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Underutilized crops for diversified agri-food systems: spatial modeling and farmer adoption of buckwheat in Italy

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The widespread standardization of agri-food systems through monoculture practices has resulted in biodiversity loss and reduced ecosystem resilience. Incorporating underutilized crops such as buckwheat into crop rotations offers a viable strategy to enhance biodiversity, improve soil health, and foster more sustainable and resilient agricultural systems. This study examines the potential adoption of buckwheat in Italy and analyzes its economic viability across different crop rotations. It evaluates how factors such as financial incentives, peer influence, and farmers' willingness to adopt affect the diffusion of this underutilized crop. To this end, a spatial agent-based model (ABM) is employed to simulate farmers' decision-making processes based on profit maximization and peer influence. The model evaluates two diffusion scenarios (traditional and expansion) alongside two levels of willingness to adopt (high and low), comparing the profitability of traditional crop rotations with rotations that include buckwheat across nine Italian regions. The results revealed that while increased contract prices can incentivize buckwheat adoption, financial incentives alone are insufficient to generate widespread adoption, particularly when the willingness to adopt is low. Peer influence and intrinsic motivation emerged as key drivers, highlighting the need for strategies beyond monetary incentives. These findings suggest that policies should combine financial support with initiatives that foster knowledge-sharing, educational outreach, and improved supply chain integration. The study provides a framework for evaluating the adoption of other underutilized crops and emphasizes the need for further research on risk aversion, environmental variability, and broader supply chain interactions to refine adoption strategies.

KEYWORDS
buckwheat, farmers, spatial modeling, agent-based model, adoption of underutilized crops

Introduction

Agricultural systems worldwide have become increasingly standardized to meet the food production demands of a growing global population. Currently, just nine crops account for 66% of total global crop production, with industrial-scale monocultures dominating vast agricultural landscapes (FAO, 2019). While these systems optimize large-scale efficiency and economic profitability, they also contribute to severe ecological consequences. Monocultures and intensive farming practices, including the excessive use of chemical inputs, have led to widespread soil degradation and increased vulnerability to climate change (Ramankutty et al., 2018). Researchers have expressed concerns about the risks posed by these simplified cropping systems, emphasizing their lack in meeting human nutritional needs and diversified diet (Snapp, 2020), deplete soil health, and accelerate biodiversity decline (FAO, 2019).

In response to these challenges, crop diversification is gaining recognition as a strategy that offers considerable benefits for biodiversity and agricultural landscapes, while also strengthening supply chains though increased market opportunities and promoting more stable and diverse food trade (Morel et al., 2020). A particularly promising aspect of this approach is the inclusion of neglected and underutilized species (NUS) in crop rotation strategies. NUS contribute to soil health and enhance on-farm biodiversity, fostering more sustainable and robust agricultural systems (Mabhaudhi et al., 2022), while their rich micronutrient content supports dietary diversification and helps addressing food security challenges (Padulosi et al., 2013; Ali and Bhattacharjee, 2023). Despite their considerable ecological, nutritional, and economic advantages, NUS have been largely overlooked by modern agriculture and commercial markets (Padulosi et al., 2013).

Within this context, the European Union's Common Agricultural Policy (CAP) for 2023–2027 has introduced Eco-schemes that financially incentivize farmers to adopt sustainable practices, including crop diversification (European Commission, 2022). Italy provides a relevant case for examining how these policies support diversification efforts, particularly through the promotion of crop rotation (Eco-scheme 4) and melliferous crops (Eco-scheme 5) (Atorino et al., 2023). Despite these policy efforts, the integration of NUS remains limited, highlighting the need for a deeper understanding of the factors influencing their adoption.

In this regard, buckwheat (*Fagopyrum esculentum*) serves as a pertinent case study, as its characteristics align closely with Italy's CAP objectives and exemplify the broader challenges surrounding NUS adoption. Its short growth cycle makes it suitable for crop rotations, directly supporting Eco-scheme 4 (Knez et al., 2023) while its nectar-rich flowers contribute to pollination services, making it relevant for Eco-scheme 5 (Small, 2017). Additionally, buckwheat's ability to thrive in poor soils with minimal inputs makes it an ecologically sustainable option. However, despite these advantages, its adoption remains low due to uncertain market demand, underdeveloped value chains, and limited policy incentives (Padulosi et al., 2013). As such, buckwheat not only exemplifies the potential of NUS but also highlights the existing policy and market barriers that hinder their wider adoption.

While research on crop diversification has grown, little attention has been given to the socio-economic factors shaping the adoption of specific NUS, particularly within the framework of EU agricultural policies. This gap in research limits our understanding of how policy incentives and market conditions influence farmers' decisions to integrate underutilized crops into their rotations. Addressing this gap is crucial for developing targeted policy and managerial recommendations that promote NUS adoption while ensuring economic viability for farmers.

This paper, therefore, aims to explore the factors influencing the adoption of an underutilized crop—buckwheat—among farmers in Italy. Specifically, the study seeks to assess the effects of variables such as contract prices, farmers' willingness to adopt, and the impact of different diffusion scenarios on buckwheat adoption over time and space.

To achieve these objectives, a spatially explicit agent-based model (ABM) is employed, which simulates farmers' crop rotation decisions under different economic and behavioral conditions. By analyzing how economic incentives and diffusion mechanisms shape adoption patterns, this research provides insights into the potential for scaling up NUS within sustainable agricultural systems. The findings of this study aim to inform agricultural policy discussions by providing insights into how financial incentives, market mechanisms, and diffusion processes influence farmers' adoption of underutilized crops. These insights are particularly relevant for refining CAP Eco-schemes to better support crop diversification and biodiversity conservation. Beyond policy, this research offers practical guidance for farmers and supply chain actors, identifying key economic and structural barriers to NUS adoption. By addressing these challenges, the study contributes to developing targeted market strategies and supports mechanisms that enhance the sustainability and resilience of farming systems.

This paper is structured as follows. Section 2 provides a critical review of the literature on factors influencing the adoption of NUS. Section 3 details the data and the area of analysis, the parameters, and the sub-models. Following this, Section 4 presents the results. Section 5 discusses the results, highlighting the key implications of the study, along with its limitations and potential directions for future research. Finally, Section 6 presents the conclusion of the paper.

Challenges and opportunities in adopting crop diversification with NUS

Based on relevant literature review, this section lays the groundwork for understanding the key factors influencing the adoption of neglected and underutilized species (NUS) within agricultural systems. By identifying the challenges and opportunities associated with NUS crops, this section highlights the core economic, behavioral, and environmental variables that shape farmers' adoption decisions.

