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Understanding Farmer Behaviour for Successful Climate Change Mitigation in Voluntary Initiatives

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ABSTRACT

Private and voluntary initiatives, such as voluntary carbon markets, can support public policies aimed at reducing greenhouse gas (GHG) emissions in agriculture. This study investigates the impact of behavioural factors (reluctance to change) and social dynamics (peer imitation) on the adoption of two mitigation practices on Swiss dairy and beef farms: the use of the feed additive 3-nitrooxypropanol (3-NOP), the commercial product Bovaer and substituting concentrate feeds with on-farm cultivated legumes. Using a bio-economic agent-based model and a diverse sample of farms, we simulated outcomes for reducing GHG emissions under increasing levels of financial compensation in scenarios reflecting behavioural and social influences. The results show that, assuming profit-maximising behaviour, emissions could be reduced by up to 24% at a price of 150 CHF per tonne of CO_2-equivalent. However, when farmers' reluctance to change is considered, the mitigation potential decreases significantly. Introducing social network effects, such as peer imitation, improves outcomes, increasing the potential reduction and showing that social influence can help overcome behavioural resistance. These findings suggest that, although private and voluntary schemes offer meaningful potential for reducing agricultural emissions, their effectiveness is limited when real-world behavioural dynamics are considered. The study highlights the importance of aligning voluntary market mechanisms with supportive public policies to maximise GHG reductions.

JEL Classification: Q12, Q13, Q18, Q58

1 | Introduction

Agricultural and food systems are responsible for a third of global anthropogenic greenhouse gas (GHG) emissions (Crippa et al. 2021). Thus, climate change mitigation in agriculture is high on political agendas globally and is especially reflected in European agri-environmental policy (Fellmann et al. 2018; IPCC 2019; Richards et al. 2016; Wuepper et al. 2024). However, current policies applied in European agriculture are often ineffective in reducing GHG emissions and are very costly in terms of public spending and farms' opportunity costs (Balogh 2023; Domínguez and Fellmann 2015; Pe'er et al. 2019, 2020; Solazzo et al. 2016). Beyond public policy measures, private actors (e.g., up- and downstream industries) are also pushing to reduce GHG emissions in the agricultural sector. In this regard, voluntary schemes such as voluntary carbon markets have become an important option for private actors to get compensation for reducing GHG emissions (OECD 2019; Streck 2021), and the first examples are emerging in European agriculture (Laine et al. 2023; Nonini and Fiala 2021). Unlike regulated carbon markets, such as the EU Emissions Trading Scheme, which enforce mandatory caps and compliance, voluntary carbon markets are optional. In these markets, farmers have the opportunity (but no obligation) to earn carbon credits for reducing their emissions below a predetermined baseline and to sell them to private firms (OECD 2019).

The success of these approaches, that is, the potential to reduce carbon emissions through voluntary and private schemes, depends on the farmers' uptake of climate change mitigation measures. This uptake is influenced by factors such as cost-efficiency of mitigation measures, opportunity costs, farm structures, personal characteristics of farmers or the social environment (Buck and Palumbo-Compton 2022; Rong and Hou 2022). Although behavioural and social factors are known to be potentially decisive for farmer decisions in the context of sustainable production practices (Dessart et al. 2019), the effect of these factors on the adoption of mitigation measures and thus on the efficacy and efficiency of voluntary programmes, including voluntary carbon markets in agriculture, remains unexplored.

Here, we develop and apply a bio-economic agent-based modelling approach to provide an ex-ante assessment of the impact of behavioural and social factors on the adoption of two mitigation measures appropriate for a voluntary scheme, such as a voluntary carbon market, at different economic compensation levels. Our main question is how these farmer-specific factors and their heterogeneity across the farmer population influence GHG emission reduction potentials and at what level of economic compensation the maximum abatement is reached. We specifically evaluate the impact of reluctance to change as a behavioural factor and the influence of social networks on peer behaviour through imitation. Agent-based models (ABMs) are well suited for this analysis, as they can incorporate these behavioural and social factors and the heterogeneity in farmer decision-making, which are seldom considered (Huber et al. 2018). We here quantify the impact of (i) farmers' reluctance to change their current production practices, (ii) social networks that support the imitation of successful adoption by peers and (iii) the combination of both. Reluctance to change is based on a set of empirically collected dispositional, cognitive and social factors from 49 dairy and beef farmers in Switzerland. The social network, that is, the basis for imitating peer behaviour, is based on a social network analysis using interviews with farmers. We compare the simulation results to a scenario in which we assume that farmers are profit maximisers. We apply this analysis to mitigation measures with a high potential for voluntary carbon markets: (a) the feed additive 3-nitrooxypropanol (3-NOP), which, like the commercial product Bovaer, reduces methane from enteric fermentation in cattle and (b) substituting concentrate feeds with on-farm cultivated legumes that allow the reduction of upstream GHG emissions. These measures were selected for their ability to lower GHG emissions without compromising food production. This makes them attractive to farmers and may increase their adoption.

