechanisms of agricultural

ecosystems, and assessing trade-offs between productivity and environmental impacts are central to constructing decision-support tools consistent with agro-environmental policy objectives (Srivastava et al., 2002; Li et al., 2020). Such tools must be capable not only of forecasting the effects of alternative management strategies but also of identifying solutions that ensure both economic and ecological sustainability.

There are examples of ecological modelling developed at different levels of biological organisation, ranging from individual species to populations and entire ecosystems. Among pioneering contributions, the work of Wallace et al. (1992) represents a key reference for the classification and analysis of plant communities within the *National Vegetation Classification* (NVC), demonstrating how changes in land management can lead to significant shifts in floristic composition and vegetation structure. When integrated into broader frameworks that also consider economic and social dimensions, such models provide a more realistic representation of the interactions between production processes and the environment.

Despite progress in this area, integrating the ecological component into farm-level economic models remains challenging. Profit-maximising optimisation models are sometimes ill-suited to accurately represent the dynamics underlying the adoption of sustainable practices. In practice, farmers' decisions to implement environmentally beneficial measures often depend on economic incentives or regulatory constraints, as such practices do not always deliver immediate productivity gains. This makes it essential to develop flexible models capable of adapting to the territorial and socio-economic specificities of different agricultural systems. As early as the 1990s, models applied at the territorial scale addressed specific issues related to gaseous emissions, soil erosion, and nutrient flows (Arah, 1990; Potter & Williams, 1993). However, the longstanding difficulty of transferring these models into complex economic frameworks has largely been attributed to the lack of generic, scalable algorithms capable of operating across different spatial and managerial levels (Calvet et al., 2020).

2.2 The Importance of the Relational and Social Dimension

While the connection between agriculture and the environment cannot be overlooked, the social dimension likewise represents a fundamental element for understanding and modelling agricultural systems, in which individuals are the primary actors in decision-making processes and management dynamics (Grzelak et al., 2022). The farmer, as the person responsible for the farm, makes decisions that directly shape the organisation of production activities and the use of resources, thereby influencing the overall structure and performance of the agricultural system (Berger, 2006).

These decisions, however, are never made in isolation: they are shaped by a network of environmental, social, and institutional interactions that significantly influence individual decision-making behaviour (Heckman, 2001; Macal, 2016; Berger & Troost, 2014). The interaction between humans and the environment represents one of the central nodes of this complexity. Natural agents, such as soil, climate, and water resources, do not merely act as constraints or production inputs, but as dynamic variables that respond to management actions and, in turn, influence the farmer's future choices (McLane et al., 2011). For instance, in crop growth simulation models, managerial technical decisions, although rational and planned, constantly interact with biotic and abiotic factors that may alter expected production outcomes (Lang & Ertsen, 2023). This reciprocal relationship between human decision-making and environmental response therefore calls for a modelling approach capable of representing the parallel evolution of both human and natural systems.

Beyond interaction with the ecological component, decision-making processes in agriculture are also influenced by a network of social relationships that develop both within and outside the farm. Relationships with workers, family members, technical advisers, institutions, and market networks contribute to shaping the context in which decisions are made. The diversity of these interactions, as well as their intensity and direction, varies considerably across territorial contexts and farm types, making it necessary to adopt a flexible modelling approach capable of adapting to different socio-economic realities.

Within this framework, Agent-Based Models (ABM) have recently been introduced, for example, to describe and simulate more effectively the behaviour of agricultural actors and their interactions (Macy & Willer, 2002). These models, previously conceptualised in a simpler framework of autonomous and interacting "actors" within a system (Amir et al., 1991; Ghadim et al., 1991), allow individuals to be represented explicitly by assigning them goals, preferences, knowledge, and constraints, and enable analysis of how interactions between agents and their environment generate emergent effects at the farm or territorial level (Hailegiorgis & Cioffi-Revilla, 2018). This makes it possible to derive cause, effect insights and to generate realistic scenarios that support managerial decision-making and sectoral policy design.

Nevertheless, the systematic inclusion of the social component in agricultural optimisation or simulation models remains a significant challenge. Historically, agri-economic modelling has tended to oversimplify farmers' decision-making behaviour, assuming that production units operate as perfectly rational agents oriented towards profit maximisation. Although this assumption facilitates the development of analytically tractable models, it is limited in its ability to reflect real-world dynamics. Numerous studies have shown that farm decisions are not driven solely by economic criteria, but also by personal attitudes, past experience, risk perception, and social influences (Korsching & Hoban, 1990; Duff et al., 1991; Balint et al., 2017).

Some authors note that models explicitly incorporating social variables have often been perceived as opposed to, or alternative to, traditional economic models, and in some cases as difficult to apply in practice (Dent, 1995; Macal, 2016; Balint et al., 2017). Moreover, modelling individual behaviour raises issues of scale and aggregation: representing the actions of single actors may be of limited usefulness for policymakers, who require tools capable of synthesising outcomes at collective or system level (Berger & Troost, 2014). This highlights the need to balance micro-level behavioural representation with a degree of generalisation suited to policy objectives. Additional complexity arises from the qualitative and context-dependent nature of social variables. Factors such as perception, trust, propensity to innovate, or inter-farm cooperation are difficult to quantify and can often only be identified through direct observation or empirical investigation (Edwards-Jones & McGregor, 1994). Nonetheless, it is precisely the structured encoding of behaviours and decisions that can enable a more realistic representation of agricultural decision-making processes (Edwards-Jones & McGregor, 1994; Macal & North, 2009).

The analysis of social interactions in agriculture should therefore begin with direct observation of production contexts and their specific characteristics. In some cases, as suggested by Dent (1995) and more recently by De Keyser et al. (2025), building robust models requires identifying behavioural regularities within homogeneous groups of farms (for example, irrigated, horticultural, or livestock farms) and subsequently formalising these patterns into transferable models. This approach makes it possible to tailor "social" variables and their associated coefficients to the specific contexts under study, while maintaining a general modelling structure applicable across different production systems. Overall, integrating the social and interactive components into agricultural models clearly represents a necessary step towards more realistic and multidimensional modelling.

3. Decision Models: Main Approaches

With reference to models applied at the farm level, two broad functional families can be distinguished: optimisation models, designed to identify the combination of resources and practices that maximises a given objective function, and simulation models, originally developed to reproduce biotic and abiotic dynamics in order to compare management scenarios and predict system responses to changes in inputs and techniques (Nolan et al., 2009; Ascough & Ahuja, 2019). Over recent decades, models have been developed that simulate crop growth, nutrient flows, the effects of fertilisation and irrigation practices, as well as production and welfare dynamics in livestock systems with increasing detail (Valipour et al., 2015; Marinov & Marinov, 2014; Niloofar et al., 2020). These tools are used both to assess alternative management scenarios and to support decision-making processes, enabling more targeted interventions and more informed management strategies. Experience accumulated through numerous case studies and empirical analyses has created a solid methodological foundation that allows existing models to be adapted and extended to incorporate new data and context-specific relationships.

However, critical analysis of farm-level modelling highlights recurring structural limitations.

First, a single model, in its initial formulation, is rarely able to represent the full complexity of a farm system, and modular extensions are often required to integrate aspects not originally considered. Second, the systematic inclusion of socio-economic dimensions and relational networks that influence farm decisions remains limited: management choices do not stem solely from rational profit-maximisation processes, but are frequently mediated by factors such as family relationships, commercial and advisory ties, risk perceptions, and institutional constraints, all of which play a decisive role in the adoption of practices and technologies (Macal, 2016; Carli et al., 2017; Kremmydas et al., 2018).

From this perspective, models that explicitly integrate social actors appear particularly promising (Ghadim, 1991; Schreinemachers & Berger, 2011). They enable the representation of interpersonal relationships, learning processes and innovation diffusion, as well as feedback loops between management decisions and biophysical conditions, offering a more realistic depiction of decision-making mechanisms within and around the farm. The adoption of these approaches can partially address the lack of "holism" that characterises many traditional models, but it requires careful design of data structures and aggregation levels in order to preserve transferability and analytical robustness.

Future research directions converge on two main trajectories: on the one hand, the continued evolution and progressive integration of well-validated modular models that combine optimisation and simulation in a coherent manner; on the other, the development of foundational frameworks that incorporate socio-economic components and interaction networks among actors from the earliest stages. A pragmatic approach involves the incremental construction of such modelling infrastructure, beginning with the careful selection of key information to be collected during the observation phase, followed by modular expansion of relationships and variables, so as to ensure that the model remains both reproducible and adaptable to different geographical contexts and production specialisations.

4. The Optimisation Approach

4.1 General Characteristics of Optimisation Models

The use of models with an economic and environmental focus stems from the need for analytical and exploratory tools capable of assessing, ex ante, the effects of business decisions and future agricultural policies on farm management (Rossing et al., 1997; Zander & Kächele, 1999). These models, based on mathematical structures that describe the functioning of agricultural systems, are particularly well suited to exploring uncertain future scenarios across multiple dimensions, providing valuable support for farm planning and the evaluation of management strategies (Ge et al., 2015).

Among the tools developed, a prominent role is played by farm-level bio-economic models (BEFM). Models based on optimisation procedures incorporate constraints that reflect the real operating conditions faced by farms (Anderson et al., 1985). These constraints represent limited resource availability and define the context within which farmers make their decisions. The primary objective of such tools is to identify efficient production combinations through the optimal reallocation of inputs, thereby maximising outputs typically expressed in terms of farm income and, where relevant, associated environmental benefits. The structural adaptability of BEFM makes it possible to include a wide range of production techniques, including alternative or simultaneous options, rendering these models suitable both for short-term assessments and long-term forecasting exercises (Van Ittersum et al., 1998). More recent developments have focused on analysing the effects of technological, managerial, and product innovations, as well as policy changes within agricultural systems, with applications across diverse territorial and production contexts (Gibbons et al., 2005; Torkamani, 2005; Mosnier et al., 2009; Galán-Martín et al., 2017; Li et al., 2024). In this respect, one of the key strengths of BEFM lies in their ability to assess the technical and economic feasibility of adopting innovations and to estimate their environmental impacts, whether positive or negative (Ghadim, 2000; Britz et al., 2021; Chopin et al., 2021).

An important distinction concerns the nature of the models themselves. Mechanistic BEFM, considered closer to real-world operational conditions, construct detailed representations of farm processes based on established knowledge and assumptions consistent with the biological and economic functioning of production systems (Pandey & Hardaker, 1995; Janssen & Van Ittersum, 2007). These models are particularly suitable for long-term analyses. By contrast, empirical models rely on the statistical identification of relationships observed in historical data and management practices, making them less capable of incorporating new technological or production options (Falconer & Hodge, 2000).

A further distinction relates to the modelling approach. Positive models aim to reproduce actual farmer behaviour by incorporating observed management and production responses into the model (Mérel & Howitt, 2014). Normative models, by contrast, identify optimal solutions relative to a specific objective, regardless of their practical feasibility for farmers. Although useful for identifying theoretically efficient strategies, the normative approach may produce results that diverge from real management practices, as it does not fully account for information constraints, technical capacity, or operator preferences (Falconer & Hodge, 2000).

For a long time, mechanistic normative bio-economic models represented a central reference point in ex ante agricultural policy evaluation, particularly when estimating the effects of introducing new technologies or management changes. These models describe production processes in detail and enable the simulation of potentially optimal scenarios. Their effectiveness, however, is limited by their reliance on idealised decision-making behaviour that often departs from the operational realities of farms (Janssen & Van Ittersum, 2007). Within the normative framework, it is assumed that farmers will necessarily adopt the technically and economically most advantageous solution (Wossink & Renkema, 1994). In practice, the model indicates what "should be done" to achieve optimal conditions, rather than what actually occurs. The gap between these representations and real farmer behaviour is substantial. Farm decisions are shaped by uncertainty, transaction costs, information constraints, and individual preferences, all of which help explain why technology adoption is neither uniform nor immediate. When considering feasible changes in farm systems—ranging from the introduction of new or alternative production techniques to the use of new resources—it becomes essential to understand the multiple dynamics underlying these processes. This makes it necessary to draw on diffusion of innovations theory (Rogers, 1995), which highlights the role of subjective perceptions, technical complexity, and the resources required by innovations. Farmers, as is well recognised, do not constitute a homogeneous group: innovators, early adopters, early and late majorities, and laggards respond differently to technological opportunities. Studies on BEFM confirm that these factors make representations based on instantaneous optimising behaviour unrealistic (Janssen & Van Ittersum, 2007; Wossink & Renkema, 1994).

In response to these limitations, a shift towards positive modelling approaches has gained increasing importance. In particular, Positive Mathematical Programming (PMP) allows models to be anchored to observed choices, providing a more realistic representation of farms' adjustment margins. As proposed by Howitt (1995), introducing a quadratic cost function makes it possible to simulate gradual changes in production decisions, overcoming the rigidity of linear models and reflecting farms' tendency to avoid extreme specialisation. In this way, BEFM acquire the capacity to analyse not only the effectiveness of innovations and management changes, but also the trade-offs between economic and environmental objectives.

The flexibility of optimisation models derives from the ability to represent the complexity of production systems through different mathematical programming formulations. Linear Programming (LP) forms the foundation of many BEFM and is particularly effective when relationships between activities, inputs, and outputs can be expressed in linear form, enabling identification of the production combination that maximises the defined objective, typically net farm income (Singh & Panda, 2012).

However, agronomic reality is often more complex than linearity can capture. Where technical relationships are non-linear (such as those characterising production functions with diminishing marginal returns) Non-Linear Programming (NLP) becomes more appropriate, as it can represent production dynamics more closely aligned with biological processes (Howitt, 1995; Mérel & Howitt, 2014).

Similarly, when farm decisions are made under uncertainty, related to prices, yields, or water availability, Stochastic Programming allows risk to be incorporated into the objective function or constraints, providing a decision framework that better reflects the inherently uncertain nature of agricultural contexts.

Moreover, farm objectives are rarely one-dimensional. The need to balance economic, environmental, and managerial criteria has encouraged the use of Multi-Objective Programming (MOP), which enables the analysis of not a single optimum but a set of efficient solutions representing trade-offs among often conflicting goals (Amini, 2015; Calvet et al., 2020). This perspective makes it possible to explore scenarios that balance competing performance criteria, offering a more nuanced view of farmers' decision preferences. Overall, while linear programming remains the core of many bio-economic models, advances in modelling have led to the integration of non-linear, stochastic, and multi-objective approaches. This methodological expansion responds to the need to more faithfully represent the complexity of agricultural systems and the uncertainty permeating entrepreneurial decisions, thereby enhancing the reliability of ex ante assessments and strengthening the role of models as decision-support tools for farm planning (Janssen & Van Ittersum, 2007).

4.2 The Objective Function

If the farmer is regarded as a purely rational decision-maker, their ultimate goal is typically represented as the maximisation of profit. Although profit is undeniably a central component of entrepreneurial activity, such a formulation is reductive when the aim is to describe real farmer behaviour and provide meaningful guidance to policymakers (Dent, 1995; Singh & Panda, 2012). Previous studies have shown that profit maximisation constitutes only one of the motivations underlying farm decisions and does not fully capture the complexity of observable behaviour in real-world contexts (Dent et al., 1995; McCown, 2001; Mirzaei & Zibaei, 2018). In light of this evidence, farm-level modelling has increasingly shifted towards multicriteria approaches capable of representing the plurality and potential conflict of the objectives pursued by farmers (Rehman & Romero, 1993; Masoumi et al., 2020; Galán-Martín et al., 2017).