Crop diversification, especially through the inclusion of neglected and underutilized species (NUS), presents both significant opportunities and challenges in the pursuit of more sustainable agricultural practices. NUSs include non-commodity wild or cultivated plant species and crop wild relatives once popular but now marginalized by mainstream agriculture due to various agronomic, economic, social, and cultural factors (Mabhaudhi et al., 2022). The renewed interest in NUSs, driven by concerns over biodiversity loss and the need for more resilient agricultural systems, has highlighted their potential benefits. Practices like crop rotation and inter-cropping with NUS crops are increasingly recognized for their ability to contribute to productivity and resilience (Makate et al., 2016), improve biodiversity and ecosystem services including pollination, soil nutrients, and water regulation (Sánchez et al., 2022), and improve adaptation to climatic challenges (Mustafa et al., 2019; Mabhaudhi et al., 2022). From a nutritional perspective, NUS crops, such as quinoa, buckwheat, lentils and millets, offer significant potential for diversifying diets and improving food security (Zhu, 2021; Ali and Bhattacharjee, 2023). Buckwheat, for instance, has gained attention for its gluten-free properties, making it a valuable crop for the growing market of gluten-intolerant consumers (Brunori et al., 2005). Despite these promising attributes, research on the use of NUS crops, particularly buckwheat, in intercropping systems remains limited. The lack of comprehensive research on buckwheat highlights the need for further investigation across different contexts to fully understand its role as an intercropping partner (Landschoot et al., 2024).

Nevertheless, the adoption of underutilized crops in agriculture presents numerous economic, behavioral, and environmental challenges. These include price and yield uncertainties (Knez et al., 2023), limited experience with new management practices, and the high cost of crop-specific equipment (Odeku et al., 2024). Behavioral factors — particularly the influence of neighboring farmers —also play an important role, as peer behavior can either encourage or discourage new crop adoption (Defrancesco et al., 2008; Ha Thu et al., 2020; Tran-Nam and Tiet, 2022). While NUSs often exhibit resilience to temperature extremes and water scarcity, farmers tend to perceive greater uncertainty and risks associated with these crops, making them more reluctant to invest in underutilized crops under unpredictable climate conditions (Mabhaudhi et al., 2022). Furthermore, the lack of an established market remains a critical obstacle to the widespread adoption of these crops (Knez et al., 2023), with fluctuating market structures and global disruptions—such as conflicts and pandemics—exacerbating supply chain vulnerabilities. The interconnected nature of these challenges highlights the structural difficulties that underutilized crops face in today's agricultural landscape. Traditional agribusinesses and global food supply chains tend to prioritize large-scale producers who specialize on a narrow selection of conventional crops, making it increasingly difficult for diversified farms cultivating more ancient or underutilized crops to compete and maintain viable economic returns (Stringer et al., 2020).

Overall, while NUSs offer significant potential to enhance agricultural sustainability through greater resilience, dietary diversification, and environmental benefits, their widespread adoption depends on reducing market uncertainties, addressing behavioral barriers, and bolstering research on best practices in different settings. Continued investigation into the economic viability of these crops—alongside policies that support their marketing, risk-sharing mechanisms, and farmer education—can pave the way for NUS crops to become integrated more successfully into mainstream agricultural systems. By addressing these challenges, NUSs can play an increasingly important role in meeting the global need for sustainable food production in the face of ongoing climate, market, and social uncertainties.

Materials and methods

In light of the accelerating decline in biodiversity and the complex repercussions of agricultural practices on the economy and environment, research is increasingly focusing on the use of mathematical programming models, particularly agent-based modeling (ABM), for their ability to assess these multifaceted challenges (Gohin, 2006; Dessart et al., 2019). ABM has evolved as an essential tool for simulating the interactions between autonomous entities, known as agents, and the environmental context in which they operate. This methodological approach has been employed to dissect and understand the transformation of agricultural systems, assessing the enduring effects of agricultural decisions on the ecological and economic aspects of agri-food systems (Murray-Rust et al., 2014; Dobbie et al., 2018).

Recent state-of-the-art applications of ABM in agri-food systems have shown promising results in exploring complex socio-ecological dynamics, capturing farmers' adaptive behaviors, and predicting the outcomes of policy interventions (Fernandez-Mena et al., 2020; Zagaria et al., 2021). These models increasingly incorporate spatially explicit data, utilizing geographical information systems to more accurately capture the spatial heterogeneity and interactions inherent in real-world agricultural landscapes (Robinson et al., 2018; Johnson and Salemi, 2022). However, despite these advances, the application of ABM in agri-food systems still faces notable challenges and necessitates further developments. Key obstacles include scalability, computational efficiency, and the integration of diverse data sources, including remote sensing and big data analytics (Sun and Müller, 2013). Moreover, the representation of complex human behavior and decision-making processes in these models requires further refinement and calibration through interdisciplinary collaboration and the integration of insights from behavioral economics and social psychology (Steinbacher et al., 2021).

Based on the TAPAS ("Take A Previous model and Add Something") approach, which emphasizes enhancing existing models and applying them to new geographical contexts and case studies (Frenken, 2006), this study builds upon a previously established framework (Ullah and Crooks, 2022) to simulate farmers' adoption of buckwheat in a spatially explicit ABM. Rather than introducing entirely new methodological developments, the study primarily adapts the model to the Italian context, allowing for a cumulative advancement of knowledge by testing its applicability in a different environment. By grounding the analysis in a defined study area and incorporating context-specific data, this approach aims to generate relevant insights and improve the model's predictive capacity (Murray-Rust et al., 2014; Castellani et al., 2019). This study adheres to the ODD (Overview, Design concepts, and Details) protocol for model description as proposed by Grimm et al. (2010) to ensure transparency and reproducibility (see Supplementary materials).

Study area

Italy has a rich genetic diversity, agricultural heritage, and culinary tradition with buckwheat (Brunori et al., 2005). However, there remains a considerable gap between domestic production and imports, with only 126.6 tons produced in 2022 across approximately 118 hectares, while annual imports exceed 10,000 tons (ISTAT, 2020).

Optimal conditions for buckwheat are found in mountainous and high hill areas, particularly in Central-Northern Italy. Nine regions were selected as case studies based on data coming from the RICA[1] database: Veneto, Emilia-Romagna, Lazio, Tuscany, Marche, Lombardy, Umbria, Piedmont and Friuli-Venezia Giulia (RICA, 2022; Figure 1). These data underscore regional disparities in utilized land for buckwheat cultivation, stressing the importance of strategic regional planning. Furthermore, the growing demand for

1 La Rete di Informazione Contabile Agricola (R.I.C.A.) is an annual sample survey established by the European Economic Commission (EEC) in 1965 under EEC Regulation 79/56, later updated by EC Regulation 1217/2009 and its amendments. The acronym RICA originates from the French *Réseau d'Information Comptable Agricole*, commonly known as the Farm Accountancy Data Network (FADN), which consists of multiple accounting networks, including a European Community network and national networks, each with unique characteristics. Implemented in Italy since 1968, RICA is the only harmonized source of microeconomic data tracking farm income trends and the economic-structural dynamics of agricultural enterprises.