Previous research has identified the efficacy of different strategies for reducing GHG emissions in agriculture (Haenel et al. 2018; Kebreab et al. 2023; Maigaard et al. 2024). Economic aspects have also been addressed in previous research, for example, by addressing the cost-efficiency of GHG emission measures in agriculture (Huber et al. 2023; Lanigan and Donnellan 2018; MacLeod et al. 2010, 2015; Moran et al. 2008, 2011). Moreover, previous research has assessed the suitability of different public policy designs, including taxation (Abadie et al. 2016; Bakam et al. 2012; Grosjean et al. 2018; Mosnier et al. 2019; Vermont and De Cara 2010; Weersink et al. 1998), emission trading schemes (ETS) (Bakam et al. 2012; Bakam and Matthews 2009; Bognar et al. 2023; Breen 2008; De Cara and Jayet 2011; Grosjean et al. 2018; Latinopoulos and Sartzetakis 2015), and regional level policy targets (Tarruella et al. 2023). In addition to these public policies, voluntary carbon markets have been identified as a promising way to achieve GHG reduction targets for agricultural emissions (Guigon 2010; Kreibich and Obergassel 2019; Streck 2021). These markets provide a platform for individuals and organisations to voluntarily offset their emissions by purchasing carbon credits or converting their own emission reductions into economic value. This voluntary nature contrasts with the mandatory nature of emission trading schemes set up by governments, where participation is mandatory and caps or compliance are imposed (Pinto 2010). Due to the voluntary nature of participation in these schemes, farmers' behaviour and acceptance of these schemes are crucial (Burton et al. 2008; Godefroid et al. 2023).

Few studies have explored how behavioural and social factors influence farmers' participation in voluntary carbon markets (i.e., Kragt et al. 2017). For example, studies such as those by Buck and Palumbo-Compton (2022) and Rong and Hou (2022) recognise the importance of factors such as social networks, cognitive barriers and profit expectations. Kreft, Finger, and Huber (2024) demonstrate that behavioural factors influence the effectiveness of voluntary action-based and results-based payments depending on whether the mitigation measure creates co-benefits or not. In addition, Kreft, Huber, et al. (2024) show that social networks can increase farmers' uptake of climate change mitigation measures. However, a research gap remains in quantifying how behavioural and social factors may affect the potential of voluntary schemes at different compensation levels. Quantifying this potential in ex-ante assessment can provide valuable additional insights into the role of voluntary carbon markets in achieving GHG emission reduction targets (Gillenwater et al. 2007; Guigon 2010; Kreibich and Obergassel 2019; Streck 2021).

In this paper, we address this research gap by providing a modelling framework to perform ex-ante simulations of farmers' uptake of climate change mitigation measures suitable for a voluntary carbon market scheme. This allows us to assess the potential of such private initiatives to achieve climate reduction targets. Based on the work by Kreft, Finger, and Huber 2024; Kreft, Huber, et al. (2024), we employ a bio-economic agent-based modelling approach that combines the farm-level bio-economic model FarmDyn (Britz et al. 2019) with the agent-based model FARMIND (Huber et al. 2021). This enables us to assess the impact of economic compensation (i.e., carbon credit prices) and determine the price per tonne of CO_2-equivalent that maximises emission reductions under different behavioural and social scenarios. Additionally, we account for the uncertainty of our results by considering the upper and lower bounds of the mitigation potential for the feed additive 3-NOP as reported in the literature. We focus on a Swiss case study, where the national climate strategy explicitly relies on private initiatives to complement public policies

(BLW 2022b). This makes Switzerland a relevant context for exploring the potential of voluntary adoption of mitigation measures to help achieve emissions targets.

Our study contributes to the existing literature by illustrating the potential of two mitigation measures suitable for a private initiative like a voluntary carbon market in agriculture and by considering farmers' behavioural and social factors that affect participation in these markets. This complements studies that focus on governmental strategies (e.g., carbon prices) to reduce carbon emissions in agriculture and thus informs the debate about potential synergies between public and private efforts in climate change mitigation (Gillenwater et al. 2007; Guigon 2010; Kreibich and Obergassel 2019; Streck 2021; Winter et al. 2024). By exploring the reduction potential of voluntary alternatives, our study goes beyond the work of Kreft (2022) and exemplifies to what extent private initiatives can contribute to reaching governmental targets with respect to GHG emissions. This can benefit both the government and farmers by reducing the need for regulatory enforcement.

Our findings show that these mitigation measures can contribute to significant reductions in agricultural GHG emissions. We find that when farmers aim to maximise profit, emission reduction at the current carbon prices in Swiss voluntary carbon markets (70 CHF)[1] ranges from 6% to 17%, depending on the efficiency of 3-NOP. The maximum possible reduction is achieved with a price of 150 CHF and lies between 18% to 24%, depending on the assumed efficiency of 3-NOP. However, we observe that the potential depends critically on farmers' behavioural and social factors. When the model considers reluctance to change only, the maximum emission reduction ranges from 6% to 7%, which is 12 to 18 percentage points lower than the reduction achieved under profit maximisation. When imitation through social networks is considered alongside reluctance to change, emission reductions are lower than in the profit maximisation scenario but higher than in the reluctance to change scenario. In this case, the reductions range from 15% to 19%, only 3 to 5 percentage points below those achieved when farmers optimise profits.

The remainder of this paper is organised as follows: the next section provides a background on behavioural and social factors in the context of climate change mitigation measures, followed by the description of the conceptual framework underlying this study and a section describing the case study context. Section 3 presents the agent-based modelling framework and its application. The results are then presented in Section 4, followed by a discussion and conclusions in Sections 5 and 6, respectively.