From a mathematical standpoint, multicriteria approaches seek to capture this complexity by embedding multiple farm objectives within a single formulation. Typically, one primary objective is defined as the function to be optimised, while additional objectives are converted into constraints that determine the conditions under which the solution must be achieved (Weersink et al., 2004). Table 1 provides a summary of the main characteristics that distinguish the two approaches to defining the objective function.

Table 1. Main Characteristics of approaches focused on defining the objective function

Characteristic	**Profit Maximisation Approach**	**Multi-Criteria Decision-Making (MCDM) Approach**
Underlying Assumption	Farmer as a purely rational actor with a single objective.	Farmer with multiple, often conflicting objectives that reflect complex preferences.
Objectives	Financial profit, net income.	Profit, environment, individual preferences, risk, family and social values.
Model Complexity	Low. Simple and linear model.	High. Complex model that must balance and weight multiple objectives.
Main Purpose	Normative approach: to show farmers the effects of a technological change.	Descriptive approach: to predict farm responses to new policies; to facilitate negotiation among stakeholders with differing interests.
Types of Decisions	Primarily focused on short-term operational and tactical decisions.	Suitable for long-term strategic decisions involving complex trade-offs.
Influencing Factors	Input and output prices; perfect market knowledge.	Personality, life goals, off-farm income, social and environmental pressures.

4.3 Uncertainty

Uncertainty is an unavoidable component of agricultural decision-making, as farmers operate in a context characterised by climatic variability, price fluctuations, and other sources of risk (English, 1981; Ghadim et al., 2005). The literature distinguishes between non-intrinsic risk, linked to external and uncontrollable factors such as weather events, and intrinsic risk, which is instead associated with operational choices that can be adjusted during the season (Dorward, 1999). Non-intrinsic risk is reflected in income volatility and, although it may only marginally affect farm welfare (Pannell et al., 2000), it is essential in agricultural policy analysis: ignoring it would lead to an overestimation of crops that are, on average, more profitable but highly unstable. To account for this, models typically adopt utility functions that penalise income variability in proportion to the farmer's degree of risk aversion (Freund, 1956; Oubelkacem et al., 2020).

Conversely, modelling intrinsic risk requires greater caution, as increasing the number of scenarios can make the model excessively complex. It is therefore advisable to include only those sources of uncertainty that genuinely influence expected decisions. Several studies show that, when farms have sufficient managerial flexibility, an explicit representation of intrinsic risk may not be necessary (Dorward, 1999).

4.4 Representation of Agricultural Activities

The accurate definition of agricultural activities is central to the construction of a reliable model. These activities encompass the entire production process, from technical operations to managerial aspects, reflecting the complexity of real-world farming systems (Janssen & Van Ittersum, 2007). Their representation is based on technical coefficients, which describe input–output relationships and allow the quantification of resource use, costs, and environmental impacts, such as nutrient releases into soil or greenhouse gas emissions (Hengsdijk & van Ittersum, 2003; Pathak & Wassmann, 2007; Pandey & Pandey, 2011).

This framework comprises a set of discrete activities, typically distinguished between current activities, already practised, and alternative activities, representing potential innovations. However, selecting alternative activities poses a methodological challenge, as it requires identifying a representative set without excessively narrowing decision diversity or introducing arbitrariness (Falconer & Hodge, 2000; Hengsdijk & van Ittersum, 2003; Dogliotti et al., 2003).

4.5 Environmental Impacts

Agricultural activities also generate environmental effects that must be incorporated into models in order to ensure consistency with real farm conditions (Falconer & Hodge, 2000; Lindgren & Elmquist, 2005; Abdo et al., 2025). This is typically achieved through the use of environmental indicators, whose selection represents a critical methodological step. Indicators based on direct damage are particularly effective, as they enable immediate comparisons between different practices, such as nitrate concentrations in groundwater (Tahir & Darton, 2010; Marinov & Marinov, 2014; Farlin et al., 2019).

Conversely, indicators referring to inputs and implemented techniques merely describe the practices adopted and function as proxies for actual impacts, making them less directly informative for evaluative purposes (Payraudeau & Van der Werf, 2005).

4.6 Strengths and Weaknesses of Optimisation Models

It is evident that optimisation models represent one of the most well-established tools in bio-economic modelling. Owing to their prescriptive approach, they enable the simulation of farm organisation by identifying the most efficient combination of decisions with respect to a defined objective function and a set of technical, economic, and environmental constraints. Their ability to operate across multiple scales, from individual farms to territorial-level analysis, has strengthened their role in decision support and agricultural policy evaluation (Bartolini et al., 2007; Mosnier et al., 2009; Li et al., 2024).

Nevertheless, several structural limitations emerge. The quality of simulations depends heavily on data accuracy and validation, processes that are often resource-intensive and require in-depth knowledge of production systems (Pannell, 1997). Moreover, linear models tend to generate highly specialised optimal solutions that diverge from real-world practices, in which diversification is a key strategy for risk mitigation and economic stability (Ge et al., 2015). In addition, results are highly sensitive to parameter values: even minor changes in yields, prices, or available resources can substantially alter the optimal configuration, thereby weakening the robustness of simulations. One of the main limitations, however, is that, despite their analytical rigour, farm-level optimisation models tend to underestimate the role of the social context in agricultural decision-making, assuming behaviour driven solely by economically rational criteria (Austin et al., 1998; Edward-Jones, 2006). This assumption can reduce the explanatory power of the model, as individual values, knowledge, family dynamics, and social networks exert a profound influence on entrepreneurial choices (Anderson et al., 1985; Dent et al., 1995). To incorporate these dimensions, some authors have proposed more articulated utility functions, for example weighted according to family preferences, or the adoption of classifications based on "farming styles", which reflect different worldviews and production strategies (Wossink et al., 1994; Austin et al., 1998; Viaggi et al., 2010). However, a comprehensive representation of agroecosystems ultimately requires an evolution towards "socio-bio-economic" models, capable of capturing not only biophysical and economic processes, but also the complexity of social dynamics that shape farm behaviour.

5. The Simulation Approach

The prescriptive nature of optimisation models provides theoretically optimal solutions, whose validity nevertheless depends on the robustness of the underlying assumptions and on the model's ability to represent the real constraints faced by farms. This approach is effective when the analytical focus is on identifying efficient strategies, but it can be limiting when the objective is to study the dynamic evolution of agricultural systems or to explore scenarios characterised by high levels of uncertainty. Simulation models adopt a different logic. Rather than seeking a single "best" solution, they aim to describe system behaviour over time, highlighting how interactions among biological, economic, and managerial processes generate specific evolutionary trajectories (Dent, 2012).

Economic–ecological simulation models, for example, integrate components that describe crop physiology or animal productivity with economic and decision-making modules (Stoorvogel et al., 2004; Münier et al., 2004; Feola et al., 2012; Bizimana & Richardson, 2019). This structure makes it possible to explore multiple scenarios, assessing how factors such as market fluctuations, climate change, or alternative managerial choices influence farm stability and resilience.

Compared with optimisation models, simulation offers a more flexible and interpretative perspective, capable of capturing the complexity of agricultural systems and analysing the variability of responses as contextual conditions change. For this reason, simulation models are playing an increasingly important role as tools for integrated analysis, combining scientific rigour, economic consistency, and biological realism to support farm management and planning processes (Li et al., 2010).

5.1 Objectives and Evolutionary Trajectories of Simulation Models

The growing complexity of agricultural challenges, from resource management and climate change impacts to socio-economic and institutional transformations, requires analytical tools capable of integrating biophysical, economic, and social components within a coherent framework (Rossing et al., 2007; Papajorgji & Pardalos, 2009).

Simulation models are distinguished by their ability to reveal interdependencies among processes and actors, highlighting feedback mechanisms that shape the functioning of agroecosystems across multiple scales, from field to farm and up to the territorial level (Dent et al., 1995; Milestad et al., 2012; Schiere et al., 2012). They serve multiple purposes, ranging from evaluating the effects of new technologies or agronomic practices, to simulating the impacts of public policies, and assessing environmental sustainability through composite indicators (Georgiadis et al., 2005; Belcher et al., 2004; Bizimana & Richardson, 2019). In this sense, simulation does not merely describe isolated phenomena, but promotes a systemic perspective that transcends sectoral analysis and enables a holistic investigation of processes.

In recent years, methodological advances have increasingly moved towards participatory modelling, in which the contributions of farmers, advisers, and public decision-makers become an integral part of the modelling process (Hubert et al., 2012; Herrera et al., 2022). This approach supports the co-production of knowledge and enhances the social legitimacy of analytical tools, thereby increasing their effectiveness in informing management decisions and agricultural development policies.

Among the modelling tools applicable to agriculture, System Dynamics (SD) enables the analysis of temporal changes in stocks and flows within agricultural systems, while Agent-Based Modelling

(ABM) allows individual behaviours and interactions among heterogeneous actors to be represented, showing how collective dynamics can emerge from such interactions in ways that are not directly predictable ex ante (Macal, 2010; Feola et al., 2012). An increasingly established trend is the integration of these approaches into hybrid models. The objective is twofold: on the one hand, to combine complementary disciplinary expertise, for instance, merging the rigour of physical sciences with insights into social dynamics; on the other, to leverage the specific strengths of each methodology in a synergistic manner in order to offset their respective limitations (Macal, 2010; Macal, 2016).

In light of these considerations, key remaining challenges concern the realistic, rather than overly simplistic, representation of human behaviour and the complexity of institutional practices. Indeed, the structured and continuous involvement of stakeholders throughout the entire analytical process, from defining objectives to parameter calibration and result validation, is now recognised as a central element in developing models that are both scientifically robust and representative of real-world systems and social dynamics (Feola & Binder, 2010; Schreinemachers & Berger, 2011).

5.2 Pure Simulation: System Dynamics

System Dynamics (SD) models (Sterman, 2002; Qudrat-Ullah, 2012) do not aim to predict individual events, but rather to understand the behaviour and temporal evolution of a system as a whole by analysing the underlying structure that governs it. The core assumption is that a system's dynamic behaviour emerges directly from its internal architecture, characterised by networks of feedback loops (Richardson, 1991). The development of a System Dynamics model follows a well-structured process, articulated into the following conceptual and operational phases:

1. Definition of the Dynamic Problem over Time;
2. Formulation of a Dynamic Hypothesis. The objective is to identify the system's causal feedback structure;
3. Construction of the Formal Model (Stock and Flow). The dynamic hypothesis is translated into a formal mathematical model using the stock-and-flow language. Stocks represent resources or states that accumulate over time (e.g. groundwater volume, biomass, financial capital). Flows, governed by decision rules, represent the rates of change that increase or deplete stocks. This step transforms the qualitative relationships expressed in causal diagrams into a system of differential equations, often non-linear (Saysel et al., 2002; Yin & Struik, 2010);
4. Simulation, Analysis, and Validation. The formalised model is subjected to simulation procedures, and the resulting behaviour is tested through rigorous validation processes to assess its consistency with observed data and the structure of the real system.

Once validated, the model can be used to simulate the impact of alternative strategies, identifying those capable of modifying the system's structure in ways that generate more desirable long-term behaviours (Barlas, 2007; Martinez-Moyano & Richardson, 2013). Overall, the principles underlying SD require an inherently holistic and interdisciplinary approach. To illustrate this, consider the example of water scarcity in an agricultural district (Sušnik et al., 2012). A mechanistic interpretation might attribute water shortages solely to climatic variables. An SD approach, by contrast, recognises that the problem arises from a complex network of feedbacks involving physical, economic, social, managerial, and institutional factors. Within this system, the farmer acts as an "observer–decision-maker" who, based on perceived water availability (a stock), activates decision rules (flows) that determine groundwater abstraction (another flow), which in turn affects the water stock, thereby closing a critical feedback loop.

It is important to emphasise that SD models are not predictive tools in a narrow sense. Their value is primarily heuristic: they serve to enhance understanding of system structure. Simplification is therefore a requirement rather than a limitation. The model must provide an adequate but abstract representation of reality, including only those variables that are theoretically and empirically meaningful for the problem under investigation. In general, the overall model structure incorporates the physical, economic, and institutional environment (Sušnik et al., 2012). Decision rules are embedded within the structure itself, rather than treated as external inputs. Flows thus represent specific decisions per unit of time (e.g. cubic metres of irrigation water applied daily or seasonally), while stocks capture slowly changing and cumulative elements, which may be tangible (water reserves, capital) or intangible (perceptions, expectations, collective knowledge). It is precisely this ability to model decision-making and accumulation processes explicitly within a framework of dynamic feedbacks that gives SD its distinctive explanatory power in the study of complex and adaptive agricultural systems (Walters et al., 2016).

As descriptive models, SD does not prescribe how decisions should be made to achieve optimal or equilibrium outcomes, as in mathematical programming and optimisation models. Instead, it illustrates what might happen based on the decision rules in place. This is where the principles of bounded rationality and behavioural decision theory become relevant, guiding the modelling of decision-making processes within SD (Sterman, 2002; Feola et al., 2012). Accordingly, factors such as habits and individual experience play a significant role. Following direct and indirect validation iterations and the development of a robust and reliable model structure, it becomes possible to design future policies by introducing alternative decision rules that may lead to different outcomes and the construction of desirable scenarios (Barlas, 2002; Qudrat-Ullah, 2012).

To obtain a model that, albeit simplified, reproduces observed real-world dynamics, it is necessary to incorporate concrete solutions rather than arbitrary assumptions or researcher-imposed "test" choices. Implementing such solutions is complex and demanding, requiring the communicative involvement of managers, domain experts, and farm decision-makers, as well as group learning processes aimed first at identifying the system and the problem under investigation, and subsequently at carrying out the actual model-building phases (Richardson, 1991; Weber & Schwaninger, 2002; Martinez-Moyano & Richardson, 2013).

Currenty System Dynamics models can incorporate not only internal system dynamics, but also those of interconnected external environments, such as environmental drivers or social contexts closely linked to the core issue (Turner et al., 2016; Walters et al., 2016; Shamsuddoha et al., 2023). Model complexity may therefore vary depending on the level of detail and the degree of integration among components. Nevertheless, even relatively simple models that represent only part of the related domains can provide meaningful causal insights and help elucidate underlying dynamics. In this domain, agent-based models can also be distinguished, as they examine emergent behaviour arising from interactions among individuals governed by simple rules (Bianchi & Squazzoni, 2015).

5.3 Agent-Based Modelling

Agent-Based Modelling (ABM) represents a computational paradigm that enables the simulation of complex systems starting from the behaviour of their individual components. Unlike mathematical models that describe a system at an aggregate level, ABM "constructs" system reality from the local interactions among its constituent elements, namely agents (Bousquet & Le Page, 2004; Freeman et al., 2009).

Within this framework, an agent is an autonomous entity (such as an individual, a farm, a social actor, or even an environmental unit) situated within a virtual environment. Each agent is endowed with a set of decision rules that allow it to perceive its surroundings, interact with other agents, and act according to its situation and intrinsic characteristics (Bonabeau, 2002; Macal & North, 2009; Helbing, 2012; Bianchi & Squazzoni, 2015).

Although the underlying rules may be shared across agents, the parameters governing their behaviour are unique to each one (Feola et al., 2012). For instance, in a model designed to simulate changes in farmers' decision-making, all agents might follow an "imitation" rule, but their propensity to imitate could vary according to age, experience, or risk aversion (Maes & Van Passel, 2017; Berger & Troost, 2014). Interactions and actions are also constrained by agents' intrinsic properties and spatial positioning. An agent may not interact with all others due to distance or physical barriers, thereby reproducing realistic dynamics of proximity and accessibility (Filatova et al., 2013).