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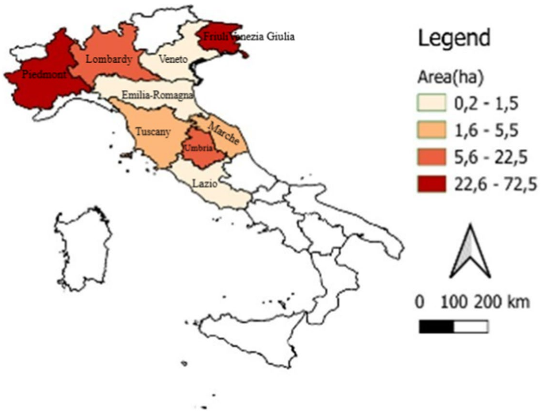

FIGURE 1
Regional land utilized for buckwheat production.

buckwheat-based food supports the potential for expanding buckwheat cultivation also in plain regions like Veneto and Emilia-Romagna, where buckwheat may represent an alternative and innovative crop (Gaifami and Piazzi, 2022).

TABLE 1 Model parameters and values for simulation (μ, σ).

Parameters		Values for simulation
Yield	Soft wheat yield	54 q/ha, 5.3
	Maize yield	107.5 q/ha, 5.7
	Barley yield	40.3 q/ha, 1.4
	Soybean yield	35.3 q/ha, 1.9
	Buckwheat yield	8 q/ha 15 q/ha 37 q/ha
Price	Soft wheat price	€21.8/q, 4.1
	Maize price	€19.2/q, 4.04
	Barley price	€20/q, 3.1
	Soybean price	€39/q, 6.1
	Buckwheat price	25€/q €45/q €65/q €85/q €100/q* €125/q*
Cost	Soft wheat cost	€509.7/ha, 61.2
	Maize cost	€840.5/ha, 124.4
	Barley cost	€337.9/ha, 44.2
	Soybean cost	€564/ha, 53.4
	Buckwheat cost	€200/ha €350/ha €500/ha

*Predicted price values.

Data description

Geospatial data

Geospatial data of the nine Italian regions were imported from an open shapefile of the EEA geospatial data catalog and processed in Q-GIS (European Environment Agency, 2024). Since farmers in close proximity are likely to know each other and influence each other's decisions (Marvuglia et al., 2022), defining neighborhood boundaries was essential for capturing these spatial dynamics. To achieve this, adjacent relationships between regions were identified based on shared borders in the shapefile. The IDs of adjacent polygons for each region were stored in a text file and imported into NetLogo 6.3.0, establishing the neighborhood structure within the model. To protect data privacy, information on provinces and altimetric zones was omitted, and no precise farm-level information or direct farm-to-farm adjacency were used, given the small representative sample of buckwheat farmers in the RICA database (average of 14 farmers in last 5 years) (RICA, 2022).

Key economic and production variables

The key variables—yield, production cost, and price— are used to evaluate the profitability of integrating buckwheat into traditional crop rotations. Production costs include operating expenses such as fertilizers, pesticides, seeds, contracting, irrigation, insurance, and certifications, excluding overhead costs like labor, machinery, and taxes. Since buckwheat is typically cultivated as interlayer row crop, it does not require additional machinery, meaning that only operational costs are taken into account. Table 1 presents data on yields, prices, and production costs for four major traditional crops, along with buckwheat, from 2011 to 2022 (RICA, 2022). Based on RICA data, buckwheat yield and costs have been classified into three categories—low, average, and high—each associated with distinct contract prices over the last 10 years (Table 1). Additionally, two predicted price levels (€100/q and €125/q) have been included in the analysis. These values were estimated using a comparative approach, considering the price evolution of other underutilized crops in Italy, particularly lentils (RICA, 2022). Given that buckwheat and lentils share similar market structures and contractors —including mills, pasta processors, and specialty retailers— it is assumed that buckwheat prices could follow a comparable trajectory. This assumption is further supported by the increasing demand for niche products in health-conscious, gluten-free, and organic markets (Zhu, 2021; Ali and Bhattacharjee, 2023).

These data have been used to feed the model, enabling it to simulate various scenarios of buckwheat adoption and to assess the potential economic outcomes under different profit conditions.

Initialization of the model

The ABM was developed in NetLogo version 6.3.0 using the GIS extension (Wilensky, 1999) and initialized at farm, neighborhood, and national levels across nine Italian regions.

Farmer agents represent all simulated farmers within the selected nine regions. Each agent manages 23.73 ha of land, reflecting the average Utilized Agricultural Area in Italy, and follows one of three common three-year crop rotations in central-northern Italy: Soft wheat–Soybean–Maize (Rot1), Soft wheat–Barley–Maize (Rot2), or Barley–Soybean–Maize (Rot3), involving the most widely cultivated crops in these regions (RICA, 2022). To ensure a representative distribution, farmer agents are not directly sampled from real-world populations but are proportionally generated using regional crop rotation data. In each region, three types of farmer agents are randomly created based on the proportion of farmland dedicated to their respective crop rotations. This proportion is calculated by dividing the total area of each crop by the average crop land area. The final proportion calculated resulted in 48% of farmers following Rot1, 27% following Rot 2, and 25% following Rot 3. Overall, a total of 3,576 farmers were included in the model. This method aggregates regional information to preserve farmer privacy (Happe et al., 2006), while the use of actual crop rotation histories allowed to build a more spatially and temporarily informed agent-based model (Johnson and Salemi, 2022). National crop yields, prices, and costs are set at the model's start. The model simulates a three-year rotational period over 33 years (2022–2055), with each time step (t) representing three years (years of crop rotation).

Sub-models

Farmer agents' decisions to adopt buckwheat are driven by two sub-models: profit modeling and diffusion modeling. The profit model compares profits from crop rotations with and without buckwheat, while the diffusion model evaluates farmers' attitudes under neighborhood influences. Farmers will adopt buckwheat only if their profit from crop rotation with buckwheat (Pb) exceeds that with only traditional crops (Pt) in the previous period, and if the neighborhood influences create a positive outlook for adoption. Adoption decisions are updated each period and continue recursively until the simulation ends (Figure 2).

Profit modeling

The expected profit from the three-year rotation of traditional row crops is a critical factor in evaluating farmers' crop rotation decisions. The profitability of different crops over time is calculated using the Net Present Value (NPV) method, accounting for the yields, market prices, and production costs from the previous rotation period (year "t-1").

Thus, the profit from traditional rotations without buckwheat for period t is calculated using Equation 1.

$$Pt = \Sigma\left(y_{t-1,n,c}{}^{*}p_{t-1,n,c} - C_{t-1,n,c}\right) * NP_{t,n} \quad (1)$$

where:

$t = 0, 1, 2, \ldots 11$ steps of time with each three-year rotation period, t = 0 is the base period n = 1st, 2nd, and 3rd year of period t, respectively.