2 | Background

2.1 | The Role of Behavioural and Social Factors in the Adoption of Voluntary Mitigation Measures

Understanding the impact of behavioural and social factors is essential in voluntary schemes such as voluntary carbon markets because their success depends on farmers' willingness to participate. Dessart et al. (2019) and OECD (2012) emphasise that understanding the impact of behavioural factors is essential in voluntary agri-environmental schemes, with factors such as farmers' personalities, awareness of human-made GHG emissions, innovativeness and social networks influencing participation in schemes like agri-environmental programmes (Adenaeuer et al. 2021; Klebl et al. 2024; Kragt et al. 2017; Kreft, Huber, et al. 2021; Kreft, Angst, et al. 2021; Kreft et al. 2023; Schaub et al. 2023; Schulze et al. 2024). However, only a few studies have directly assessed the behavioural and social factors influencing participation in a voluntary scheme, although cognitive factors such as educational barriers, dispositional factors such as profit and cost expectations, and the influence of social networks have been found to influence participation in voluntary carbon markets (Buck and Palumbo-Compton 2022; Rong and Hou 2022).

In this paper, we specifically focus on behavioural and social factors, namely reluctance to change and the impact of imitation through the social network, respectively, in our sample. Reluctance to change has been identified in various studies as a significant obstacle for farmers when adopting more sustainable practices (Burton et al. 2008; Dessart et al. 2019). This reluctance to change is often attributed to the status quo bias, where individuals prefer maintaining their current choices as they perceive changes as losses (Ritov and Baron 1992; Samuelson and Zeckhauser 1988). In the agricultural sector, status quo bias has been observed to influence and affect farmers' decision-making and contribute to a partial resistance to certain measures (Burton et al. 2008; Hermann et al. 2016; Peterson et al. 2012). In this study, reluctance to change is operationalised using a set of empirically collected dispositional, cognitive and social factors (see Section 3). We expect reluctance to change to affect farmers' decision-making (Dessart et al. 2019) and thus influence the uptake of mitigation measures suitable for a voluntary scheme like a voluntary carbon market.

By contrast, social factors, such as descriptive and injunctive norms, are promoted by social networks, particularly through the imitation of peers (Dessart et al. 2019). Studies have shown that farmers' decisions to adopt mitigation measures are influenced by the behaviour of their peers (Dessart et al. 2019; Kreft 2022; Lapple and Kelley 2015; Schmidtner et al. 2012), and social networks have been demonstrated to enhance the reduction of GHG emissions (Kreft, Huber, et al. 2024). This influence stems from farmers' decisions being shaped by social learning, as they learn from observing and interacting with others (Skaalsveen et al. 2020; Wood et al. 2014), which, in turn, is a key driver of technology and innovation diffusion processes in agriculture (Shang et al. 2021; Xiong et al. 2016; Zhang and Vorobeychik 2019). We assume that farmers' decision-making processes will be influenced by interactions with their peers, as they tend to learn from one another. This assumption is based on the idea that individuals tend to conform to social norms. Therefore, if a farmer's decision significantly differs from that of their peers, they may be inclined to emulate the behaviour observed within their social network (Jager and Janssen 2012).

To evaluate the impacts of behavioural and social factors in voluntary schemes ex-ante, it is crucial to use a model that incorporates and simulates farmers' decision-making while accounting for these factors. However, many existing ex-ante modelling approaches assume that farmers aim to maximise their utility or profit (Arnsperger and Varoufakis 2006; Huijps et al. 2010) and often ignore concepts such as personal preferences, emotions and intuitive and unconscious decision-making (Kahneman 2003). Despite this, various studies highlight the necessity of including these factors when modelling farmer behaviour (Dessart et al. 2019; Wuepper et al. 2023). ABMs serve as a significant ex-ante approach for incorporating and simulating the heterogeneity of farmer decision-making while considering behavioural and social factors (Huber et al. 2018). These models are crucial for understanding how farmers respond to changing conditions, such as environmental factors (An 2012; Berger and Troost 2014; Huber et al. 2021; Magliocca et al. 2015). From a behavioural and social perspective, these models typically integrate prospect value theory[2], social networks and farming preferences to simulate farmers' choices (Huber et al. 2021).

Here, we use the agent-based model framework FARMIND to evaluate the reduction potential of mitigation measures for a voluntary carbon market. This model allows to combine farm specific abatement costs, for example, due to different farm structures and production types, with the effect of behavioural factors and the imitation of peers through social networks.

2.2 | Conceptual Framework

To assess the potential for voluntary adoption of climate change mitigation measures, we here consider three categories of factors that influence farmers' decision-making process in our modelling framework: (1) behavioural and social factors, (2) farm structure and production-related opportunity costs and (3) economic incentives for reducing GHG emissions (Figure 1).

First, based on the arguments in Section 2.1, we consider the role of behavioural and social networks—in particular, reluctance to change and imitation of peers—in farmers' decision making. We assume that these factors shape the options a farmer considers when deciding whether to adopt climate change mitigation measures.

Second, farm structure and production type influence participation through opportunity costs. Larger farms or those with less intensive production systems may face different cost–benefit trade-offs when adopting mitigation measures. We assume that farmers will only adopt measures if benefits outweigh the costs for their individual farms.

Third, economic incentives to reduce GHG emissions provide financial compensation for adopting mitigation measures. Higher compensation levels can offset costs, making these measures more attractive, also for farms with high abatement costs.