The core of the simulation lies in the iterative repetition of these local interactions. As simulated time progresses, agents' actions can modify the surrounding environment, which in turn influences their subsequent decisions, generating real-time feedback loops (Freeman et al., 2009). It is precisely from this continuous and dynamic process that complex system-level behaviour emerges. In other words, the system as a whole displays properties that cannot be predicted or reduced to the simple sum of individual actions (Macy & Willer, 2002; Bonabeau, 2002; Macal & North, 2009). This implies that such systems cannot be decomposed into deterministic parts without losing their essential nature, often making a purely analytical solution of the underlying equations impossible.

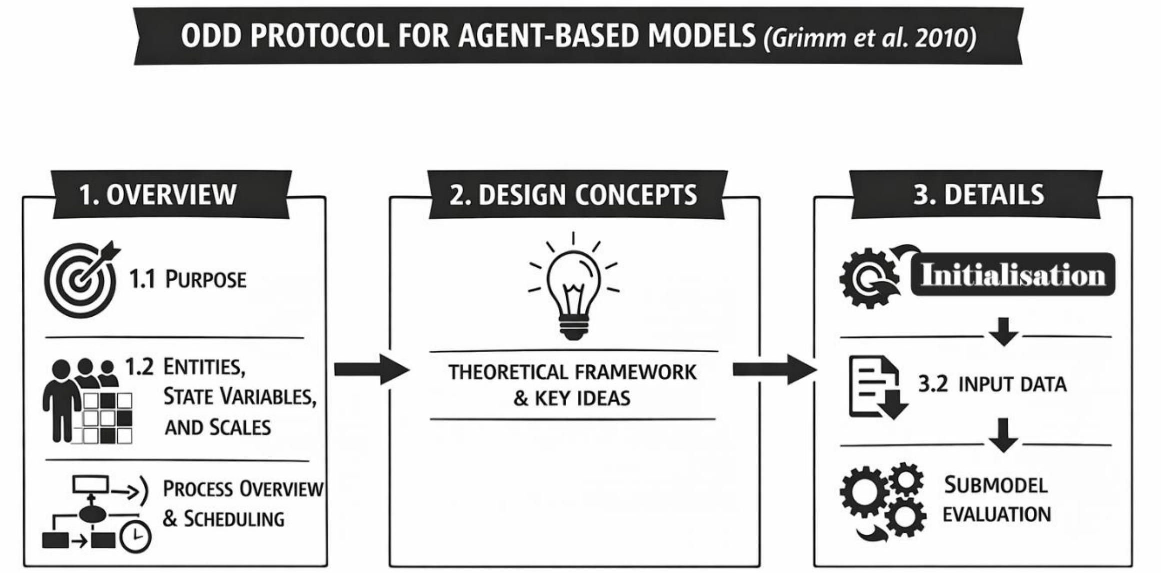
As a result, ABM simulations rely on dedicated software: only by observing the system in execution is it possible to study its dynamics. A further level of sophistication is introduced by allowing agents to modify their own nature and structure. Farmers, for example, may learn and evolve during the simulation, developing behaviours that are not pre-programmed, which makes these models particularly powerful for exploring long-term adaptation and change scenarios (Kremmydas et al., 2018).

When modelling agricultural systems, the main challenge is represented by their complexity. These systems are not simple mechanisms governed by deterministic laws, but rather living systems characterised by dynamics that often defy linear logic. This is where ABM demonstrates its primary strength: the ability to embrace such complexity by representing a world of heterogeneous actors, such as farmers and farms in this specific context, operating within an equally diverse environment, making decisions under uncertainty, and influencing one another through social networks (Bonabeau, 2002; Nolan et al., 2009; Balint et al., 2017).

Unlike other approaches, ABM does not attempt to compress reality into averaged equations. Instead, while still simplifying it, ABM enables the exploration of advanced contexts and the simulation of responses to key research questions, such as: How does an innovation spread? What impact would a new policy have on the use of specific natural resources? The answers emerge from the interaction of multiple individual decisions, each shaped by unique social and environmental contexts (Berger et al., 2006; Schreinemachers & Berger, 2011).

However, building an ABM with high explanatory power requires substantial investment in data collection and computational effort (Sun et al., 2016). This raises a critical question: how can one be confident that such a complex model is truly reliable? Validation is therefore particularly challenging, as it cannot rely solely on numerical benchmarks but must instead depend on simulating the constructed process and comparing encoded dynamics with real-world observations (Matthews, 2006; Barnaud et al., 2008). The purpose of ABM is thus to provide genuine platforms for dialogue, tools to "simulate" complexity and foster collective understanding of problems (Bousquet & Le Page, 2004; Voinov & Bousquet, 2010). In line with this core objective, model credibility does not rest exclusively on numerical accuracy, but also on the ability to facilitate information exchange and support the emergence of shared interpretations.

Unlike traditional modelling approaches, such as econometric models rooted in established communication protocols, Agent-Based Models had to define their own standards in order to be recognised as rigorous scientific tools. A major milestone in this process was the development of the ODD (Overview, Design concepts, Details) protocol by Grimm et al. (2010), now widely regarded as the standard for documenting and communicating ABM in a transparent and replicable way (Figure 1).



F**igure 1.** Steps outlined in the ODD protocol for setting up Agent-based models

6. Perspectives for Modelling in the Analysis of Agricultural Systems

The analysis of agricultural systems in the context of wastewater and reclaimed water use requires interpretative tools capable of capturing the interdependencies among environmental processes, resource management, technological options, and human decision-making. In line with the objectives of this thesis, the adoption of modelling approaches should therefore not be understood as an abstract methodological exercise, but as a research choice strictly connected to the need to analyse agricultural systems in relation to resource management, decision-making processes, and sustainability transitions. In this perspective, modelling becomes essential for linking technical, environmental, and socio-economic dimensions, thus supporting the interpretation of complex dynamics that cannot be captured through sectoral or static perspectives alone. For this reason, the choice of a modelling tool should stem from a careful and well-informed methodological reflection, closely aligned with the specific research questions being addressed. Different approaches are neither equivalent nor interchangeable, as they respond to distinct analytical logics (Almeder et al., 2009).

In transdisciplinary contexts, models can evolve into genuine mediation platforms that facilitate dialogue among diverse stakeholders, structuring complementary problem-solving processes. This is particularly relevant when addressing issues such as the agricultural reuse of wastewater, where farmers, institutions, water managers, and other actors interact within interconnected ecological and socio-economic systems. Within this framework, System Dynamics (SD) and Agent-Based Modelling (ABM), owing to their inherent capacity to represent dynamic processes and multi-actor interactions, constitute a more mature and established participatory approach than models based purely on optimisation.

However, efforts to develop more comprehensive and sophisticated models inevitably raise a range of challenges.

A first category of issues concerns the integration of paradigms, as in the case of combining biophysical and socio-economic modelling. This process requires the integration not only of quantitative and qualitative data, but also of entire sets of theoretical assumptions, analytical methods, and validation criteria, which are often difficult to reconcile. This challenge is especially relevant in the analysis of wastewater-related agricultural systems, where environmental processes, technological constraints, regulatory conditions, and social acceptance must be considered jointly. As a result, divergences may arise in the treatment of uncertainty and in validation procedures (Persson et al., 2005). In this respect, hybrid modelling represents a promising direction for overcoming these limitations (Schreinemachers & Berger, 2011; Mirzaei & Zibaei, 2018).

A second critical issue relates to the representation of social agents. Unrealistic assumptions, such as strict profit-maximising rationality, fail to capture the real nature of decision-makers, whose choices are instead shaped by bounded rationality, cultural norms, and social dynamics (Day, 2019). This aspect is central to the thesis objectives, since the adoption of sustainable water management practices, including wastewater reuse, depends not only on technical feasibility but also on the behaviour, perceptions, and interactions of the actors involved. Although participatory modelling is widely recognised as a valuable tool for supporting transitions towards sustainability, it remains in a phase of methodological consolidation. Its full scientific recognition depends on the development of greater procedural standardisation, even as the field continues to evolve, as evidenced by a growing body of case studies demonstrating its practical potential (Filatova et al., 2013; Khodabandelu & Park, 2021).

Table 2 provides a concise yet comprehensive overview of the main model categories discussed, highlighting their defining characteristics, strengths, limitations, and ideal application domains, while also clarifying their relevance to the analytical goals of this thesis.

Table 2. Characteristics, strengths, limitations, and application admains of the main model categories

Characteristics	Optimisation Models (LP, NLP, MOP)	System Dynamics Simulation Models (SD)	Agent-Based Models (ABM)
Objective	To find the optimal solution (e.g. maximum profit) subject to a set of constraints.	To simulate aggregate system behaviour over time, focusing on stocks, flows, and feedback loops.	To derive system behaviour from the interactions of autonomous and heterogeneous agents.
Strengths	• Provides a clear and quantifiable "best" solution. • Enables scenario analysis and efficient resource allocation. • Models are relatively transparent and verifiable.	• Supports understanding of system dynamics and temporal trends. • Effective for modelling complex feedbacks and delays. • Handles aggregated-level processes satisfactorily.	• Captures actor heterogeneity and social interactions. • Models the emergence of complex patterns through simple rules. • Can be spatially explicit and well suited to participatory processes.
Limitations	• Assumes well-defined rationality. • Limited ability to incorporate adaptive behaviour and learning processes. • May be unrealistic in contexts of high uncertainty and social complexity.	• Aggregates individual behaviour, losing detail at the actor level. • Difficulty in representing heterogeneity and social networks. • Limited capacity to represent micro-level decision-making processes.	• Model design and calibration can be time-consuming. • Data requirements depend on model scope and parametrisation. • Validation is often complex and partly qualitative. • Risk of excessive complexity and limited standardisation.
Ideal Application Domains	• Farm planning (cropping plans, production mix). • Cost–benefit analysis of technologies or policies. • Analysis of regulatory or market scenarios under known conditions.	• Study of common-pool resource dynamics (e.g. water, soil) at area or basin scale. • Models of practice diffusion or pollutant spread at aggregated level. • Understanding of system cycles and trends (e.g. carbon, nutrients).	• Study of innovation adoption and information diffusion. • Policy analysis with unevenly distributed effects. • Management of common-pool resources involving heterogeneous and interconnected actors. • Exploration of complex and adaptive change scenarios.

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Chapter 6

Applying an Agent-Based Model to the Use of Treated Wastewater for Irrigation

1. Introduction

The selection of a model for analysing agro-ecological systems may depend on several factors, including the context of application, the specific analytical scope, the objectives pursued, the relative importance assigned to economic and environmental components, and the assumptions regarding the relationships among these components. Real-world contexts often exhibit specific characteristics, such as biophysical processes, management constraints, environmental conditions, and socio-economic objectives, that make either optimisation-based models or simulation-based approaches more suitable. A review of studies applying different modelling frameworks in agriculture shows a growing tendency, from an evolutionary perspective, to integrate elements from both approaches in order to better capture the multidimensional nature of agricultural decision-making.

This chapter presents a review of empirical studies that have applied optimisation and simulation models in agriculture, with a particular focus on resource use and the environmental impacts of decision-making. Then, it introduces an example of an Agent-Based Model designed to represent farmers' decision processes regarding the use of treated wastewater for irrigation. The analysis of this model highlights the parameters and data required for its implementation, the way agent behaviour is modelled, the interactions between environmental and economic dimensions, and the range of potentially measurable effects.

2. Modelling Applied to the Agricultural Sector: A Review of the Literature

2.1 The Application of Optimisation Models

Farm-level optimisation models constitute a widely used tool to support decisions on land use and productive resource allocation, with increasing emphasis on the simultaneous pursuit of environmental, economic, and social objectives (De Rocquigny, 2012; Castro & Lechthale, 2022). Beyond describing production processes and interactions among system components, these models enable the anticipation of management impacts across multiple dimensions of sustainability (Castro et al., 2018). They are therefore particularly suited to addressing challenges characterised by resource allocation constraints, conflicting objectives, and the need to assess alternative scenarios.

The literature documents the application of optimisation techniques across a broad range of agricultural systems, often combining biophysical and economic dimensions (Kragt, 2012).

Areas of use include the representation of intensive or mixed farms, forest systems for determining harvesting cycles and forest management strategies (Kragt, 2012), models for soil and water resource management (Semaan et al., 2007; Alary et al., 2016), pest and plant disease control approaches (Atallah et al., 2018), as well as tools for ecosystem conservation and environmental risk assessment (Townsend et al., 2016; Clasen et al., 2011).

A shared feature of these applications is the ability to represent systems in which production components are tightly interlinked with environmental and socio-economic factors, underscoring the need for integrated ecosystem management.

Historically, optimisation-based modelling has already been employed to guide environmentally beneficial management decisions (Miljkovic, 1995; Srivastava et al., 2002). More recent methodological advances have expanded its scope, enabling the treatment of complex issues such as uncertainty, multi-objective optimisation, and integrated environmental policy evaluation (Masoumi et al., 2020; Galán-Martín et al., 2017; Li et al., 2024). Nevertheless, some limitations persist, including insufficient stakeholder involvement in model development and the lack of communication platforms that make these tools fully accessible to public and private decision-makers. Despite these constraints, optimisation remains one of the most effective approaches for analysing agricultural systems characterised by complex interactions among heterogeneous variables.

A major application strand concerns the identification of optimal combinations of inputs and productive resources, increasingly incorporating environmental and ecological services that were previously not explicitly modelled (Cotter et al., 2014). In this context, Li et al. (2020) highlight how the expansion of intensive agricultural areas has heightened environmental risks and intensified pressure on natural resources, thereby requiring tools capable of guiding farmers towards more efficient input reallocation under stricter environmental constraints. The model developed by the authors provides operational support for designing farm-level sustainable land-use plans that simultaneously pursue economic and environmental objectives.

Growing attention to specific ecosystem services has further stimulated the development of targeted models. Kleftodimos et al. (2021) examine the role of pollination services in insect-dependent crops, addressing the trade-off between crop protection through pesticide use and pollinator conservation. Using a farm-level calibrated ecological-economic model based on Positive Mathematical Programming (PMP), the authors show that explicitly recognising the economic value of pollination can underpin more effective and differentiated public policies. Similarly, Mosnier et al. (2009) analyse the effects of agri-environmental measures under the Common Agricultural Policy on farm profitability and environmental impacts. Through a bio-economic model calibrated on French farms, the study incorporates production uncertainty and agro-environmental indicators, demonstrating that appropriate combinations of decoupled payments and mandatory measures can enhance environmental performance without causing substantial income losses.

More recent developments in modelling point towards multi-objective frameworks and hybrid systems that integrate optimisation and simulation procedures within structured sequences (Calvet et al., 2020). A considerable example is provided by Galán-Martín et al. (2017), who develop a multi-objective model for the sustainable management of irrigated and rain-fed wheat systems, aiming jointly to maximise production and minimise environmental impacts, particularly those associated with water consumption, assessed through ecosystem quality and water depletion indicators.

Water resource management represents one of the most recurrent themes in the literature. Several studies conducted across diverse agricultural contexts place irrigation, water scarcity, and the identification of alternative water-efficient strategies at the centre of their analyses (Tan et al., 2021; Li et al., 2024; Kelly et al., 2023), based on the premise that integrated soil-water management is a key lever to counter growing water shortages and ecological degradation (Tan et al., 2021). Kelly et al. (2023), using a coupled simulation–optimisation model integrated with a crop growth model, compare annually adaptive irrigation strategies with fixed strategies optimised ex ante. Their results indicate that, in certain contexts, well-calibrated fixed strategies may outperform complex adaptive systems. From a different but complementary perspective on rational resource use, Li et al. (2024) introduce a multi-objective optimisation model for crop planning in China, embedding both economic and environmental objectives and incorporating a resilience constraint for the water system. This approach highlights that environmental and resource sustainability cannot be treated as an emergent outcome, but must instead be explicitly embedded within the problem formulation.