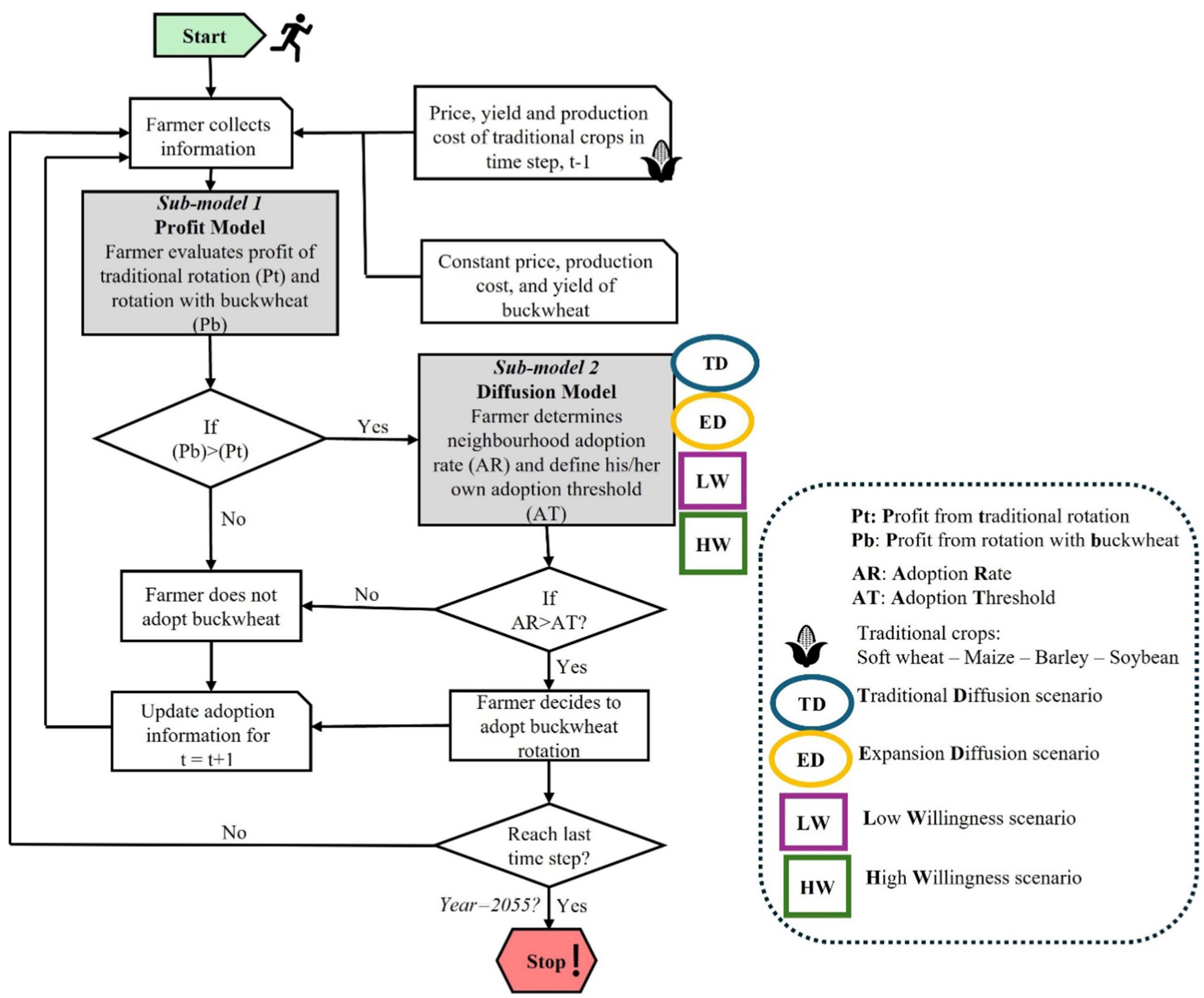

FIGURE 2
Process flow of farmers' decision-making.

c = types of crops, where 1 = soft wheat, 2 = maize, 3 = barley, 4 = soybean.

Pt = the profit of a crop for a particular year.

$y_{t-1,n,c}$= yield of a crop for a particular year.

$p_{t-1,n,c}$ = price of a crop for a particular year.

$c_{t-1,n,c}$= cost of a crop for a particular year.

$NP_{t,n}$= the multiplier to determine the NPV, where $NP_{t,n} = \left(\frac{1}{1+r}\right)^{(3t+n)}$, and r is the real discount rate (Godsey, 2010). By using a discount rate of 6% (Ullah and Crooks, 2022; Upadhaya and Dwivedi, 2019), the model ensures that farmers' decisions take into account the diminishing value of future earnings, leading to more realistic and rational economic behavior.

The profit from a crop rotation with buckwheat is calculated using Equation 2, where the contract price, yield, and production cost impacts for buckwheat is constant over the simulation period (Figure 2).

$$Pb = P_c{}^{*}NP_{t,n=1} + P_c{}^{*}NP_{t,n=2} + P_{bu}{}^{*}NP_{t,n=2} + P_c{}^{*}NP_{t,n=3} \quad (2)$$

where:

Pb = profit from crop rotation with buckwheat.

P_c = profit from one of the three crops (c values are 1, 2, 3, 4 types of crops) ∀ profit = Y*P-C.

P_{bu} = profit from buckwheat.

$NP_{t,n=1,2,3}$ = multiplier of NPV values in the 1st year, 2nd year, and 3rd year, respectively.

Diffusion modeling

Adopting buckwheat is a new experience for most farmers in Italy. The cumulative adoption of new or underutilized crops resembles the diffusion of innovation (DOI), which follows an S-shaped curve (Rogers, 2003; Alexander et al., 2013). This theory has been widely applied to study the adoption process of agricultural innovations over time and it has specifically been used to explore the adoption of organic management systems and cover crops (Padel, 2001; Lavoie et al., 2021). While crop rotation has historically served as a regenerative farming method, some producers now view it as an innovative practice due to its renewed promotion across the EU policy (European Commission, 2022).

Two diffusion scenarios are selected in this study (Jordan-Bychkov, 1997):

- *Traditional diffusion (TD)*- this model begins at a pilot site in Piedmont, the leading buckwheat cultivation area in Italy (RICA, 2022). Adoption behavior spreads from early adopters to neighboring farmers and gradually spreads all over Italy throughout the simulation (Figure 3A).
- *Expansion diffusion (ED)*- early adopters are spread all over Italy at the initial stage rather than located within a single small geographical area. Neighboring farmers learn from their experiences, leading to the diffusion of adoption behavior throughout the study area (Figure 3B).

In this study, we used an adoption threshold approach (Ullah and Crooks, 2022) with two key parameters: local adoption rate (AR) and individual adoption threshold (AT), reflecting farmers' willingness to adopt (Alexander et al., 2013). Initially since no farmers have experience with buckwheat, the AR was set at 0 for the base year (Alexander et al., 2013; Ullah and Crooks, 2022). Different standard deviations of AT parameters were used to set the innovator category as 2.5 and 5% of total farmers, reflecting low and high willingness to adopt, respectively (Alexander et al., 2013; Ullah and Crooks, 2022). Innovative, risk-taking farmers adopt buckwheat in the first-time step if profits are favorable,