In our conceptual modelling framework, the three factors interact through a two-step decision-making process: First, behavioural and social factors shape each farmer's strategy. These strategies may include repeating past behaviour, maximising profit, imitating peers or choosing not to adopt (see Section 3.3 for details). Each strategy determines which mitigation options the farmer considers. Second, the farmer adopts a mitigation measure only if the expected economic benefits exceed the costs. These benefits depend on the level of financial compensation. To explore the potential for voluntary adoption, we analyse scenarios with increasing compensation payments.

Please note that our contribution focuses on farmers' decision making when voluntarily adopting climate change mitigation

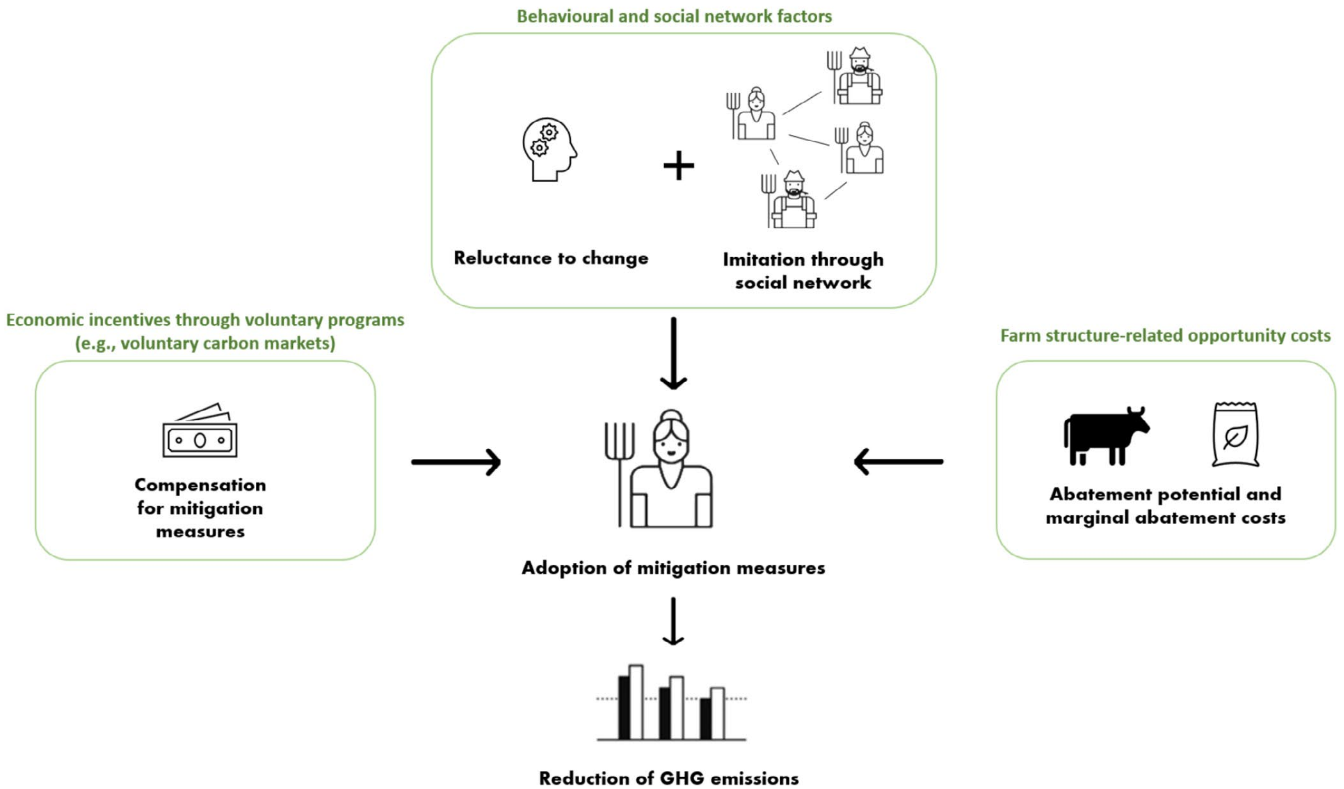

FIGURE 1 | Conceptual framework for farmers' decision-making in adopting climate change mitigation measures.

measures rather than modelling a formal carbon market structure. However, the analysis of these three factors allows us to assess the potential of private economic incentives to promote the adoption of selected mitigation measures and to support the achievement of public GHG reduction targets in such markets.

2.3 | Swiss Case Study: Policy Context and Mitigation Measures

Voluntary projects have become increasingly important in reducing agricultural GHG emissions and meeting climate targets, offering a promising approach for efficient mitigation (Gillenwater et al. 2007; Guigon 2010; Kreibich and Obergassel 2019; Raina et al. 2024; Streck 2021). This is of specific importance in Switzerland where the official climate strategy considers voluntary and private initiatives as an important pillar of achieving GHG mitigation targets (BLW 2022a, 2022b).

Agriculture accounts for 14.6% of Switzerland's total emissions (BAFU 2022), primarily from milk and meat production. Switzerland aims to reduce agricultural emissions by 25% from 1990 levels by 2030 and by 40% by 2050 while maintaining over 50% self-sufficiency in food production (BAFU 2022; BLW 2022a, 2022b). However, progress has been slow, with only an 11% reduction achieved by 2021 (BAFU 2022). Switzerland's current agricultural policies primarily rely on direct payments, which focus on biodiversity and environmentally friendly production systems rather than direct GHG reductions (FOAG 2020; Huber, El Benni, and Finger 2024; OECD 2017). While a new voluntary agri-environmental scheme to promote cow longevity began in 2024 (Winter et al. 2024)[3], no direct payment scheme currently targets GHG reductions.