2.2 The Application of Simulation Models

As previously discussed, simulation establishes a well-established component of agricultural research, as it enables the structured yet simplified representation of the key processes governing the functioning of production systems. By integrating large volumes of data, including agronomic, pedological, meteorological, and sometimes economic information, these models allow the analysis of agricultural system dynamics under varying conditions and management scenarios. They therefore provide a valuable experimental tool for understanding system responses to both endogenous and exogenous changes. Their versatility makes it possible to evaluate a wide range of management alternatives, from adjustments in resource use to the adoption of innovative practices, as well as the simulation of impacts arising from climatic stressors or structural transformations in the agricultural sector.

Although they share a methodological foundation based on abstract representations of real-world processes, simulation models differ in terms of objectives, level of detail, scale of application, and the types of phenomena they capture. Among the most established strands are crop simulation models (commonly referred to as "crop models") which adopt a mechanistic approach aimed at the detailed description of the physiological processes governing crop growth and development (Soltani & Hoogenboom, 2007; Wang et al., 2017). These models integrate the main factors influencing agricultural production, including climate, soil, agronomic practices, and genetic varieties, in order to estimate potential yields, water and nutrient requirements, and the effects of specific cultivation techniques. Although they have undergone substantial enhancements over time—particularly through the expansion of biophysical modules and the inclusion of new crop varieties—their structure remains centred on the functional unit represented by the "crop–soil–management" complex (Soltani & Hoogenboom, 2007; Ferrise et al., 2011; Zhang et al., 2002). Their accuracy is strongly dependent on the availability and quality of meteorological data.

A particularly relevant contribution in this area is provided by Soltani & Hoogenboom (2007), who examine the role of climate data in the predictive capacity of crop models. The authors compare the use of observed historical time series with synthetic climate data generated through two different statistical generators, with the aim of assessing their reliability for simulation purposes. Their study extends beyond a single comparison of management practices, emphasising the methodological importance of incorporating realistic and statistically consistent climate data. It demonstrates that access to appropriate datasets is a fundamental prerequisite for the validity of simulation outputs. The findings highlight the need to adopt hybrid solutions that combine different modelling approaches in order to broaden applicability, particularly in contexts where meteorological monitoring is incomplete or unavailable.

A similar developmental trajectory is reflected in the work of Ferrise et al. (2011), in which a durum wheat growth simulation model, based on the integration of climatic, soil, and management data, is subsequently simplified through a statistical model. This latter model enables the training of an artificial neural network using outputs generated by the biophysical model under multiple experimental combinations. The authors' objective is to estimate, based on a reduced set of key climatic variables, the probability that future yields will fall below a critical threshold. This represents a particularly significant methodological step, as it illustrates how crop simulation techniques can be combined with advanced statistical tools to manage climatic uncertainty and simplify complex decision-making processes, while maintaining high predictive accuracy.

The evolution of agricultural modelling extends beyond crop-focused applications. The increasing interconnectedness of agricultural systems and their exposure to multiple influencing factors have driven research towards the development of integrated agro-ecosystem models capable of incorporating, alongside biophysical components, climatic, hydrological, biogeochemical, and socio-economic elements (Wei et al., 2009; Maharjan et al., 2018; Martínez-López et al., 2022).

These models move beyond field-scale analysis and adopt a multi-level perspective in which heterogeneous processes are integrated through modular platforms designed to simulate complex agro-ecosystem dynamics. The shift towards such integration is already highlighted by Zhang et al. (2002), who stress the need to complement traditional crop models with dedicated modules, such as crop and biogeochemical sub-models, to more realistically represent nutrient cycles, soil fertility dynamics, and the impacts of alternative management practices.

The need to improve adaptability across diverse application contexts has led to the evaluation of models that integrate the economic dimension either centrally or as a supplementary component. Ochieng et al. (2016), for example, analyse the effects of climate change on high-demand crop yields in Kenya by integrating an agricultural production simulation model with panel and climate data. Through an economic module incorporating estimated elasticities, the authors project production revenues under future climate trajectories, illustrating how temperature and precipitation influence both yields and farm profitability. The need for a more integrated approach is also strongly evident in studies that combine simulation models with optimisation techniques, particularly when the primary objective is to maximise economic returns while ensuring the sustainability of water resources (Ines et al., 2006; Bharati et al., 2008). Typical research questions include identifying optimal crop combinations or irrigation regimes under conditions of limited water availability. In such cases, simulation provides the representation of production processes, while optimisation identifies the most advantageous management strategies, integrating sustainability criteria and physical constraints within the agricultural system.

Seeking to advance beyond purely simulation-based approaches, Donatelli et al. (2017), in their review, underscore the need to move beyond empirical methods based solely on historical data, advocating the development of process-based models capable of dynamically simulating interactions among crops, pests, and environmental conditions (Aggarwal et al., 2006). The overarching goal is to enhance the formulation of more accurate tools for producing reliable farm-level estimates and forecasts.

The integration of economic dimensions is also regarded as essential in simulations focused on the introduction of new technologies or resources with potential agricultural applications (Bizimana & Richardson, 2019; Kadigi et al., 2020; Balana et al., 2020; Li et al., 2023). For example, Balana et al. (2020) employ a farm-level simulation model to assess the economic feasibility of introducing small-scale irrigation technologies in subsistence farming contexts in Ghana. At the same time, the model evaluates economic, production, and nutritional effects, shifting the analytical focus from purely biophysical considerations towards a broader agro-economic simulation framework.

Within this diverse modelling landscape, System Dynamics (SD) approaches occupy a distinctive position, as they adopt a highly abstract perspective that conceptualises systems as sets of interdependent variables linked through stocks, flows, and feedback structures (Feola et al., 2012). Rather than providing detailed representations of biophysical processes, SD models emphasise the dynamic mechanisms that drive system evolution over time. SD modelling is particularly suited to analysing policy scenarios, sustainability transitions, and long-term structural changes. In the literature, these models have been applied to simulate both direct and cumulative effects of fertilisation and irrigation practices (Saysel et al., 2002; Yin & Struik, 2010), demonstrating, for example, how practices that appear beneficial in the short term may lead to long-term soil degradation processes such as nutrient depletion or salinisation.

System Dynamics approaches have also been successfully applied at the farm level. Walters et al. (2016) develop a model aimed at comparatively evaluating three alternative production systems, incorporating economic, environmental, and social drivers within the simulations. The model analyses the evolution of farm wealth, input-related cash flows, and overall profitability, enabling the identification of the most sustainable configuration. Shamsuddoha et al. (2023) propose a comparable application in a livestock context, where the adoption of circular economy practices, such as the recovery of effluents and manure, is assessed in terms of economic, managerial, and environmental impacts over the medium to long term.

Further methodological advances have led to the introduction of multi-level System Dynamics models, which allow the representation of aggregated agricultural systems by modelling average behaviours and interactions among farms, institutions, and territorial actors (Herrera et al., 2022). These models highlight how agricultural systems are shaped by social dynamics, collective learning processes, and strategic behaviour, underscoring the role of social interaction in innovation adoption and management decisions. The capacity of SD approaches to capture these dynamics makes them particularly well suited to studying contemporary agricultural and environmental challenges that require systemic change and long-term strategies (Turner et al., 2016).

The usefulness of System Dynamics approaches also extends to territorial and policy scales. Numerous studies demonstrate how these models can simulate the combined effects of policy measures, resource management interventions, and climate scenarios (Georgiadis et al., 2005; Weber & Schwaninger, 2002; Shi & Gill, 2005; Kotir et al., 2016; Wang et al., 2022; Bai et al., 2022). Bai et al. (2022), for example, employ an integrated hydrological and socio-economic model to assess the long-term impacts of irrigation efficiency policies, showing that the actual effectiveness of such measures depends on adaptive capacities that develop progressively within agricultural systems and the communities involved.

Overall, the reviewed evidence indicates that the System Dynamics approach enables the integration of social dynamics and multi-level interactions, effectively functioning as an interactive virtual laboratory (Weber & Schwaninger, 2002). From this perspective, the objective extends beyond simulating ecosystem processes or production dynamics to include the representation of interactions and behavioural patterns among the actors involved.

2.3. The Application of Agent-Based Models in the Agricultural Sector

Agent-Based Models (ABMs) represent a significant shift from traditional modelling approaches, which are typically based on representative agents, firms, or farm typologies. The behavioural literature shows that individuals, including farmers, exhibit substantial heterogeneity in preferences, resource endowments, and decision-making processes (Heckman, 2001). This heterogeneity, combined with the intrinsic complexity of agro-ecosystems, often necessitates modelling tools capable of capturing articulated system configurations, particularly in the presence of innovations, new technologies, new products, or changes in production processes, as well as in response to climatic shocks or public policy interventions (Kremmydas et al., 2018; Brown et al., 2017). In this context, ABMs allow the explicit, dynamic, and adaptive representation of the behaviour of actors within agricultural systems, including farmers, cooperatives, processing firms, consumers, and institutions (Macy & Willer, 2002; Macal & North, 2009). Their bottom-up structure makes it possible to define simple decision rules at the individual agent level from which macro-level phenomena emerge, not as a mere aggregation of individual actions, but as the result of non-linear interactions among agents and their operating environment (Macal & North, 2009). This generative process makes ABMs particularly well suited to exploring complex and counter-intuitive scenarios, in which small behavioural changes at the local level can produce substantial system-wide effects.

The advantages of using ABMs in agriculture are numerous. They enable a realistic representation of heterogeneous farmer groups within a given region or territory, distinguishing them by farm size, resource availability, operational constraints, time horizons, and preferences. They also allow the modelling of strategic interactions among neighbouring agents, the assessment of investment profitability or economic feasibility under uncertainty, and the simulation of the impacts of public policies and subsidies on both individual and collective behaviour (Macal, 2016; Macy & Willer, 2002). The ability to generate macro-level outcomes from micro-level rules, while maintaining a detailed representation of actors, results in a process-based framework that links individual choices to collective outcomes and makes the influence of dynamic interactions explicit (Macal & North, 2009; Macal, 2016).

Macal (2016) emphasises that one of the main strengths of agent-based modelling lies in its capacity to reproduce human decision-making processes and social interactions with a degree of realism that is difficult to achieve with other modelling approaches. For this reason, ABMs are not intended to replace but rather to complement frameworks such as System Dynamics, as they operate at different analytical levels: ABMs stress heterogeneity and decentralisation, whereas System Dynamics focuses on aggregate dynamics. A similar argument is advanced by Balint et al. (2017), who contend that research in climate change economics characterised by complexity, uncertainty, multi-scale interactions, and non-linear phenomena, cannot be adequately conducted using traditional equilibrium models, which often fail to capture critical thresholds, tipping points, and heterogeneous behaviour.

Filatova et al. (2013) discuss the application of ABMs in socio-ecological systems, where they have been used in water resource management, pest control, and drought adaptation strategies, showing that such models can receive environmental inputs either through unidirectional linkages or via bi-directional feedback structures between society and the environment (Heckbert et al., 2010).

In plant ecology, Zhang & DeAngelis (2020) document the extensive use of ABMs to represent plant and forest communities and to simulate their evolutionary trajectories under future climate scenarios. In agricultural economics, ABMs have found particularly significant application in policy evaluation. Kremmydas et al. (2018) highlight their use in simulating land-use change, adaptation to variable environmental conditions, structural transformation in farms, and the impacts of innovation, citing Berger (2006) as one of the earliest contributions to modelling structural and income changes in agricultural enterprises. In these models, the farmer or farm serves as the primary unit of analysis from which decisions and behavioural patterns emerge.

Alongside methodological advances, there has also been an evolution in the software tools used to build ABMs. At present, a wide range of modelling platforms and toolkits exists, differing in application domains, usability, scalability, and performance, each being more or less suitable depending on modelling objectives and the required level of detail (Abar et al., 2017).

Nevertheless, rigorous documentation of an agent-based model requires adherence to the ODD (Overview, Design Concepts, Details) protocol, which constitutes a widely recognised standard in

ABM research (Grimm et al., 2010). This framework systematically defines the model's objectives, the types of agents involved, the sequence of their actions and interactions, the underlying theoretical concepts, as well as the data, equations, rules, and algorithms employed, thereby ensuring transparency, comparability, and reproducibility of results.

Overall, the analysis of case studies in which ABMs have been used for simulation purposes indicates that this approach is particularly effective in the management of natural resources and ecological systems (Nagarajan et al., 2022; McLane et al., 2011). McLane et al. (2011), for example, use an ABM to design conservation strategies for habitats of endangered species, demonstrating that agent-based modelling can support policy decisions requiring a balance between economic development and environmental protection. Although the economic dimension is not the primary focus of their study, the authors stress the importance of accounting for the opportunity costs associated with the designation of protected areas. Similarly, Hailegiorgis et al. (2018) implement an ABM to analyse adaptation strategies of farming households in southern Ethiopia in response to climate change. Their focus is not on conventional economic indicators, but rather on perceptions, expectations, and learning capacities, integrating these elements within a socio-cognitive framework that captures the complexity of decision-making under conditions of risk and vulnerability.

By contrast, Morgan & Daigneault (2015) underscore the critical importance of the economic dimension in environmental policy assessment. In their agent-based model, integrated with a partial equilibrium framework, they simulate farmers' responses to greenhouse gas emission pricing, analysing land-use decisions and their effects on net income and environmental indicators. In doing so, they combine profit maximisation with behavioural, social, and perceptual factors that influence decision-making.

Further studies confirm that ABMs are well adapted to capturing the complexity of farm-level decision-making (Lang & Ertsen, 2023). Bert et al. (2011), modelling farms in the Argentine Pampas, simulate changes in land use and production structures while incorporating economic variables such as working capital, production costs, and crop profitability. Their results show that economic sustainability is closely linked to farm size, with smaller farms being more exposed to the risk of exiting the sector.

Following a similar approach, Burg et al. (2021) apply an ABM to analyse farmers' decisions regarding the adoption of biogas plants under different economic and social incentive schemes. The model integrates information on energy prices, subsidy availability, and cooperative interactions among farmers, with the aim of assessing how varying combinations of incentives and social interactions influence investment choices.

The growing need to represent interactions among diverse actors with increasing accuracy has led to the development of more complex multi-agent models capable of overcoming the limitations of pre-aggregated modelling frameworks (Berger & Troost, 2014; De Keyser et al., 2025). Malawska & Topping (2016) show how a farm-level economic optimisation model can be progressively enriched by integrating technical constraints and, subsequently, behavioural assumptions derived from agent-based modelling, resulting in a representation that more closely reflects agricultural reality. Mirzaei & Zibaei (2018), in contrast, adopt an integrated approach combining an optimisation model, a hydrological model, and an ABM to evaluate the effects of agricultural decisions on water availability and wetland conservation, demonstrating that this combination can reveal impacts that would otherwise remain unobserved.

The representation of the environment constitutes a crucial element in ABMs: it may be conceptualised either as a static background context or as an active entity characterised by autonomous dynamics that both influence and are influenced by agents through bi-directional feedback mechanisms (Matthews, 2006). An advanced example of integration is provided by the Mathematical Programming-based Multi-Agent System (MP-MAS), developed by Schreinemachers & Berger (2011), which combines Positive Mathematical Programming with biophysical dynamics and multi-agent social interactions, while systematically incorporating the economic dimension. This framework enables a more realistic treatment of complex policy analysis challenges, particularly in contexts characterised by climate change, water scarcity, and the need for ecological transition.