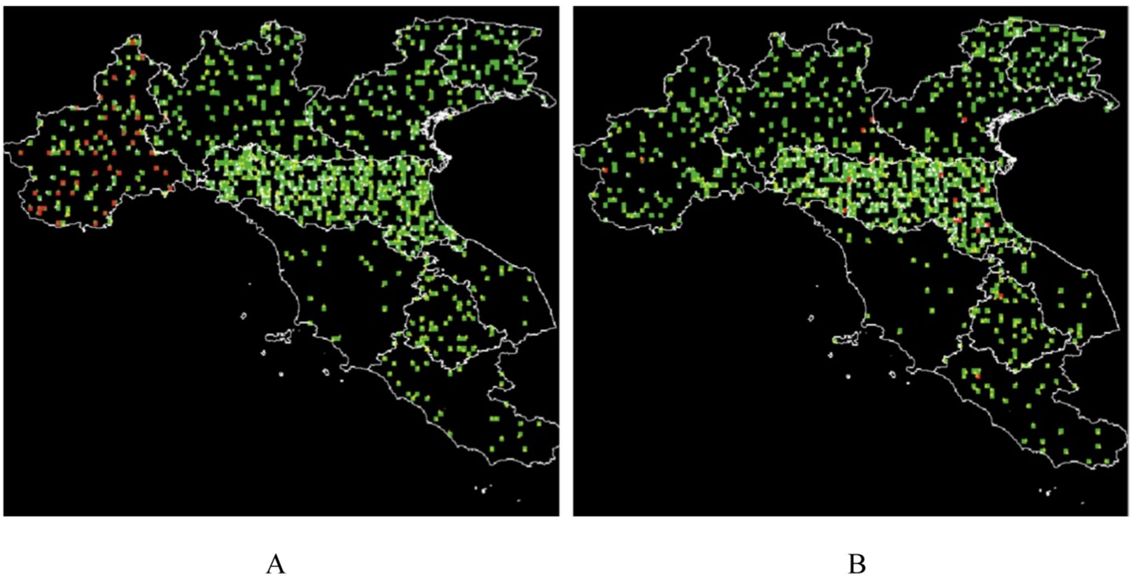

FIGURE 3
Adoption scenarios. At time step 1 red agents - i.e., farmers - are the early adopters under **(A)** Traditional Diffusion scenario and **(B)** Expansion diffusion scenario.

establishing the first positive AR. As shown in Figure 2, if AR exceeds a farmer's AT, they adopt due to neighborhood influence. If the initial contract price of buckwheat is not profitable, a new price is set, with innovators' positive experiences encouraging others to adopt in later steps. Farmers continuously update their experiences each simulation period.

Results

The model was simulated under three distinct profit conditions, each tested across a range of contract prices: €25/q, €45/q, €65/q, €85/q, €100/q, and €125/q. Additionally, the analysis incorporated two levels of willingness to adopt (High and Low) combined with two diffusion models (Traditional and Expansion), leading to four different scenarios.

This approach enables the exploration of how varying profit conditions, adoption willingness, and diffusion dynamics influence farmers' decisions to adopt buckwheat over time. The three profit conditions are as follows: (i) *Low profit condition*, calculated with the lowest yield (8 q/ha) and the highest production cost (€500/ha) for buckwheat; (ii) *Average profit condition*, calculated with average yield (15 q/ha) and average production cost (€350/ha); (iii) *High profit condition*, calculated with the highest yield (37 q/ha) and the lowest production cost (€200/ha). Figures 4–6 present the potential number of farmers adopting buckwheat across 30 simulation runs, showing results for each price point under each scenario.

Low profit condition

Figure 4 presents the results for the low-profit condition, examining adoption across different price levels and under the willingness-to-adopt and diffusion scenarios. The four subplots illustrate how adoption evolves over time for each combination of diffusion model and willingness level, showing the cumulative number of farmers who have integrated buckwheat into their crop rotation.

Under low willingness to adopt (i.e., an innovator category representing 2.5% of total farmers), both the traditional and expansion diffusion models show very limited adoption across all price points (Figures 4A–C). The lines remain close to zero throughout the simulation period, indicating that only a small number of farmers venture into buckwheat under these conditions. Even when contract price reaches the highest level (€125/q), the traditional diffusion model shows that only 214 farmers adopt by 2055—a slight upward slope visible in the final years of the simulation but totaling only 6% of potential adopters (3,576 farmers). In the expansion diffusion model, this modest rise is even lower, with 127 adopters (about 3.55% of the total) at the same contract price. At the lower price points of €25/q and €45/q, the adoption lines remain substantially flat, indicating that no farmers adopt buckwheat throughout the 2055 horizon. Even at intermediate prices (€65/q, €85/q, and €100/q), the curves barely inch upward, reflecting adoption rates below 5.5% in both models.

In contrast, under high willingness to adopt (i.e., an innovator category representing 5% of total farmers), Figure 4 shows that the adoption curves—particularly at higher contract prices—take on a

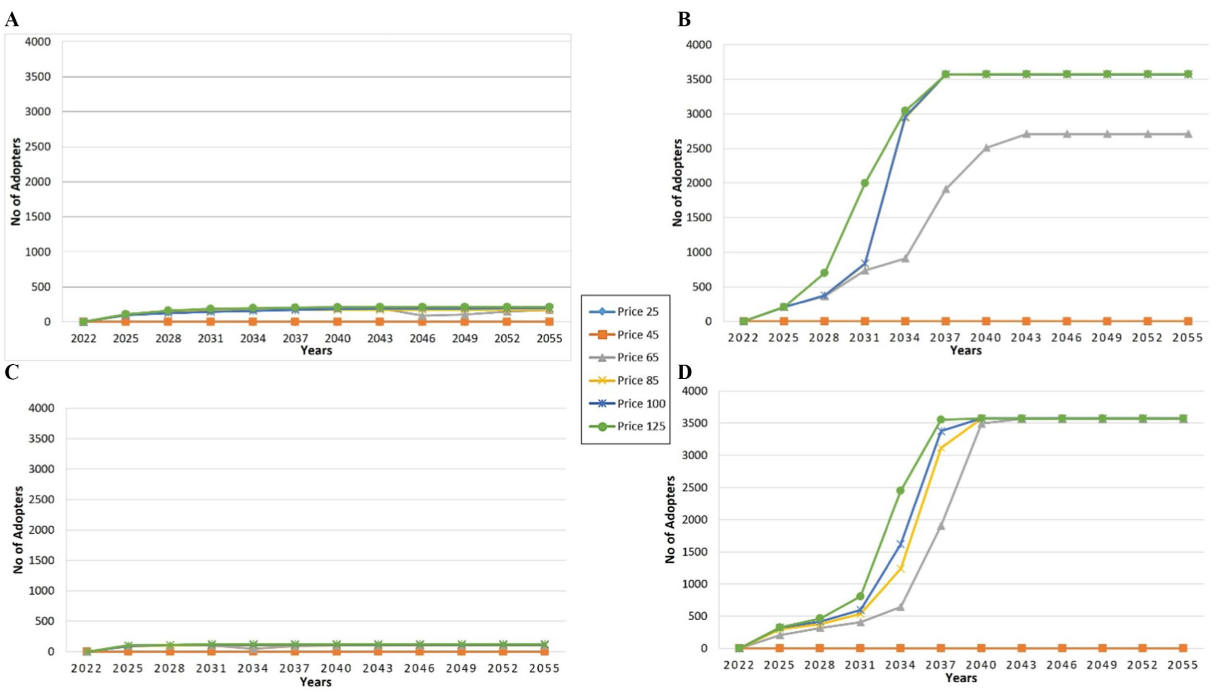

FIGURE 4
Low profit condition (yield 8 q./ha, production cost €500/ha). **(A)** Traditional diffusion and low willingness. **(B)** Traditional diffusion and high willingness. **(C)** Expansion diffusion and low willingness. **(D)** Expansion diffusion and high willingness.