In its 2050 climate strategy for agriculture and food, the Federal Office for Agriculture (FOAG) explicitly highlights the role of private initiatives in contributing to climate targets. It argues that all actors in the food system should take responsibility by implementing their own measures (BLW 2022a, 2022b). As a result, public policy expects the farming sector to actively participate in programmes such as voluntary carbon markets to complement public efforts.

Existing voluntary carbon market programmes in Switzerland are entirely privately organised. Swiss producer cooperatives Mooh and Fenaco, for example, have launched programs aimed at reducing methane emissions by providing feed additives for farmers to include in cattle diets. The carbon credits generated through these programmes are priced between 65 and 80 CHF per tonne of CO_2-equivalent, aligning with prices in the EU compliance markets (Fenaco 2022; Mooh|Climate Program 2022). The cooperatives then sell the carbon credits to private actors to offset the costs of the feed additives. These examples highlight the growing significance of private compensation schemes in Swiss agriculture. Understanding their potential contribution to the overall targets requires estimating the benefits and costs of mitigation measures suitable for certification on voluntary markets and considering behavioural and social factors, which are critical for assessing the abatement potential of voluntary programmes.

To be effective, the mitigation measures offered must be feasible, easy to monitor and aligned with the additionality criterion—the idea that emission reductions should only be credited if they would not have occurred without financial incentives (Gillenwater et al. 2007; Kollmuss et al. 2008). In this context, we analyse the suitability of two mitigation measures:

1. The feed additive 3-NOP (Bovaer): Inhibiting methanogenesis in livestock digestion with 3-NOP can significantly reduce methane emissions. However, due to the added costs, it is unlikely to be adopted without financial support, making it a strong candidate for voluntary carbon markets.
2. Locally grown legumes: Replacing imported concentrate feed with locally grown legumes reduces emissions associated with transportation, land use change and fertiliser use. Financial incentives may be necessary to offset the costs and risks involved in shifting to local production.

Both measures show strong potential to meet the additionality criterion, with well-documented emission reductions that facilitate monitoring and demonstrate cost-effectiveness (see Table 1)[4]. They also offer synergies with food production, making them attractive to farmers as well as not requiring an immediate adjustment to production. By evaluating the adoption of these measures under increasing compensation levels and behavioural scenarios, this study examines to what extent private incentives could increase the adoption of these mitigation measures and support national reduction targets.

3 | Methodology: Agent-Based Modelling Framework (FARMIND)

Our agent-based modelling framework, FARMIND (see Huber et al. 2021), aims to simulate the effects of accounting for reluctance to change as well as imitation through social networks on farmers' uptake of GHG mitigation measures suitable for a voluntary carbon market scheme. We do this by analysing the abatement potential achieved for different economic compensations, that is, the compensation per tonne of CO_2-equivalent avoided by implementing mitigation measures.

FARMIND incorporates aspects of cumulative prospect theory (Tversky and Kahneman 1992) and social network theory and allows the simulation of decisions made by individual agents representing farmers with certain behavioural and social factors, that is, cognitive, social and dispositional factors. These factors are empirically based on a survey of farmers in our case study region (Kreft et al. 2020; Kreft, Huber, et al. 2021; Kreft, Angst, et al. 2021). The agents' decision-making process is defined by a two-step procedure. First, FARMIND calculates the behavioural and social heuristics for each agent by incorporating behavioural factors and considering the social network into their decision making (see Table 2). The implementation of these heuristics is based on the CONSUMAT framework. This framework integrates different theoretical concepts into a structured sequence of modelling steps

TABLE 1 | Description of climate change mitigation measures.

Mitigation measure	Mechanisms of GHG emissions reduction	On-farm costs	Mean abatement potential in farm sample	Type of emissions reduced	References
Replacement of imported concentrates with on-farm production of legumes	Substituting concentrate feed, like imported soybean, with legumes produced on the farm (we specifically consider peas or horse beans) helps mitigate upstream GHG emissions by minimising the impact of transportation and land-use changes, as well as lowering fertiliser-related emissions, as leguminous crops fix nitrogen in the soil, reducing the need for synthetic fertilisers.	The farmer cuts down on purchasing expenses for concentrate while simultaneously having an increase in on-farm fodder production costs. The expansion of fodder production leads to the displacement of land previously allocated to cash crops. The calculation of these costs is model endogenous.	4 t CO_2-eq (average abatement potential based on the upstream emissions associated per type of imported crop and fertiliser emissions reduced). Further details on the values of the upstream and fertiliser emissions used to quantify the abatement potentials can be found in the Appendix S1.	NH_3 N_2O NOx N_2 CO_2	(Baumgartner et al. 2008; Haenel et al. 2018; Hörtenhuber et al. 2010; Knudsen et al. 2014)
Feed additive: 3-NOP	Mitigation of methane emissions by reducing enteric fermentation	80–120 CHF per cow per year These costs are model exogenous.	Dairy cattle: 15%–30% tonnes of CH_4 or CO_2-eq Beef cattle: 15%–22% tonnes of CH_4 or CO_2-eq	CH_4	(Kebreab et al. 2023; KlimaStaR-Milch 2023; Maigaard et al. 2024)

(e.g., Jager and Janssen 2012). Second, based on the corresponding strategy, an agent adopts the mitigation measure if it is profitable for its own farm at a given economic compensation.