3. Agent-Based Models Applied to Water Resource Use in Agriculture

3.1. Introduction

Across several applied studies, agent-based models have been used to analyse scenarios related to water resource management in agriculture. Water scarcity represents one of the major challenges for irrigated agriculture, requiring the development of adaptation strategies that integrate new supply approaches, technological innovations, and appropriate institutional pathways (Binswanger et al., 2009). In many developing countries, this challenge is further exacerbated by the lack of water storage infrastructure, distribution networks, and modern technological solutions. In such contexts, competition among agricultural, domestic, and industrial water uses is often intensified by the limited availability of surface and groundwater resources, sometimes leading to disputes over water property rights and access (Easter et al., 1998).

To understand, predict, and support water-related decision-making processes, several authors have proposed simulation models capable of representing, at an aggregated level, hydrological basin dynamics, user choices, and their associated economic outcomes (Perry, 2011; Arnold et al., 2015). Although these models require substantial and structured datasets, they allow for realistic assessments of how individual decisions affect overall system-wide water availability. A particularly notable application is presented by Arnold et al. (2015) in a severely water-stressed region of south-central Chile. The model, fully based on autonomous farmer decision-making, integrates elements such as water consumption and recovery, incurred costs, market prices, and hydrological interactions among users. Among the simulated scenarios, drought emerges as capable of reducing agricultural production by up to 41%, while water reuse gains increasing relevance, contributing up to 28% of value added. This evidence confirms the strategic importance of water reuse as a component of water management analyses and irrigation policy, especially in contexts where infrastructure and distribution systems remain limited.

In parallel, Berger et al. (2007) demonstrate how multi-agent simulation can be used to analyse water resource use at the micro level, exploring interactions among water users and the social dynamics that influence management behaviour. In semi-arid regions specialising in high-value production, simulations highlight the importance of cooperation among users to ensure irrigation infrastructure stability and improve water-use efficiency, as well as the need for policies that account for distributional effects and the protection of more vulnerable users. In Berger's pioneering studies (2001), the integration of farm-level mathematical programming, cellular automata, and spatial dynamics enabled the analysis of farm decisions regarding investment,

production, and the adoption of irrigation innovations, underscoring the role of economic and social interactions in shaping the evolution of resource use.
In light of these contributions, this doctoral research develops a simplified and preliminary case study aimed at analysing water availability and the potential adoption of treated wastewater reuse in agriculture in a region of southern Italy, Basilicata, which has long been exposed to recurrent drought events and limited availability of conventional water resources. Although the reuse of treated wastewater has been discussed for years as a potential alternative, its adoption continues to face numerous barriers, including economic constraints, risk perception, trust in institutions, limited access to technical information, and the availability of adequate support mechanisms. Furthermore, the regional regulatory framework, the adequacy of wastewater treatment facilities, the definition of appropriate tariff structures, and the efficiency of distribution systems remain under development, restricting the full implementation of agricultural water reuse and resulting in an operational context that is not yet fully mature.
The construction of the model and the case study analysis are based on data and information collected through a field survey conducted on a sample of farmers in Basilicata, as well as interviews with key informants. The agent-based model developed here represents a preliminary formalisation of farmers' decision-making processes regarding the potential adoption of treated wastewater. Although not yet a fully established model, it incorporates the elements considered essential to understanding the system's potential dynamics: the role of individual perceptions, the availability of informational support, and the economic response to the use of alternative water sources. Through targeted simulations, the model enables the observation of how these factors may influence both the intention to adopt wastewater reuse and farm profitability under different operating conditions.
The following sections describe the general characteristics of the case study, the software used for simulation, the structure of the model, and the data employed, selected to represent the real-world system. Finally, the simulation results and the implications arising from observed changes in decision-making behaviour and economic outcomes will be discussed. Although still at an early stage of development, this work represents a preliminary step towards the creation of a Decision Support System (DSS) capable of identifying critical areas requiring enhancement and guiding future actions aimed at achieving more sustainable water resource management in Basilicata.

3.2 Case Study Analysis: The Reference Context

The study focuses on the challenges affecting irrigated agriculture in Basilicata, a southern Italian region that has increasingly been exposed in recent years to prolonged drought events and pronounced variability in rainfall patterns (Bentivenga et al., 2020; Bentivenga & Piccarreta, 2023). Within this context, the local agricultural sector, characterised in the study area by irrigated farms that rely heavily on water for high-value crops, appears particularly vulnerable. The primary conventional water source consists of supplies distributed by land reclamation consortia, whose unit cost is relatively low (approximately €0.06 per m^3), but whose availability has become increasingly irregular and uncertain, especially during drought years.

Among the possible responses to growing water scarcity is the reuse of appropriately treated wastewater for irrigation. Although this solution has already been tested in Italy across various contexts and crops (Michetti et al., 2019; Manganiello et al., 2024), in Basilicata - as in many other regions - it remains only marginally implemented at an operational scale. The main constraints on adoption include the limited modernisation and upgrading of wastewater treatment plants to meet the latest European standards, the absence or fragmentation of dedicated treated wastewater distribution networks, and the lack of a clear tariff framework defining both the price of the resource and the allocation of treatment costs. Despite these institutional and infrastructural shortcomings, treated wastewater represents a water source whose potential remains largely unexplored and often underestimated.

Within this framework, the analysis concentrates on the representation of specialised monoculture irrigated farms. The simulation focuses on farms dedicated to processing tomato cultivation, located in irrigated areas of Basilicata. Primary data and reference information for experimental purposes were collected through interviews with key informants (farm entrepreneurs and producer organisations) and relate to production performance, average irrigation requirements, available volumes of consortium-supplied water, farm profitability, and the propensity to adopt treated wastewater under conditions of water scarcity.

3.3. Structure of the ABM on Water Availability

The agent-based model was developed in accordance with the formulation and specification rules set out in the updated ODD protocol (Grimm et al., 2010), with the aim of representing in a simplified yet empirically grounded manner the decision-making behaviour of irrigated tomato farms in Basilicata, regarding the adoption of treated wastewater under conditions of water scarcity. Figure 1 summarises the definition stages prescribed by the ODD protocol, which provided the conceptual foundation for the Agent-Based Model developed.

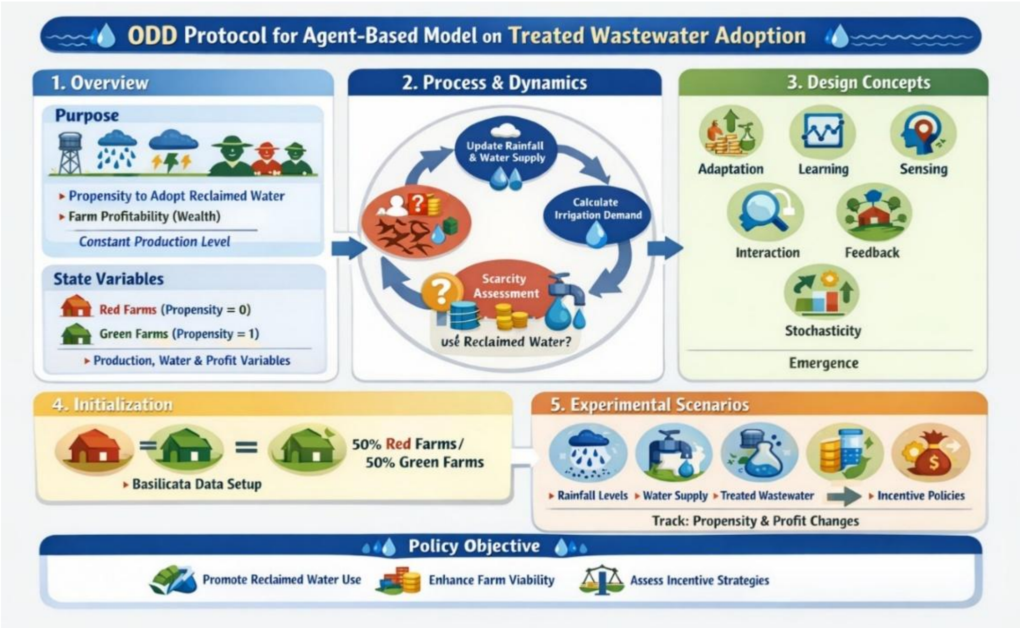


Figure 1. Phases of defining the agent-based model according to the ODD protocol (Grimm et al., 2010)

In terms of *Purpose*, the model is designed to analyse how the interaction between conventional water availability (supplied by land reclamation consortia), rainfall variability, the use and relative price of treated wastewater, and the presence of public support measures (incentives/subsidies) affects, over time, farms' propensity to use treated wastewater and, consequently, their profit (*Wealth*), while keeping production levels constant.

The *key entities* (*State variables and scales*) are irrigated farms (*patches*), initially classified into two types: "red" farms, with no propensity to use treated wastewater (*propensity* = *0*), and "green" farms, with a fully positive propensity to adopt it (*propensity* = *1*).

As noted previously, farms are monocultural (tomato) and characterised by the following state variables:

• reference annual production (constrained for green farms to an optimal level of approximately 800 quintals per hectare);
• average irrigation requirement;
• availability of consortium-supplied water;
• average rainfall;
• actual use of treated wastewater;
• farm profit, calculated by accounting for average production costs and, in particular, water-related costs.

The empirical basis for model parameterisation is drawn predominantly from primary data collected in Basilicata through questionnaires and interviews with farmers and key informants, as well as from observed technical and economic conditions in the study area. In particular, farm management choices, average production costs per hectare for tomato farms, the cost of conventional irrigation water supplied by the land reclamation consortium, rainfall patterns, and the dynamics of consortium water availability were parameterised using real-world information derived from field evidence.

The unconventional water resource is represented by treated wastewater, whose price range per cubic metre is instead parameterised on the basis of literature estimates for comparable contexts (Expósito et al., 2024), differentiated according to the level of treatment, since comparable empirical pricing data for agricultural wastewater reuse are not yet available in the Italian context.

The *model environment* is represented by a grid of irrigated farms, onto which—at a later stage—specific mobile agents are introduced to represent incentive policies. These entities do not generate agricultural output but instead activate conditions (in this case, subsidy availability or risk-coverage mechanisms) that farmers consider essential for increasing their willingness to adopt treated wastewater.

With respect to *Process overview and scheduling*, at each time step the model updates the availability of consortium water and rainfall, determines residual irrigation requirements, and decides whether farms resort to treated wastewater. When rainfall and conventional water availability are sufficient, no farm uses treated wastewater. Under scarcity conditions, green farms may activate the use of the non-conventional resource, whereas red farms may gradually adjust their propensity depending on the presence of incentives. A shift in propensity from negative to positive allows these farms to access a more expensive water source than consortium water, resulting in a corresponding impact on profit. This reduction may, however, be offset by potential future incentives linked to specific policy measures, currently not in place, whose hypothetical effects are represented in this version of the model as changes in propensity. At the same time, although green farms aim to maintain constant production levels, persistently negative profits caused by higher water costs over multiple consecutive growing seasons will also induce a change in their propensity.

The *Initialization* stage assigns an equal distribution of red and green farms and allocates to each farm production, water, and economic parameters derived from primary data collected in Basilicata. This 50/50 distribution does not directly emerge from the interviews, but represents a technical modelling choice adopted to simulate, under controlled initial conditions, the possible evolution over time of farms with opposite initial propensities towards treated wastewater use. The *simulations* include comparisons across scenarios featuring different levels of meteorological and consortium water availability, the introduction of treated wastewater, and the gradual implementation of incentive measures. This allows observation over time of changes in farms' propensity to use treated wastewater and the corresponding effects on profitability, with a view to the future formulation and economic evaluation of potential policy instruments aimed at promoting irrigational reuse of treated wastewater, an objective that currently remains beyond practical implementation.

3.4. Software Used

The model was developed using *NetLogo* (version 6.4.0), an open-source programming environment widely employed in the construction of Agent-Based Models (ABMs) due to its ability to integrate programming, execution, and visualisation of simulated processes within a single platform (Tisue & Wilensky, 2004). NetLogo is particularly well suited to analysing complex systems and exploring alternative scenarios through an interactive interface, while maintaining a logical and modular code structure (Tisue & Wilensky, 2004; Thiele et al., 2012).

The *Interface* section contains the simulation environment, consisting of a grid of cells known as *patches*, on which mobile agents (defined as *turtles)*operate. This area provides a graphical representation of agent–environment interactions, allowing visual observation of the dynamics that emerge over successive time steps. Through the configuration of specific *buttons* (*setup* and *go*), the system can be initialised according to the starting conditions and the simulation subsequently launched, running for a predefined number of steps or "seasons". Additional interface elements, such as *sliders, switches, input boxes, charts, and counters,* enable the modification of key parameters and the real-time monitoring of relevant variables, including, in this specific case, *farm profit* and *water resource use* (Figure 2).

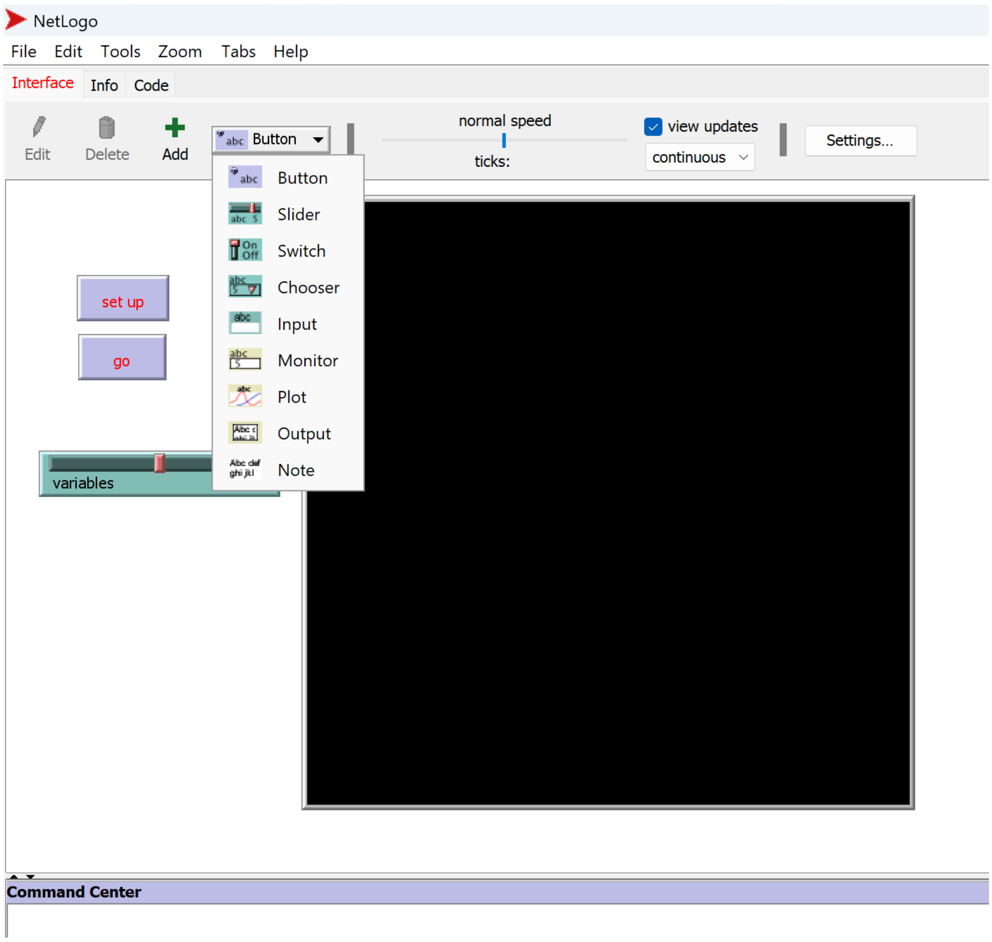


Figure 2. Interface and main commands of the implemented software (NetLogo)

The *Code* section contains the formal implementation of the model, written in the NetLogo programming language. Within this area, *global variables*, agent-specific properties (*turtles-own, patches-own)*, behavioural procedures, equations, decision constraints, and conditional rules governing system evolution over time are defined. This structure supports clear code management, facilitates potential extensions, and ensures transparency in model documentation.