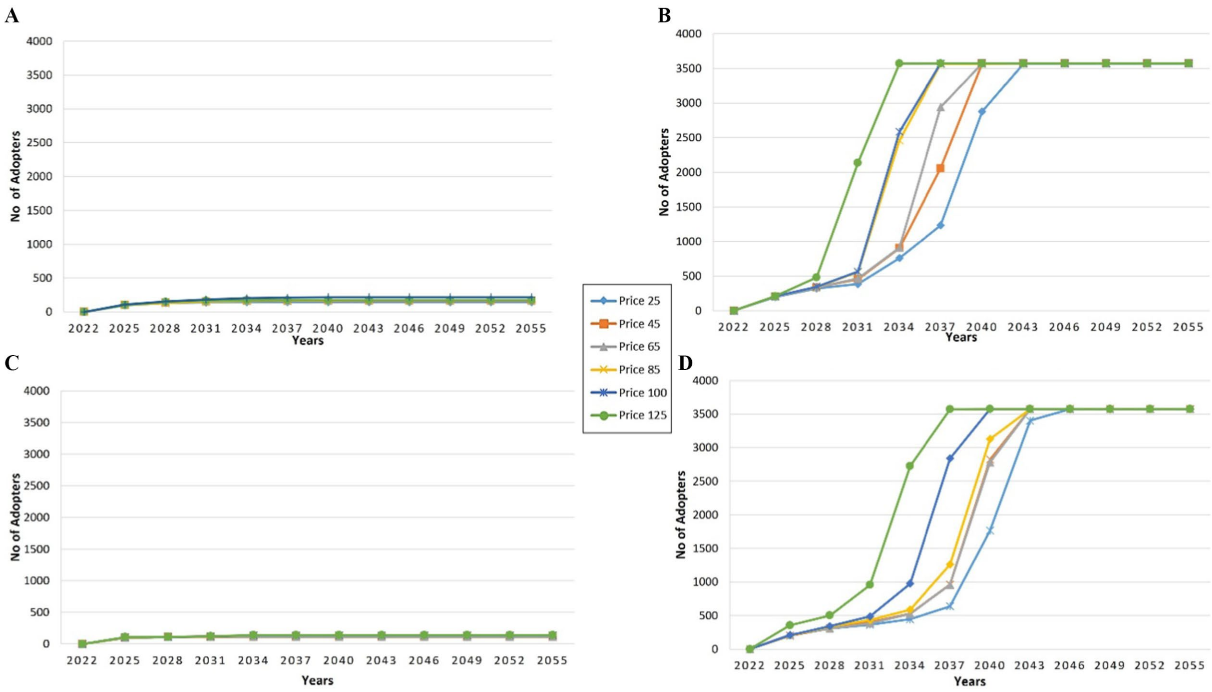

FIGURE 5
Average profit condition (yield 15 q./ha, production cost €350/ha). **(A)** Traditional diffusion and low willingness. **(B)** Traditional diffusion and high willingness. **(C)** Expansion diffusion and low willingness. **(D)** Expansion diffusion and high willingness.

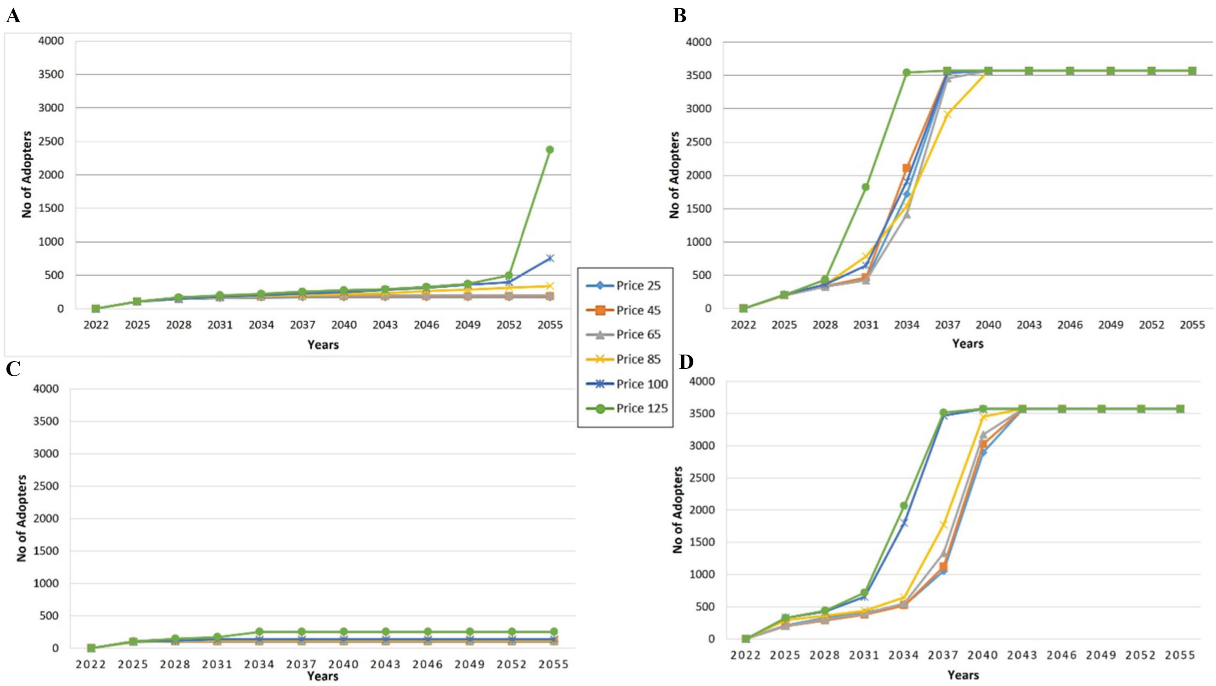

FIGURE 6
High profit condition (yield 37 q./ha, production cost €200/ha). **(A)** Traditional diffusion and low willingness. **(B)** Traditional diffusion and high willingness. **(C)** Expansion diffusion and low willingness. **(D)** Expansion diffusion and high willingness.

more pronounced growth trajectory, revealing an S-shaped pattern in some cases as more farmers decide to adopt over time (Figures 4B,D). In the traditional diffusion model (Figure 4B), adoption accelerates significantly at or above €65/q, with the lines climbing sharply after about 2030 and eventually plateauing close to the maximum number of potential adopters. By 2055, the highest contract price (€125/q) results in over 3,570 adopters, which corresponds to near-complete adoption. Even at €65/q, the number of adopters rises past 2,700—equivalent to 76% of the total population—showing the considerable impact that higher willingness combined with moderate-to-high contract prices can have. In contrast, at €25/q and €45/q, the line remains flat, meaning that the financial incentive is insufficient for adoption despite the higher inclination to innovate. Under the expansion diffusion model with high willingness (Figure 4D), the pattern is similar: adoption rates escalate more quickly at higher prices, culminating in 3,573 adopters at €125/q, whereas at the lowest price (€25/q) the line remains at zero throughout.