There are two endogenous variables in the model: (i) the agent's satisfaction with their income, which is derived from their prospect value and (ii) the tendency of a farmer to engage in social processing, which is based on their willingness to consider the behaviour of their peers. The four behavioural and social heuristics—repetition, imitation, optimisation and opting out—are then derived as follows (see Table 3):

- When a satisfied farmer does not engage in social processing, they repeat the practices from the previous simulation run and only consider mitigation measures adopted in the previous run (repetition). Farmers engaged in this strategy are reluctant to change their behaviour.
- When a satisfied farmer seeks additional information, they tend to imitate the behaviour of their peers within their social network (imitation). This implies that the agent considers mitigation measures adopted by their peers.
- If a dissatisfied farmer focuses on individual behaviour, they try to optimise their situation by considering all available practices in the model (optimisation).
- If a dissatisfied farmer engages in socially oriented behaviour, they examine the behaviour of other agents in general and seek opportunities outside the practices modelled in FARMIND, thus not adopting sustainable practices (opt-out).

Please note that other implementations of the CONSUMAT framework apply different heuristics for dissatisfied and socially oriented farmers (e.g., Malawska and Topping 2016; Pacilly et al. 2019; van Duinen et al. 2016). The main advantage of our approach is that it allows mitigation measures to vary over time, which means that disadoption can also occur during the simulation period. To test the robustness of this assumption, we evaluate alternative approaches consistent with those used in other studies (see Appendix S1). Our main results are unaffected. However, our assumption provides a more conservative estimate of the impact of social processing (see also Discussion section).

The combination of behavioural and social factors with farm-level benefits and costs of GHG mitigation measures makes FARMIND suitable for our research question to test the abatement potential of the mitigation measures under different behavioural and social scenarios. The economic costs and benefits of implementing the mitigation measures are calculated using the bio-economic farm-level model FarmDyn (Britz et al. 2019). This sub-model allows us to calculate the changes in GHG emissions and profits under the selected mitigation measures. More information on FarmDyn and details on the input and output costs can be found in Appendix S1.

The main outcomes of this modelling process in this study are the farmers' adoption of the two mitigation measures suitable for voluntary carbon markets (3-NOP and replacement of concentrate feeds) for different economic compensations, and the associated GHG emission reduction for different behavioural scenarios.

TABLE 2 | FARMIND decision heuristics.

		Farmers' satisfaction	
		Prospect value with reference income as a threshold to determine gains and losses	
		Satisfied	**Dissatisfied**
Engagement in social processing	Individual oriented	*Repetition* The agent solely considers mitigation measures conducted within the previous year.	*Optimisation* The agent evaluates all mitigation measures.
	Social oriented	*Imitation* The agent considers mitigation measures that are adopted within the social network.	*Opt-out* The agent does not adopt mitigation measures.

Note: Table adapted from Huber et al. (2021) and showing the different choice sets of strategic decisions depending on the satisfaction and social behaviour of farmers.

TABLE 3 | Behavioural and social scenarios in the simulations.

Social network (imitation of peers)	**Cognitive, dispositional and social factors**	
	No	**Yes**
No	**Scenario 1—Optimisation scenario (reference scenario)** *Decision heuristic: Optimisation* Agents are profit maximisers only.	**Scenario 3—Reluctance to change** *Decision heuristic: repetition and optimisation* Agents are reluctant to change due to cognitive and dispositional factors.
Yes	**Scenario 2—Imitation of peers** *Decision heuristic: repetition and imitation* Agents can learn by imitating the behaviour of peers in their social networks.	**Scenario 4—Reluctance to change and imitation of peers** *Decision heuristic: repetition, optimisation, imitation and opt-out* Agents may be reluctant to change but can imitate peers through social networks.

In the following, we describe the simulations in four steps. First, we describe the behavioural and social scenarios used in this study. Second, we present the agent characteristics and the data used for the parameterisation of the model. Third, we formally describe the agents' decisions and interactions. Fourth, we present a short description of our simulation setup and the sensitivity analysis. For more details of the modelling framework, we refer to the ODD+D protocol in Appendix S1.

3.1 | Scenario Description

To address our main research objective of quantitatively evaluating the influence of behavioural and social factors on the uptake of the proposed mitigation measures for a potential voluntary carbon market, we simulate and compare four different behavioural and social scenarios. These can be distinguished by the inclusion of behavioural factors and the presence of social comparisons and knowledge exchange through social networks.

In Scenario 1 (optimisation scenario), agents adhere to the neoclassical economic model, which assumes profit maximisation. In this scenario, agents evaluate all the activities in the model without behavioural biases or social influences. This scenario serves as a reference to compare the effects of behavioural and social factors in the other scenarios.

In Scenario 2 (imitating scenario), agents primarily consider the mitigation measures adopted by their peers within a given social network. In our case, we consider an observed network derived from personal interviews with the farmers. This scenario tests the impact of peer learning, which echoes findings from other studies that emphasise the critical role of social networks in enhancing participation in voluntary markets (Kreft et al. 2023). This scenario represents a situation in which all farmers frequently exchange information within their social networks about climate change mitigation measures, including their costs and benefits. This means that information about successfully implemented mitigation measures is shared among peers. This may trigger future adoption by farmers who have not yet implemented these measures.