A further important tool is *BehaviorSpace,* which enables the automated execution of experiments and systematic simulations by varying predefined parameter combinations. This functionality allows the generation of replicable simulation batches, exploration of the full parameter space, and identification of emerging patterns or sensitive conditions. The outputs produced through BehaviorSpace can be exported in tabular formats (e.g., *CSV*), making them easily compatible with external software for statistical analysis and data management. This integration supports in-depth quantitative analysis of model outputs and enhances the validation, interpretation, and comparison of the simulated scenarios.

4. The Simulation

As specified in the initial conditions and assumptions guiding the simulation, the farms included in the model were initialised within the simulation interface, under the assumption of a homogeneous distribution of propensity to use treated wastewater: 50% of farms are defined as willing to adopt treated wastewater, while the remaining 50% are classified as non-adopters. Farms are represented as monocultural and share the objective of maintaining and achieving maximum tomato production, which, for the study area (Metapontino area, Basilicata), can reasonably be set at 80 t/ha.

This production level can be attained - holding all other optimal conditions constant within the simulation - when the volume of water available during the growing season reaches 4,000 m³ per hectare (Figure 3). It should be noted that these values derive from technical reference manuals and interviews with key informants, with the aim of representing the simulated agricultural system as realistically as possible, in line with observed field conditions.

Within this framework, all farms prioritise the use of conventional water sources, namely rainfall and water supplied by the land reclamation consortium, to sustain agricultural production. As previously noted, consortium-provided water does not entail excessive costs, with an average unit price of approximately €0.06 per m³. Likewise, the average production costs assumed for tomato cultivation per hectare are based on real average values reconstructed from questionnaires and interviews conducted in the study area.

However, based on the most recent available information, analysis of average rainfall data for the area and actual consortium water supply indicates that, for several years, optimal conditions have no longer been met due to recurring drought. Precipitation has consistently been insufficient, and consortium water deliveries have never fully covered crop water requirements.

Consequently, when traditional water sources fail to meet the irrigation demand necessary to maintain constant production (80 t/ha), associated with an updated market price of €145 per tonne, the model assumes that only farms initially willing to adopt wastewater (the initial 50%, represented in green) choose to use treated wastewater (Figure 4).

Based on data from the latest ISTAT census (2024) and official reports, treated wastewater is considered highly available; for this reason, within the model it is assumed to be unlimited in quantity. Nevertheless, in the absence of an official tariff regime defining its cost, the study by Expósito et al. (2024) provides relevant indications regarding potential price variability, which may range between €0.16 per m³ and €0.66 per m³, depending on the required treatment level and associated distribution services. The use of this resource therefore entails an increase in irrigation costs, which inevitably affects farm profitability. Specifically, the lower the availability of conventional water, the greater the reliance on treated wastewater for irrigation; moreover, as both the volume of reused water and the required treatment level increase, the unit cost of the non-conventional water rises. This leads to higher total production costs and a reduction in profit (Figure 5).

The model accounts for the fact that even farms initially inclined to adopt treated wastewater reassess the economic viability of their decisions over time: if profits become persistently negative, these farms may decide to revise their propensity and abandon wastewater use in subsequent growing seasons. For non-adopting farms, the simulated dynamics differ. Evidence from interviews and field surveys indicates that these farmers choose to rely exclusively on traditional water sources, consciously accepting potential production losses. Only a small proportion are able to temporarily cope with extreme drought through self-built storage reservoirs; however, since such strategies are not yet fully institutionalised, they were not included in the model.

Therefore, as long as conventional water resources do not fall below a critical threshold, non-adopting farms continue production using only available traditional water, albeit at reduced yield levels. When the reduction in conventional water becomes severe enough to render profits negative, a condition emerges that would require a medium-term strategic shift to remain viable—although such a transition is not currently supported by existing policies.

Interviews reveal that a significant share of farmers has already been forced to abandon seasonal crops or switch in subsequent years to rainfed and extensive crops, which, given their limited cultivated area, still result in unsatisfactory production and economic outcomes. At the present stage, changes in propensity among non-adopting farms have been simulated exclusively on the basis of interview findings. In particular, in the presence of public policies offering economic incentives, a substantial proportion of currently non-adopting farmers would shift towards a more favourable attitude, as such instruments are perceived as protective mechanisms against unforeseen risks, including additional costs or potential contamination-related concerns (Figure 6).

Figures 3–6 illustrate the model interface, the simulation initialisation phase, and the evolution of farm conditions and profitability across multiple growing seasons under the specific conditions described above.

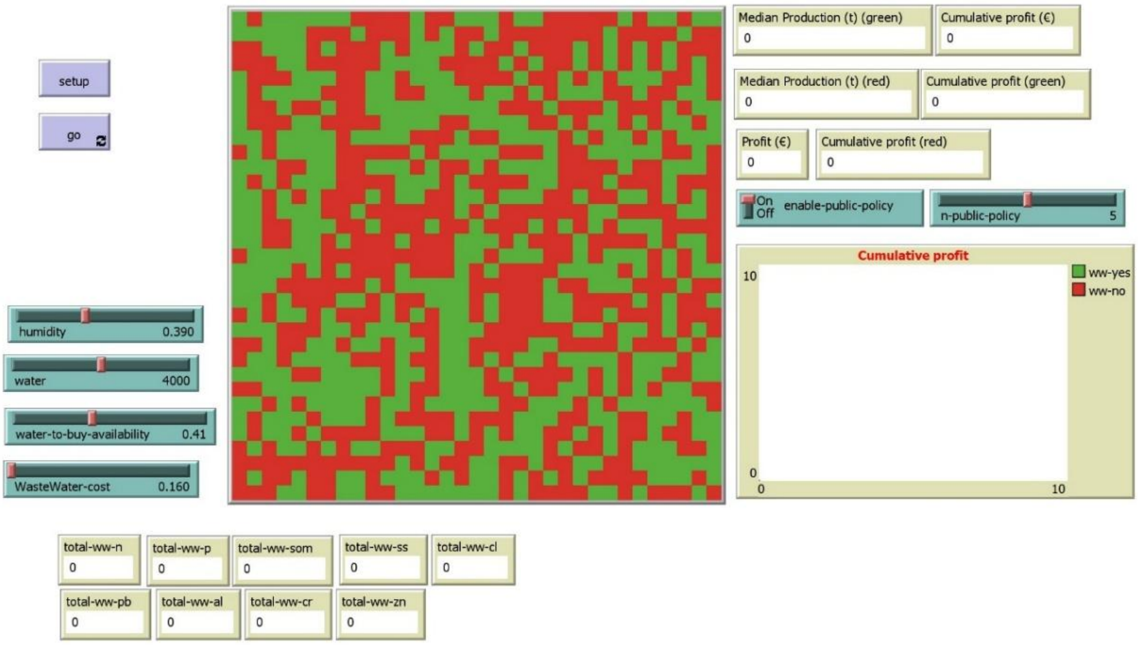


Figure 3. Initialisation - Firms starting with 50% willing and 50% unwilling, with water required for production set at 4,000 m3 and with average rainfall relevant to the context

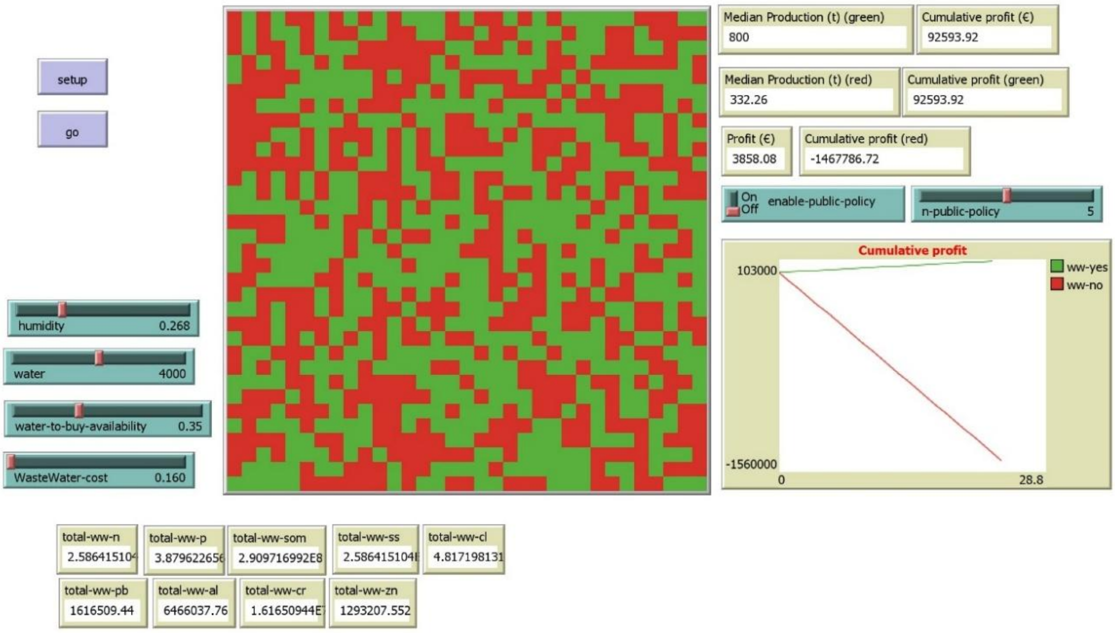


Figure 4. Start of simulation - when traditional water sources are insufficient to satisfy crop needs, the model assumes that only farms initially willing to do so will opt to use reclaimed wastewater.

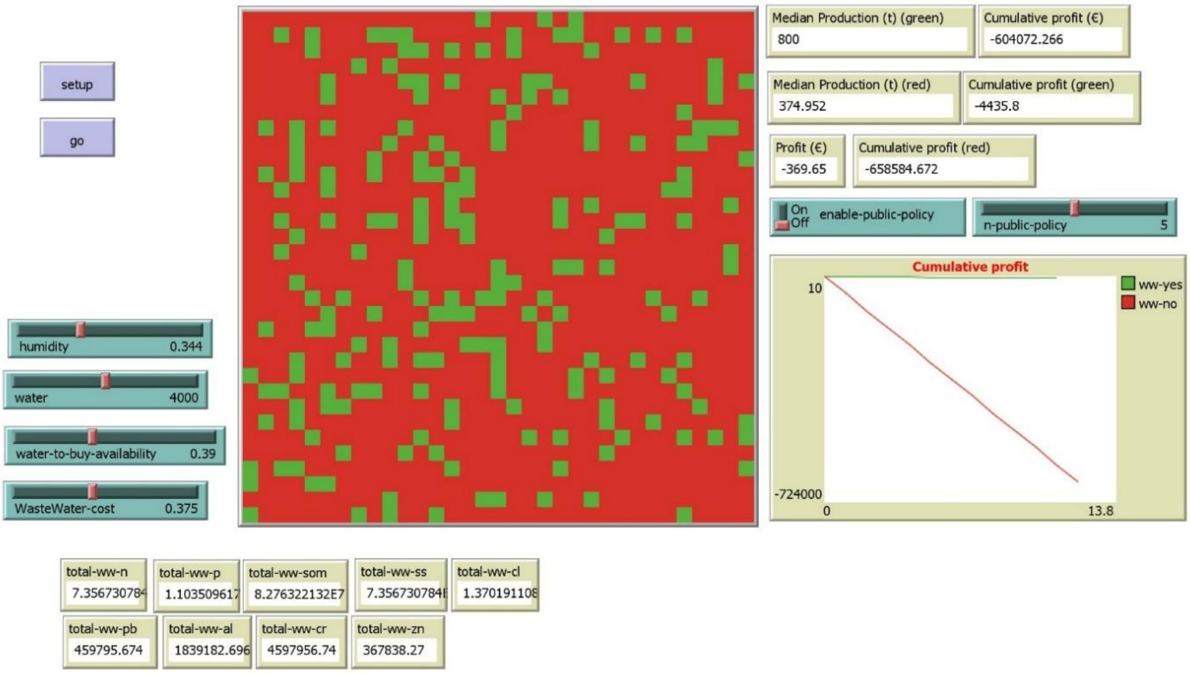


Figure 5. Simulation of increased irrigation costs - The use of this resource increases irrigation costs, which inevitably affects the farm's profits. As the volume of wastewater used and the level of treatment required increase, the unit cost of unconventional water grows.

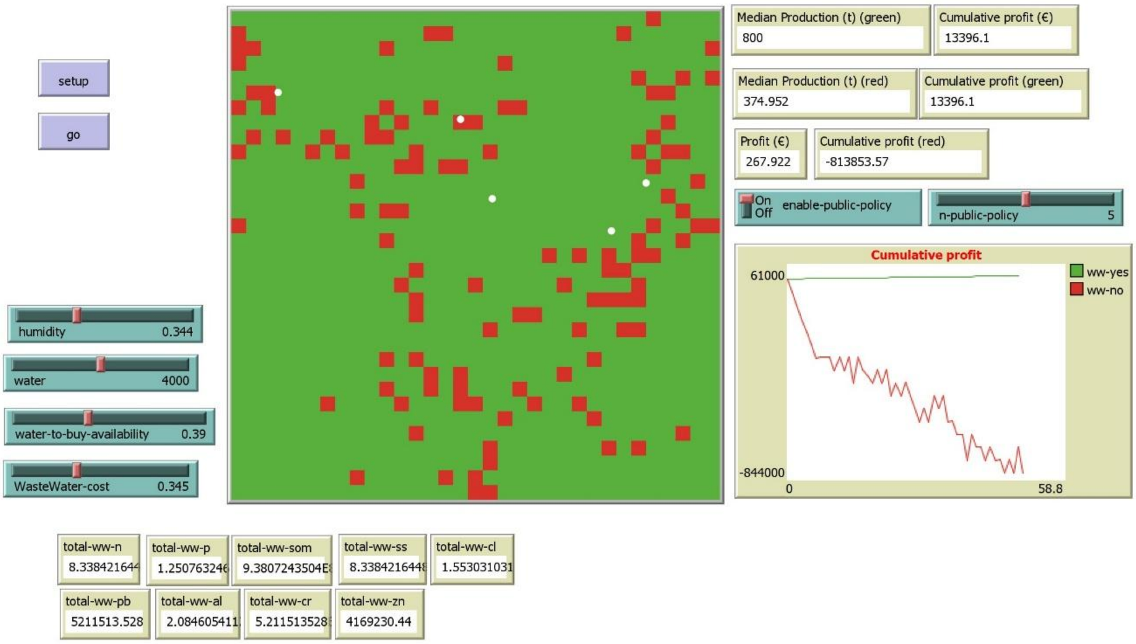


Figure 6. Simulation with incentives - When public policies provide economic incentives, a significant proportion of farmers who were unwilling to change their attitude do so in a favourable direction.

The counters embedded in the model interface record the total quantity of nutrients and the overall concentration of selected heavy metals present in treated wastewater, which may accumulate across successive growing seasons depending on the volumes of reused water applied by farms. As the model assumes that farms inclined to reuse wastewater employ it only as a supplementary source—that is, when rainfall and consortium-supplied water are insufficient to meet crop water requirements—the elements contained in the reused water and applied during each growing season are expressed as grams of nutrient or contaminant per cubic metre of water distributed across cultivated areas.