Overall, Figure 4 demonstrates that the willingness to adopt is the dominant factor influencing the number of buckwheat adopters under low-profit conditions. When willingness is low, adoption stays minimal even if contract prices are relatively high, and the graphs show only slight increases in the final years of the simulation. Conversely, when farmers have a high willingness to adopt, the adoption curves shift upward steeply at moderate-to-high price points, producing near-complete adoption by 2055 at the highest contract prices. Although price still matters—particularly apparent in the difference between the zero-adoption lines at €25/q and the steeply rising lines at €125/q—its effect is considerably amplified by whether farmers are willing to adopt new practices in the first place.

Average profit condition

Figure 5 presents the results for the average-profit condition, examining adoption rates across different price levels and under willingness to adopt and diffusion scenarios. Each subplot shows how the cumulative number of adopting farmers changes over time, illustrating clear differences in adoption trajectories based on willingness level and contract price.

In low willingness scenarios, adoption remains consistently low across all price points (Figures 5A–C), indicating consistently limited uptake of buckwheat regardless of price. Under the traditional diffusion model (Figure 5A), lower prices such as €25/q and €45/q result in a consistent low number of adopters, reaching around 143 and 163 adopters, respectively, (around 4–5% of the total) by the end of the simulation period. While increasing the contract price to €125/q produces a slight improvement to 217 adopters (6% of the total), the adoption curve still remains near the bottom of the graph, reflecting farmers' overall reluctance when willingness is low (Figure 5A). Similarly, in the expansion diffusion model, adoption does not show significant improvement. At the lower price points (€25/q and €45/q), adoption reaches 110 adopters and 135 adopters, respectively, (around 3% of the total) by the end of the simulation period. Even at the highest price point (€125/q), adoption does not increase significantly and remains at 217 adopters by 2055 (Figure 5C), indicating that price alone does not spur broad-scale adoption in a population with low willingness to adopt. Taken together, Figures 5A,C suggest that if only 2.5% of farmers are initially willing to experiment with buckwheat, higher contract prices may raise adoption levels, but they remain modest overall, maxing out at roughly 6% of the total farming population by 2055.

In contrast, high willingness scenarios exhibit a substantial increase in adoption, with both diffusion models showing rapid growth between the years 2031 and 2040. Under the traditional diffusion model, lower price points like €25/q and €45/q still result in minimal adoption initially, but once the price surpasses €65/q, the adoption curve exhibits a steeper ascent that eventually plateaus at a high level of uptake. At the top price of €125/q, the line continues to climb until it levels out at around 3,572 adopters by 2055. In the expansion diffusion model (Figure 5D), the trajectory is similarly pronounced: by 2055, near-complete adoption of 3,573 farmers is achieved at €125/q, demonstrating how strongly a higher willingness to adopt can amplify the effect of higher contract prices.

The average-profit condition exhibits similar trends to the low-profit scenario, though adoption rates are slightly higher. When willingness is low, adoption remains under 6% at any price level, confirming that financial incentives alone do not significantly increase uptake. Conversely, when willingness is high, adoption rapidly accelerates at moderate-to-high contract prices, converging on near-complete adoption by 2055 at the highest price points. This finding further confirms that while price incentives can influence farmer decision-making, a higher inherent inclination to try new crops—coupled with supportive diffusion dynamics—can lead to much broader uptake of buckwheat in crop rotations.

High profit condition

Figure 6 illustrates the results for the high-profit condition, showing adoption rates across different price levels and under willingness to adopt and diffusion scenarios. Each subplot tracks the cumulative number of adopters, revealing notable differences in the steepness and timing of adoption across scenarios.

In low willingness scenarios, adoption remains modest, particularly at lower price points with lines in both the traditional and expansion diffusion models staying near the bottom of the graph until around the mid- to late 2030s (Figures 6A,C). Under the traditional diffusion model (Figure 6A), the lowest price (€25/q) yields only 170 farmers (4.75% of the total) by 2055, reflecting a gentle upward slope that plateaus well below potential maximums. As prices increase, the adoption line becomes notably steeper, culminating in 2,370 adopters (66% of the total) at €125/q, a visible jump compared to lower price points. In contrast, the expansion diffusion model (Figure 6C) shows little improvement, as the lines remain comparatively flat even at higher prices: for instance, €125/q leads to just 250 adopters (7% of the total) by 2055, indicating that in this model, low willingness to adopt significantly hinders the spread of buckwheat despite higher profitability.

In high willingness scenarios, adoption increases significantly across all price points, with the steepest portions generally appearing between 2030 and 2040 (Figures 6B,D). Under the traditional diffusion model (Figure 6B), even the lowest price of €25/q draws in 2,705 farmers (75% of the total) by 2055, as the line quickly rises after the early 2030s. Higher prices spur even faster growth, leading to a pronounced "S-shaped" trajectory that reaches near full adoption. At €100/q or €125/q, the model shows near-complete adoption by about 2037, ending with over 3,555 farmers at €100/q and 3,573 at €125/q. A similar pattern emerges in the expansion diffusion model (Figure 6D), where the line at €25/q tops out at 2,800 adopters (78% of the total) by 2055, and the highest prices produce a rapid rise to near-total adoption before leveling off.

When comparing the high-profit condition with the low and average-profit conditions, the high-profit condition demonstrates noticeably higher adoption rates overall, especially at the upper price points in scenarios with high willingness to adopt. The lines in Figures 6B,D are much higher and steeper relative to the other two profitability conditions, reflecting a stronger response to price incentives when farmers believe in the viability of buckwheat. Even at €25/q, roughly three-quarters of the farmers adopt buckwheat by 2055 under high willingness, underscoring that farmers' intrinsic interest in the crop can play as large a role as the price itself. Nonetheless, once prices approach €100/q and above, the adoption curves rise rapidly toward full uptake, peaking around 2037 in both diffusion models—a clear indication that, under favorable profit margins, farmers embrace buckwheat as a viable rotation crop.

Discussion

Interpretation and comparison of the results

The main objective of this research was to examine how farmers' willingness to adopt, financial incentives, and peer influence affect the uptake of an underutilized crop like buckwheat. By simulating adoption under varying contract prices, yield conditions, and diffusion dynamics, we aimed to identify the key drivers behind farmers' decisions and determine the circumstances under which buckwheat adoption would most likely expand.

Overall, these results indicated that willingness to adopt a new crop plays a more critical role in driving adoption than financial incentives alone. Even when higher contract prices were offered, farmers with low willingness exhibited minimal adoption. Economic incentives, while traditionally considered a key motivator, are insufficient to overcome a lack of intrinsic motivation or perceived benefits among farmers. Conversely, when willingness to adopt is high, the role of financial incentives diminishes; adoption increases rapidly even at lower contract prices, following a typical S-shaped adoption curve. This pattern aligns with Rogers' diffusion of innovations theory (Rogers, 2003), where adoption begins slowly but accelerates over time as more farmers embrace the innovation. Therefore, while competitive pricing is important, it must be complemented by efforts to enhance willingness to adopt in order to achieve widespread adoption.