In Scenario 3 (reluctance to change scenario), agents base their decision-making on individual behaviour, initialising with personal characteristics such as satisfaction thresholds and practice preferences, without imitating peers in their social network. Unlike Scenario 2, where social imitation plays a role, here, agents rely only on their predispositions influenced by their reluctance to change. Their available decision strategies are limited to either repeating or optimising. This scenario represents a situation in which farmers make isolated decisions about adopting climate change mitigation measures in a world without influence from social networks or peer interactions. This implies that farmers may be willing to adopt mitigation measures primarily when they see a clear potential to increase profits. Otherwise, adoption rates remain low.

In Scenario 4 (combined behavioural and social network factors) both social imitation and behavioural reluctance to change influence decision-making. This scenario integrates peer effects from social networks with individual behavioural tendencies, making all decision heuristics available to the farmer. This scenario assumes the presence of both social and behavioural mechanisms, making it the closest representation of the real-world context reflected in our data collected from farmers. This means that social influence can counteract the reluctance of individual farmers to change.

By comparing the four main scenarios, we can disentangle the specific effects of social imitation and behavioural factors from purely profit-maximising strategies. These scenarios also help to identify the overall reduction potential relative to a baseline without any mitigation measures.

3.2 | Agents' Characteristics and Farm Sample

In FARMIND, each agent is characterised by three distinct sets of state variables. First, there are farm-specific costs and potential reductions in GHG emissions attributed to the two mitigation measures, 3-NOP and the substitution of concentrate feeds by on-farm-produced legumes. These variables are highly farm- and context-specific and are calculated using the bio-economic farm-level model FarmDyn, which is initialised with census data pertaining to each farm in our sample (Britz et al. 2019; Huber et al. 2023). The mitigation costs incurred are, in part, offset by the carbon credits per tonne of CO_2-equivalent mitigated, for which we test different price levels. Second, each agent possesses personal behavioural factors that parameterise the model. These include social elements (e.g., tolerance for deviation from fellow farmers), cognitive factors (e.g., preferences for particular mitigation measures and a reference income to determine satisfaction with current income levels), and dispositional factors (e.g., reluctance to change). These attributes are derived from a farm survey (Kreft et al. 2020). Third, a social network among farmers facilitates the exchange of climate change mitigation knowledge as identified through social network analysis conducted via face-to-face interviews (Kreft, Huber, et al. 2021; Kreft, Angst, et al. 2021; Kreft et al. 2023).

Whereas most behavioural and social factors are directly incorporated, parameters originating from survey questions utilising a Likert scale undergo a transformation process to maintain relative proportions between agents (for detailed methodology, refer to sections on input data, calibration and sensitivity analysis in the ODD+D protocol, Appendix S1).

In this study, we precisely evaluate the effectiveness and economic feasibility of these two on-farm mitigation measures across 49 Swiss dairy, suckler and bull-fattening farms in the Weinland region of the canton of Zürich (Switzerland). All of these farms have arable land and are situated in lower lands; thus, grassland-based farming is not included in this study. Structural data from these farms are derived from census data, and the behavioural and social network data are derived from an online survey and face-to-face interviews, respectively (Kreft et al. 2020; Kreft, Huber, et al. 2021; Kreft, Angst, et al. 2021), both of which are used to parameterise the agent-based model FARMIND. In particular, our sample consists of 24 dairy and 25 beef cattle farms including both suckler and bull-fattening, which on average are 35 ha in area and have 38 cattle livestock units, which makes them larger than the average farm in the canton of Zurich, with 25 ha (more details are provided in Appendix S1).

3.3 | Agents' Interactions and Decision-Making Processes

FARMIND employs a two-tiered decision-making process for farmers, that is, the choice of a strategy (as presented in Table 2) and, subsequently, the (non-) adoption of mitigation measures (Huber et al. 2021). This choice of strategy is modelled in several steps. First, the farmer's satisfaction is determined by the farm-specific prospect value, computed according to their individual reference income and risk preferences. The prospect value V_i, which is determined by the incomes x in year t and all preceding years within the agents' memory span (set to 5 years), categorises incomes above (below) the agent's individual reference income $V_{ref\,i}$ as gains (losses). The prospect value is calculated for each farm individually, based on parameters (risk aversion, loss aversion, probability distortion) that have been elicited using incentivised multiple price list experiments (following Tanaka et al. 2010) and using the individual reference income as a threshold; that is, this measure serves to determine satisfaction or dissatisfaction. If the prospect value is positive (negative), the agent is satisfied (unsatisfied).

Formally, given a set of past incomes of farm i in year t as $\{x_1, \cdots, x_m\}$, the value function $v(x_t)$ and the decision weight denoted $\Phi(x_t)$, the prospect value for each farm is defined as follows:

$$V_i = \sum_{t=1}^{m} v(x_t)\Phi(x_t)$$

where the value function is negative for losses and positive for gains (depending on the valuation $\alpha^{+/-}$ for gains and losses, and the loss aversion for losses λ), and the decision weight determines the probability weight in gains and losses.