The concentration of these elements in treated wastewater, expressed per litre and per cubic metre, was determined based on specific laboratory analyses provided by local wastewater treatment plants. Taken together, these counters provide an aggregate overview of the quantities of nutrients potentially available to crops through wastewater reuse, such as nitrogen, phosphorus, and organic matter, while also offering insights into the potential accumulation of elements that may pose risks, both in terms of bioaccumulation in crops and possible implications for human health.

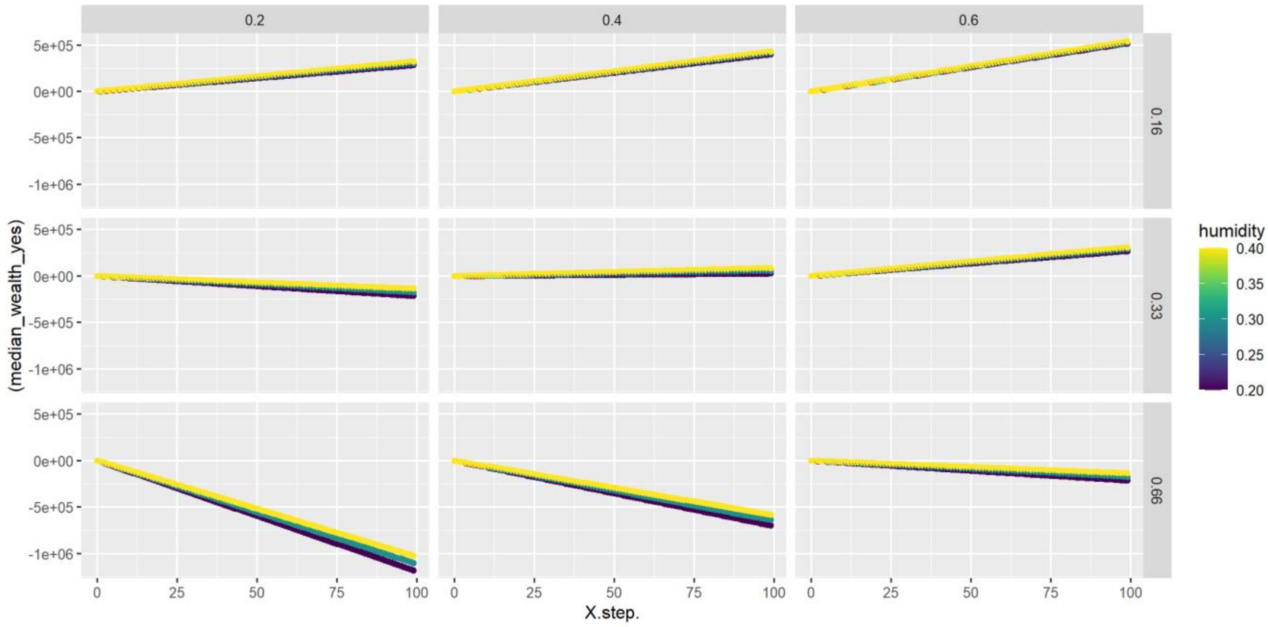
However, given that the quantification of these elements is held constant in the model (based on laboratory data and the estimated volumes of wastewater that could be applied) the current treatment processes adopted in wastewater treatment plants ensure that, for several of the most harmful elements considered, concentrations remain within the limits established by EU Regulation 741/2020.

It is important to highlight that these counters were introduced into the model as an auxiliary feature. They do not incorporate mechanisms for element degradation, soil retention, plant uptake, or biogeochemical transformation, nor do they include any economic valuation of potential positive or negative impacts associated with the presence of these substances.

5. Results

The following section presents the results of the simulations implemented through the BehaviorSpace of the agent-based model. These results illustrate the temporal evolution of farm profit and propensity, distinguishing between farms inclined and not inclined to use treated wastewater, under varying levels of water availability from the irrigation consortium and rainfall, as well as across different price ranges for treated wastewater.

The first graph (Graph 1) shows the trend in average cumulative profit over successive growing seasons for farms with a positive propensity to use treated wastewater.



Graph 1. Simulation results – median cumulative profit over growing seasons for farms initially willing to use treated wastewater. Columns show consortium water availability (0.2, 0.4, 0.6), rows show treated wastewater price bands (€0.16, €0.33, €0.66 m^{-3}), and colours represent rainfall levels.

The simulation was conducted by considering different levels of consortium water availability (0.2; 0.4; 0.6), varying precipitation inputs (represented by different colours according to the cubic metres of rainfall), and different price tiers for treated wastewater.

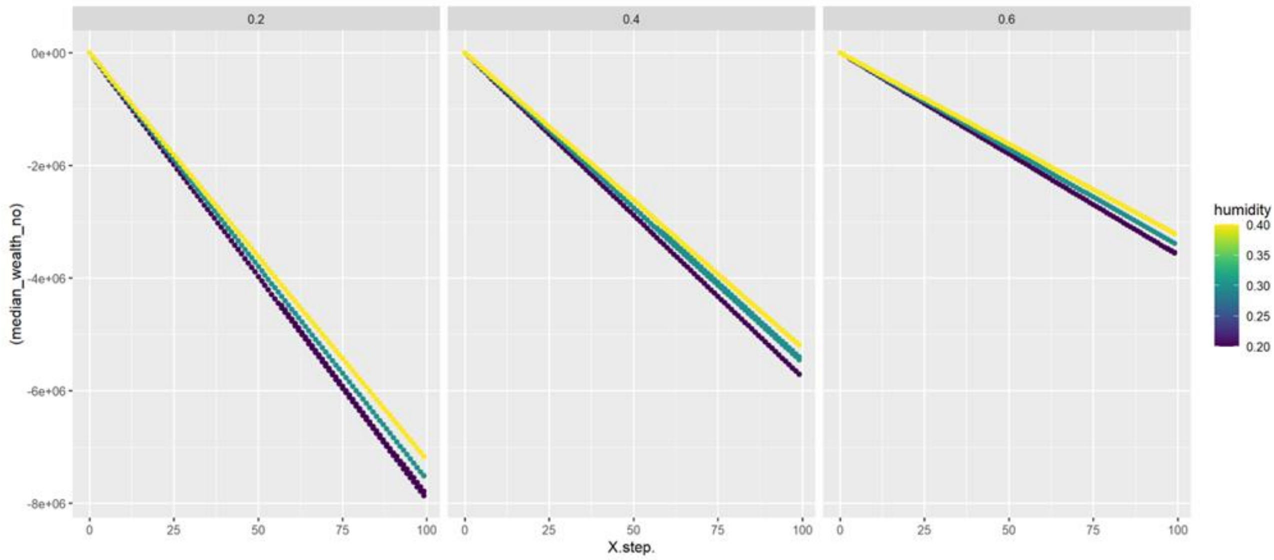
The volume of treated wastewater used depends on the share of irrigation demand not covered by conventional water sources. The results indicate that, in particularly critical scenarios characterised by low consortium water availability (left panels) and limited rainfall (purple lines), the use of treated wastewater leads to a smaller - but still positive - variation in profit, only when the wastewater price is sufficiently low.

Conversely, as the required treatment level increases, and thus the price of treated wastewater rises, profit declines progressively and markedly, eventually becoming negative.

This dynamic triggers a change in farm propensity over time, as discussed below.

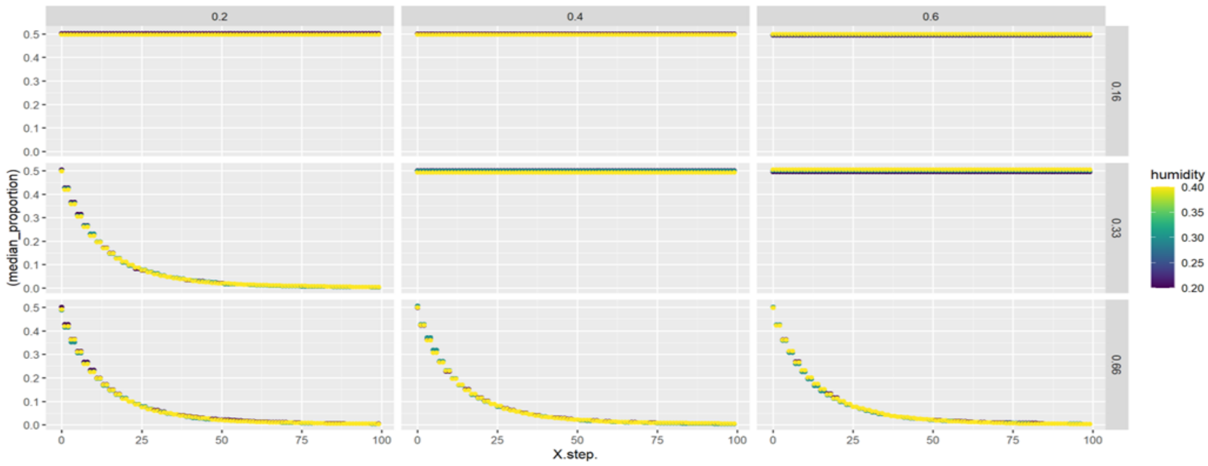
Even under conditions of relatively high consortium water availability, which nonetheless remains insufficient to fully meet crop water requirements, the use of treated wastewater priced at € 0.66 per m^3 leads to a gradual reduction in profit, albeit more moderately during the initial growing seasons.

The second graph (Graph 2) illustrates the behaviour of farms not inclined to use treated wastewater, showing that profit steadily declines over time**.** The lower the precipitation and consortium water availability, the more pronounced and negative the profit trend becomes.



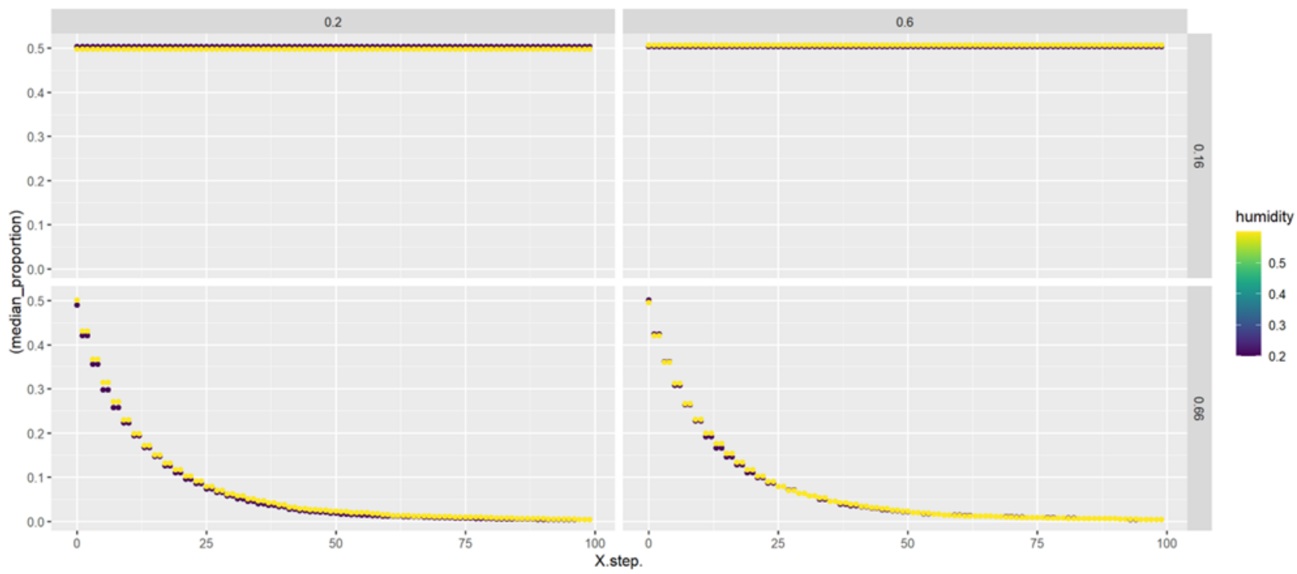
Graph 2. Simulation results – median cumulative profit over growing seasons for farms not willing to use treated wastewater under different levels of consortium water availability (columns: 0.2, 0.4, 0.6) and rainfall conditions (colours).

As noted earlier, the reduction in profit is closely linked to declining production, which is constrained by insufficient water availability. These farms are represented as a static snapshot of the current situation, and no adaptive responses—such as alternative strategies, management changes, or investments in water storage infrastructure (e.g., reservoirs)—have been implemented in the model. This is because such emergency adaptations are highly heterogeneous and not institutionalised or consolidated within policy frameworks. The third plot (Graph 3) shows that, when considering the proportional and aggregated composition of inclined and non-inclined farms, the overall system structure tends to remain similar to the initial configuration when the price of treated wastewater is significantly lower.



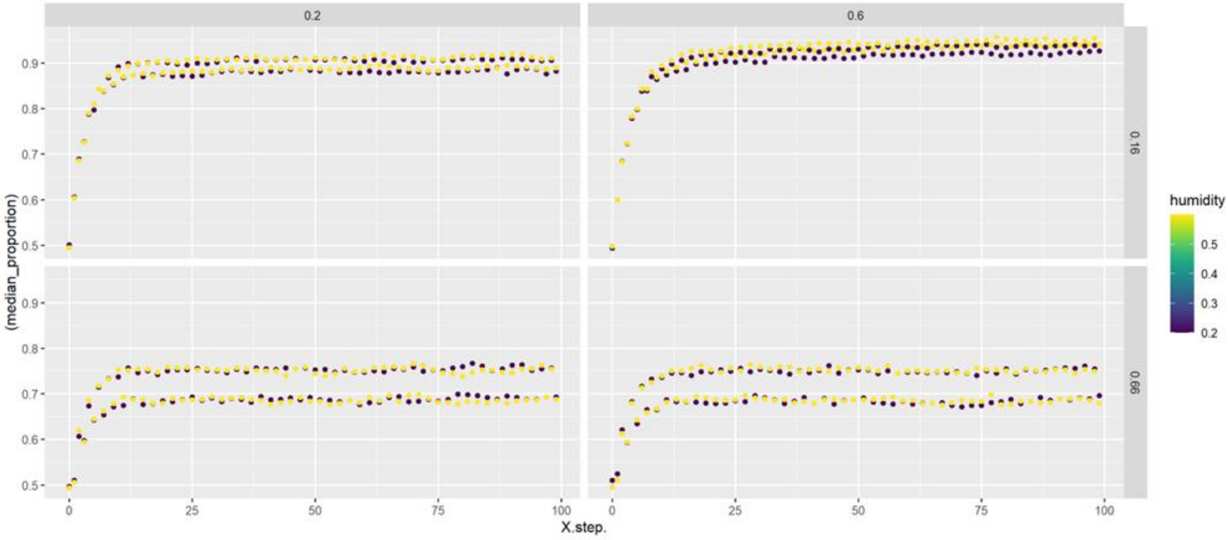
Graph 3. Simulation results – share of farms willing to use treated wastewater over growing seasons. Columns show consortium water availability (0.2, 0.4, 0.6), rows show treated wastewater price bands (€0.16, €0.33, €0.66 m^{-3}), and colours represent rainfall levels. The share of non-willing farms is the complementary proportion.

Conversely, as the price progressively increases to the maximum level considered, and under conditions of limited water availability, a rapid decline in the number of inclined farms is observed within the first 25 growing seasons, with this share approaching zero by the end of the 100 simulated seasons. This result confirms previous findings: even farms initially inclined to adopt treated wastewater may experience sustained profit losses under unfavourable conditions, ultimately leading to a shift in their propensity away from wastewater use.
A further aspect examined concerns the evolution of farm propensity under the presence of specific public policies and financial incentives supporting treated wastewater use. Field surveys conducted in Basilicata indicate that approximately 70% of irrigated farms express willingness to adopt treated wastewater if direct payments are provided to offset additional costs and perceived risks associated with this practice.
Based on this evidence, the simulation was configured to analyse how the proportion of inclined farms changes under different conditions of water availability and wastewater pricing, comparing scenarios with and without public support policies. As previously observed, high wastewater prices lead to a progressive decline in profit over time, resulting in a reduction in the number of farms inclined to adopt wastewater (Graph 4).