This is consistent with existing literature, which shows that farmers who prioritize conservation goals are intrinsically motivated to adopt sustainable practices, as these align with their personal values and beliefs (Greiner and Gregg, 2011; Greiner, 2015). Individuals with high intrinsic motivation implement such practices regardless of financial compensation, highlighting important implications for agricultural policy, as not all farmers respond equally to incentives (Bopp et al., 2019).

Moreover, the study highlights the significant role of peer influence in shaping adoption dynamics. Neighboring farmers' positive experiences stimulated further uptake in later cycles, validating previous research on the importance of knowledge-sharing networks and pro-environmental behavior within farming communities (Christ et al., 2020; Ha Thu et al., 2020; Tran-Nam and Tiet, 2022). This finding contrasts with studies reporting that unfavorable outcomes among early adopters discourage subsequent uptake (Alexander et al., 2013). Our results suggest that strong community support can avert such declines by fostering confidence in new crops. In farming communities, neighbors serve as valuable sources of information, knowledge, and motivation, which can inspire conventional farmers to transition toward more sustainable farming practices.

These observations are broadly consistent with literature examining underutilized crop adoption, which underscores the combined effects of policy (e.g., contract pricing), social factors (e.g., peer interactions), and individual attitudes (Knez et al., 2023). Although our simulations demonstrate that setting competitive contract prices (around €100/q or above) can spur initial interest—particularly in a context where buckwheat typically trades between €40/q and €80/q—our models also show that high willingness to adopt and peer support are necessary to sustain adoption. This dynamic resonates with prior studies on sustainable agriculture, indicating that only financial incentives rarely suffice in driving long-term transitions (Greiner, 2015; Bopp et al., 2019).

Overall, our findings suggest that while market strategies like higher contract prices may improve buckwheat's appeal, enhancing farmers' intrinsic motivation and leveraging social learning are crucial for achieving widespread adoption. Thus, attention to both behavioral drivers and community-level support will be pivotal in guiding policy aimed at promoting the adoption of underutilized crops.

Importance and implications of the results

Building on these findings, it is evident that financial incentives alone are insufficient to ensure sustained adoption. While economic incentives can serve as an initial motivator, their effectiveness is limited without complementary measures that strengthen farmers' intrinsic motivation and peer support networks.

This has important implications for policymakers and agricultural stakeholders. Strategies that focus solely on financial incentives, such as raising contract prices, may be less effective if farmers' willingness to adopt new crops is low. Farmers primarily motivated by economic or financial objectives tend to depend on external incentives, like government support, to implement conservation practices (Greiner and Gregg, 2011; Greiner, 2015). Therefore, measures like pre-sowing contracts, supply chain improvements, and government incentives are necessary but may not be sufficient to trigger widespread adoption.

Policy effectiveness could be improved by considering farmers' intrinsic motivations (Bopp et al., 2019). Efforts should be made to foster a more favorable adoption environment by addressing behavioral and attitudinal barriers. Educational outreach and awareness programs that enhance farmers' understanding of the economic and ecological benefits of crops like buckwheat could increase their environmental awareness and subsequent adoption behavior, while fostering peer influence and knowledge-sharing within farming communities. These initiatives can also help farmers recognize emerging market opportunities, particularly in health-conscious and gluten-free sectors, further promoting the crop's adoption in rotation systems.

Ultimately, a holistic approach combining financial incentives with behavioral and social interventions is critical to achieve meaningful progress in the widespread adoption of underutilized crops like buckwheat.

Limitations and future work

In considering future research, it is important to acknowledge models' inherent limitations. Firstly, while the values for buckwheat (yield, price, and cost) were derived from available RICA data and classified into categories based on past observations, it is crucial to note that these scenarios are hypothetical due to the currently limited production of buckwheat in Italy. This hypothetical nature should be kept in mind when interpreting the findings, as they represent possible outcomes under various conditions rather than definitive predictions. For other crops considered (soft wheat, maize, barley, and soybean), yield, price, and cost values were based on historical data and are assumed constant over the simulation period. This assumption overlooks potential dynamic environmental factors, such as weather conditions, regional yield variations due to differing soil conditions, and market fluctuations, which could significantly impact these variables over time. Future research could benefit from integrating dynamic models that account for environmental, soil and market changes for more accurate estimations of national production potential.

Moreover, this study does not incorporate farmers' risk aversion into the model, a factor that could significantly influence crop rotation decisions (Alexander et al., 2013). Future research could explore the application of risk portfolio estimation methods, such as mean–variance optimization, which could be integrated into the decision-making processes of individual farmers. Another limitation is its focus on a specific scale study area. Expanding the model to encompass a broader geographical scope, along with the broader effects of the entire supply chain and interactions with other actors, could provide deeper insights.

The study also overlooks the full spectrum of social costs and benefits associated with the adoption of underutilized species. Costs related to educational outreach and awareness programs, which play a crucial role in fostering intrinsic motivation among farmers, are not explicitly considered. Likewise, potential societal benefits, such as reduced dependency on imports and enhanced biodiversity, remain unquantified. Future research could adopt interdisciplinary approaches, such as policy impact assessments or economic valuation techniques, to capture these broader socio-economic dimensions.

Lastly, the model could be expanded to include additional farmer differentiation categories, such as age, farm size, or farming practices (organic versus conventional). This would allow for a more nuanced understanding of how different farmer profiles might impact the adoption and success of underutilized crops in diverse agricultural contexts.

Conclusion

This paper aimed to examine the adoption dynamics of underutilized crops, particularly buckwheat, within a defined geographical area, Italy. The results of our model indicate that while offering competitive contract prices can incentivize adoption, financial incentives alone are insufficient to significantly increase uptake, especially when initial willingness to adopt is low. Adoption rates for buckwheat remain initially low, as is common with new crops, but increasing initial willingness to adopt significantly accelerates uptake. Beyond financial incentives, our findings highlight the importance of peer influence and intrinsic motivation in shaping farmers' decision-making processes. Policies that integrate these behavioral factors alongside economic incentives are likely to be more effective.

The methodology employed in this study marks a substantial advancement in research on the adoption of underutilized crops. Existing literature often lacks transparency regarding modeling frameworks, spatial specificity, and the sharing of computational codes. To address these gaps, our study builds upon an innovative agent-based modeling tool, testing a previous model in a different case study and offering new insights. However, this tool requires further validation through sensitivity analysis, field verification, and the possible integration of additional decision-making factors. We expect that the modeling tool developed in this study will significantly contribute to future research, where more advanced versions may be used to predict farmers' adoption behavior regarding the adoption of other underutilized crops.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

MV: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. LC: Supervision, Writing – review & editing. LM: Supervision, Writing – review & editing. AG: Resources, Writing – review & editing. SR: Methodology, Writing – review & editing. GM: Funding acquisition, Writing – review & editing, Supervision. KM: Project administration, Supervision, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2025.1534246/full#supplementary-material

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