Graph 4. Simulation results – temporal evolution of the percentage of farms willing and unwilling to use treated wastewater in two contrasting combinations of conventional water availability (0.2 and 0.6) and treated wastewater price (€0.16 and €0.66 m^{-3}), in the absence of public support policies.

However, when public support policies are introduced, the simulations show that, during the first ten growing seasons, the availability of financial resources and subsidies increases farmers' confidence in this water source, thereby encouraging adoption (Graph 5). In particular, under conditions of low conventional water availability (0.2) and low wastewater price (€0.16 per m^3), approximately 90% of farms exhibit a positive propensity to use treated wastewater within the first 25 growing seasons.



Graph 5. Simulation results – temporal evolution of the percentage of farms willing to use treated wastewater in different combinations of conventional water availability and treated wastewater price, when public support policies are introduced. The figure highlights the increase in availability over time determined by political support, as some farms initially unwilling to adopt treated wastewater become willing to do so.

This share declines to 70–75% when wastewater prices are higher, indicating that even under moderate or extreme conditions a segment of farmers remains resistant to adopting this resource. This finding aligns with previous analyses, which highlight that farmers' willingness to use treated wastewater depends on multiple interacting factors, including economic incentives.

Nevertheless, the perception of economic, health, and quality-related risks continues to contribute to persistent reluctance among some operators, who prefer to rely on traditional water sources.

The model is currently at a preliminary stage of development and has enabled the representation of key dynamics identified in earlier chapters. Future developments will allow the expansion of the analytical scope, incorporating alternative adaptation strategies, more complex and interconnected system dynamics, and a deeper assessment of trade-offs that may foster greater acceptance of treated wastewater reuse across multiple levels, for a resource that remains largely undervalued.

6. Discussion and Conclusions

The model results show that the adoption of treated wastewater in agriculture does not constitute a dichotomous choice, but rather a continuous decision-making process based on a dynamic assessment of economic convenience and subject to recurrent revisions over time.

This behaviour highlights a structural feature of agricultural rationality: decisions regarding technological adoption are not firmly anchored to a long-term horizon, but are continuously recalibrated in response to expected profitability trends (Carrillo-Huerta, 1977). This is particularly relevant in contexts where alternative water resources, such as treated wastewater, depend on collective infrastructure and investment decisions that are not fully under the control of individual farmers; under such conditions, farmers adjust their investments according to expected returns and the perceived reliability of the resource (Carrillo-Huerta, 1977; Marra et al., 2003). When deteriorating water availability coincides with rising treatment costs, the economic attractiveness of treated wastewater becomes compromised, triggering a strategic reassessment that may ultimately lead to abandonment of the resource. This dynamic suggests that alternative and innovative agricultural practices exhibit an inherent vulnerability under conditions of economic stress, in contrast with the stability assumptions embedded in some linear adoption models (Rogers, 1995; Ghadim et al., 2005; Marra et al., 2003).

At the same time, the persistence of a substantial share of operators who maintain a negative propensity towards treated wastewater use, even in the presence of public incentives, signals the interpretative limits of approaches grounded solely in economic rationality. The observed heterogeneity cannot be explained only by differences in perceived economic risk, but reflects a plurality of factors, including hygiene and health concerns, preferences for established technologies, and greater trust in traditional water sources. These elements contribute to constraining the willingness to adopt eco-innovations, independently of economic stimuli (Rogers, 1995).

Moreover, within the limits of the sample considered and with specific reference to farms specialised in monoculture, the fact that non-adopting farmers do not appear to develop alternative adaptive strategies within the analytical context considered reveals a critical fracture within the agronomic system: water scarcity does not necessarily trigger innovation, but may instead generate processes of selection and marginalisation affecting those operators who lack the capabilities, knowledge, or resources required to diversify their water sources (Ghadim et al., 2005; Feder & Umali, 1993; Chavas & Nauges, 2020; Rizzo et al., 2024). This evidence should therefore be interpreted with caution, as other forms of adaptation—such as diversification or changes in land use—may remain outside the scope of the present analysis; nevertheless, the results underscore that, in the context examined, adaptation to new strategies is often constrained more by institutional barriers and technical capacity limitations than by a simple lack of economic incentives.The analysis of support policies further indicates that incentive mechanisms do not produce a structural and lasting transformation of operators' preferences, but instead function primarily as catalysts that facilitate the overcoming of critical transition phases (Njiraini et al., 2018; Adnan et al., 2019; Ruzzante et al., 2021). The concentration of positive effects in the early production cycles suggests that public subsidies mainly serve a risk-reduction function, temporarily easing the economic burden and allowing farmers to accumulate operational experience and build an initial level of trust in the resource. However, the gradual attenuation of this effect over time indicates that such trust remains strongly dependent on the continuity of public support. This raises important questions regarding long-term economic sustainability: policies that fail to evolve

towards a structural reduction in treatment costs or towards the consolidation of self-regulating market mechanisms risk generating forms of institutional dependency, without addressing the deeper causes of the resource's economic unacceptability (Ruzzante et al., 2021).
It follows that the adoption of treated wastewater requires not only temporary incentives, but also a transformation of the structural conditions that determine its economic viability. Overall, the results indicate that the mere availability of alternative water sources is insufficient to ensure the sustainability of an agricultural system unless accompanied by a reconfiguration of the economic constraints that hinder widespread adoption. The pursuit of non-institutionalised adaptation strategies, such as private investment in water storage infrastructure, remains marginal in the simulated data, reflecting the absence of sufficiently strong individual incentives to stimulate autonomous entrepreneurial behaviour.
This evidence suggests that water sustainability policy cannot rely exclusively on the provision of alternative or innovative solutions, but must simultaneously address three fundamental dimensions: aligning the cost of alternative water resources with the economic constraints of potential users; building institutional trust in the quality and safety of the resource; and strengthening operators' organisational capacities to manage technological transitions (Ruttan, 1977; Carrillo-Huerta, 1977; Chavas & Nauges, 2020; Rizzo et al., 2024). The persistent heterogeneity of behaviours further indicates that uniform policy instruments will inevitably leave a residual share of non-adopters, making it necessary to develop differentiated transition pathways.
Finally, in its current form, the proposed model provides a meaningful contribution to identifying the core mechanisms governing treated wastewater adoption, while operating within methodological boundaries that suggest possible extensions. The absence of endogenous adaptive strategies for non-adopting operators represents a simplification that plausibly reflects gaps present in real-world systems and linked to the intrinsic characteristics of the phenomenon. Future developments could incorporate multi-criteria decision-making processes that explicitly account for trade-offs between economic convenience, perceived risk, and coherence with farm identity. Moreover, extending the model to include collective learning dynamics and information diffusion among agents would allow the representation of how individual decisions propagate through social networks, generating mechanisms of conformity or resistance that operate beyond purely economic rationality. Understanding these processes is crucial for designing public policies effectively oriented towards the transition to more sustainable water systems.

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General Conclusions

The research conducted in this doctoral thesis highlights that the introduction of sustainable and environmentally friendly innovations in agriculture represents, in the current context, a strategic priority for safeguarding agricultural systems and ensuring production stability.

In particular, such innovations are necessary both to guarantee satisfactory and long-term profitability for farmers and to ensure global food security and availability. From this perspective, the reuse of treated wastewater for irrigation emerges as a practice with strong potential to contribute significantly to these objectives, acting as an additional resource in a context of increasing water scarcity.

The analyses carried out made it possible to identify the main properties of treated wastewater, emphasising its potential for irrigation as an additional resource that remains underutilised and undervalued. Under optimal conditions of treatment, quality and accessibility, this resource could help meet the water needs of the agricultural sector, proving technically comparable, in terms of irrigation effectiveness, to conventional water sources.

However, empirical investigations have also revealed a range of informational, perceptual, infrastructural and economic barriers which, taken together, currently limit large-scale adoption.

A first critical factor concerns the role of information. Survey results among farmers in Basilicata show that access to reliable, up-to-date information delivered through effective communication channels is a fundamental prerequisite to ensure that knowledge about treated wastewater quality, microbiological parameters, potential uses and associated risks is adequately disseminated among different agricultural stakeholders. Clear information on potential risks to human health, food safety and the environment, as well as on the most suitable crops and correct application practices, can increase farmers' awareness and support more informed adoption decisions. Within this framework, strengthening support organisations and technical advisory services appears particularly necessary, especially to engage farmers who are less inclined to adopt innovations or who have limited independent access to technical knowledge.

Alongside the informational dimension, a second key axis concerns perceptions of the risks associated with use. The findings show that concerns about potential health risks for producers and consumers, the accumulation of undesirable substances in agricultural products, and possible environmental contamination tend to significantly reduce farmers' willingness to use treated wastewater. By contrast, farmers with a more innovative profile, prior experience with technological adoption and stronger skills in independently sourcing information generally display a lower perception of risk. This suggests that a broad improvement in technical and scientific knowledge related to this resource could help reduce perceived risks and, in turn, foster greater openness to its use.

In this direction, greater transparency regarding quality parameters, monitoring procedures and actual risks under inadequate treatment conditions represents a key lever for shifting, in the medium term, the attitudes of farmers who are currently reluctant.

The evidence collected fits coherently within the specific context of the Basilicata region, where infrastructural, regulatory and economic constraints continue to hinder the effective usability of this resource. On the one hand, the lack of full modernisation of wastewater treatment plants prevents systematic compliance with European quality standards; on the other, the absence of a defined pricing scheme for treated wastewater makes it difficult for farmers to assess the cost differential relative to conventional water, which is inevitably influenced by treatment and distribution costs. This is compounded by insufficient infrastructure for conveying and distributing treated wastewater to farms, introducing further logistical and financial challenges (transport, storage and operational supply management).

In this context, although a significant share of farmers express willingness to use treated wastewater, their stated preference remains oriented towards conventional water supplied by consortia, which is regarded as the primary solution. This preference is based on two complementary factors: first, farmers possess consolidated and extensive knowledge of conventional water, built over decades of irrigation use; second, the costs associated with this resource remain relatively low and predictable in the medium term.

Nevertheless, the intensification of water scarcity in recent years, coupled with consortial supplies that frequently fail to fully meet farm irrigation needs, has progressively increased water stress across the territory, prompting a growing number of farmers to consider treated wastewater as a strategic and complementary alternative.

It is therefore evident that even farmers most inclined to adopt this resource do not view treated wastewater as a complete substitute for conventional water, but rather as a partial or total supplement - depending on seasonal availability of consortial water - within a framework of complementary water sources.

For this transition towards integrated resource use to be effectively realised, it is essential that high microbiological standards, the absence of chemical contaminants and heavy metals, and clear communication to farmers regarding safety precautions and potential damage in the event of non-compliance are guaranteed in a transparent manner. Only through such informational transparency can farmers develop the trust needed to activate this auxiliary solution when conventional supplies are insufficient, thereby ensuring production continuity.

An additional contribution of this thesis derives from the implementation of an agent-based model, which enabled dynamic simulation of the impact of treated wastewater use on farm production and economic performance. The results indicate that, under conditions of relatively low treatment costs, reliance on this resource can maintain production levels and ensure acceptable profitability in the medium term. However, as the intensity and number of required treatments increase, and as treated wastewater is used at progressively higher costs, irrigation expenses rise substantially over multiple production seasons (holding other production costs constant), making the practice economically less sustainable.

This outcome highlights the central role of the economic dimension and the need for policies and management choices that carefully balance water benefits against the financial burdens associated with treatment and distribution.

Limitations and Future Research

At the same time, the findings presented in this thesis should be interpreted in light of certain limitations that define the scope of their validity and, at the same time, indicate possible directions for further research. First, both the empirical evidence and the modelling exercise are grounded in a case study specifically circumscribed to the Basilicata region, an area characterised by distinctive climatic conditions, structural features of the agricultural sector, and recurrent exposure to drought events. These contextual characteristics make the case particularly relevant for examining the potential of treated wastewater as a complementary irrigation resource; however, they also call for caution in extending the results beyond the territorial, environmental and productive setting considered.

In different contexts, such as more intensive agricultural systems or regions that have historically been less exposed and are institutionally and operationally less accustomed to conditions of water scarcity, farmers' perceptions, adaptive capacities, economic assessments and adoption dynamics may differ substantially. Likewise, in regions where wastewater treatment and reuse systems are more advanced from an infrastructural, regulatory and managerial perspective, and where circular economy practices in agriculture are more firmly established, the patterns and determinants of adoption may diverge significantly from those observed in the Basilicata case. For this reason, the conclusions developed in this thesis should not be regarded as automatically generalisable to all agricultural contexts, but rather as analytically robust within the specific socio-environmental, institutional and productive framework in which the study is situated. From this perspective, future research should extend the analysis through comparative investigations involving regions characterised by different climatic conditions, irrigation regimes, production structures and levels of infrastructural development. Further research could also explore how the adoption of treated wastewater evolves in contexts where water scarcity is less frequent, agricultural production is more intensive, or institutional arrangements and governance systems differ significantly from those observed in Basilicata. Such developments would make it possible not only to assess the external validity of the results, but also to distinguish more clearly between mechanisms that are strongly context-dependent and those that may be generalised across a broader range of agricultural settings.

Final Considerations

The policy implications emerging from these findings are manifold:

1. First, rapid modernisation of wastewater treatment infrastructure is required to ensure consistently high quality standards while simultaneously reducing unit treatment costs through economies of scale and improved operational efficiency;
2. Second, the establishment of a clear and transparent pricing system is desirable, reflecting treatment and distribution costs while maintaining affordability for agricultural enterprises, potentially through appropriate compensation mechanisms;
3. Third, the research suggests the adoption of direct support strategies for farmers, such as targeted financial incentives to offset higher irrigation costs or temporary production losses during the transition to treated wastewater use. At the same time, complementary strategies are highlighted, including the implementation of rainwater harvesting and storage systems (reservoirs, storage tanks) to be activated under emergency water-scarcity conditions within an integrated resource-management framework.

Overall, the scientific evidence presented in this thesis demonstrates that the factors driving the adoption of agricultural innovations are not uniform, but vary substantially depending on the type of innovation considered. In the specific case of treated wastewater reuse, alongside the primary motivation of ensuring production continuity and farm resilience, technical-informational support needs and perceptual dimensions (risk perception, social acceptability) play a decisive role in shaping the adoption process.

From a broader circular-economy perspective, wastewater recovery and reuse represent a key practice for reducing pressure on natural water resources and enhancing the overall sustainability of agricultural systems. However, at present, the technical-managerial, regulatory, economic and social landscape surrounding this resource remains incomplete and fragmented, making it

premature to regard irrigated reuse of treated wastewater as a fully established and sustainable alternative to conventional irrigation practices.
Nevertheless, future development trajectories and intervention pathways are already clearly outlined. Strengthening the critical areas identified by this research - in terms of information, perceptions, infrastructure, governance and economic support instruments - constitutes one of the essential first steps towards establishing, within a socially acceptable timeframe, a system in which treated wastewater becomes a genuinely recovered, reliably available, technically safe and economically sustainable resource for agriculture. In this way, wastewater reuse could contribute not only to farm resilience, but also to broader environmental sustainability goals and the transition towards production models aligned with the principles of circularity.