Second, the calculation of whether a farmer will engage in social processing is determined by the dissimilarity index. This captures the extent to which other farmers within a farmers' network also adopt GHG reduction measures. More specifically, we calculate the average count of mitigation measures within the agent network throughout the memory length. Subsequently, we divide the average count for each adopted measure by the total number of mitigation measures carried out within the corresponding network. Formally, assuming that a activities are performed by all the peers in the social network, agent i's activity dissimilarity is as follows:

$$d_i = \frac{1}{a} \sum_{j=1}^{a} \frac{\# \text{ of peers performing } A_j}{n} \left(1 - P\left(A_j^i\right)\right)$$

here, $P\left(A_j^i\right)$ represents agent i's performance status for activity j, where $P\left(A_j^i\right) = 1$ if activity A_j is performed and $P\left(A_j^i\right) = 0$ otherwise, while n denotes the number of peers linked to an agent. The dissimilarity index d_i, indicates the extent of similarity between an agent and their peers, measured relatively, with a value of 1 indicating uniform engagement in the same activity across all farms. This index is recalculated in each simulation run and can vary for each agent based on their peers' decisions. It is important to note that the agents' dissimilarity also relies on the network's size (n) and the number of activities (a) within the network. A larger network with more activities increases the likelihood of agents being dissimilar to their peers.

The dissimilarity index is assessed against a tolerance level, representing an individual's inclination to accept divergent behaviour among fellow farmers. A low tolerance level suggests a greater likelihood for a farmer to conform to social norms, avoiding deviation from the group (i.e., the agent is socially oriented). Derived from survey responses regarding the significance of peers in decision-making, measured on a Likert scale (Kreft et al. 2020), the tolerance level remains constant for each agent throughout the simulation. If the dissimilarity index surpasses the tolerance level, the agent engages in learning from peers; otherwise, the agent remains individually oriented.

Depending on the chosen strategy, a selection of potential GHG mitigation measures is carried over to the second simulation phase. Repeating agents exclusively consider measures utilised in the previous simulation run. Optimising agents evaluate all available mitigation measures. Imitating agents replicate mitigation measures successfully employed by their peers, while agents opting out select none of the mitigation measures. Utilising this information, agents in FARMIND determine the combination of mitigation activities that maximise farm income. The resulting income and adopted GHG mitigation measures are subsequently fed back to the FARMIND strategic decision level to update the measures and income distribution among farm agents.

3.4 | Model Set Up and Sensitivity Analysis

We initialise the model with agents who have not adopted climate change mitigation measures. In this setup, agents have no prior experience with such measures. We then simulate a 6-year period using FARMIND. During this time, agents endogenously select strategies and may adopt mitigation measures. The 6-year period is chosen to allow the model to reach a saturation point, where the number of adopted measures stabilises because additional measures are not profitable at the level of compensation (see also Huber, El Benni, and Finger 2024; Huber, Kreft, et al. 2024). For the imitation scenario, where no optimisation takes place, we introduce a 'seed agent' that has adopted both mitigation measures. This agent serves as an initial example, and the adoption decisions of other agents emerge through imitation over the course of the simulation (see Huber et al. 2021).

To check the robustness of our simulations, we complement the behavioural scenarios with scenarios of different efficacy levels for the use of 3-NOP. More specifically, we use the lower and upper estimates of 3-NOP's abatement potential as reported in the literature: 15% for both dairy and beef cattle at the lower end, and 30% for dairy cattle and 22% for beef cattle at the higher end (Kebreab et al. 2023). As milk and meat prices affect farmers' opportunity costs, we also incorporate price uncertainty by simulating 200 price vectors over the six-year simulation period. These vectors are randomly drawn from a uniform distribution based on observed milk and beef prices over the last decade in Switzerland (Reflex Preiskatalog Agridea 2023). Crop prices are not included in the uncertainty analysis as they have remained comparably stable due to the Swiss tariff system. The resulting uncertainty in the abatement potential due to fluctuating output prices is reflected in our results as confidence intervals for each level of economic compensation. Finally, we test a different model implementation by allowing farmers with the opt-out strategy to imitate their peers (see Section 3.4 in ODD+D protocol in Appendix S1).

We also provide an output sensitivity analysis with respect to the amount of GHG emissions emitted, which can be found in the ODD+D protocol in Appendix S1. We do it for three different types of parameters: various social network connectivity levels (i.e., observed ties versus a full network); behavioural factors; and exogenous factors, such as the output price levels of beef and milk, the carbon price levels and different abatement potentials for 3-NOP. The method we employ in our sensitivity analysis is the standardised regression coefficient (SRC), following the protocol by Thiele et al. (2014). The sensitivity analysis shows that the social network, the economic compensation per tonne of CO_2-equivalent and the abatement potential range of 3-NOP have the strongest influence on total GHG emissions. This finding supports our choice to design scenarios that reflect the uncertainty range of these key factors.

4 | Results

We find that voluntary adoption of the considered climate change mitigation measures by farmers can reduce GHG emissions by up to 24%, which is close to the government's target of a 25% reduction by 2030 (Figure 2). This level of reduction is achieved with a payment of CHF 150 per tonne of CO_2-equivalent, assuming that farmers are profit maximisers (Scenario 1) and that the abatement potential of 3-NOP is high. At the current price level of around CHF 70 for carbon credits on the voluntary carbon market in Switzerland, the reduction potential is between 6% and 17%, depending on the effectiveness of the 3-NOP and the assumption that farmers maximise their profits.

The results of the four behavioural scenarios show that imitating successful peers (Scenario 2) can lead to significant GHG reductions. With high 3-NOP effectiveness, emissions can be reduced by up to 20% compared to a no-adoption baseline. In the reluctance to change scenario (Scenario 3), the reduction potential

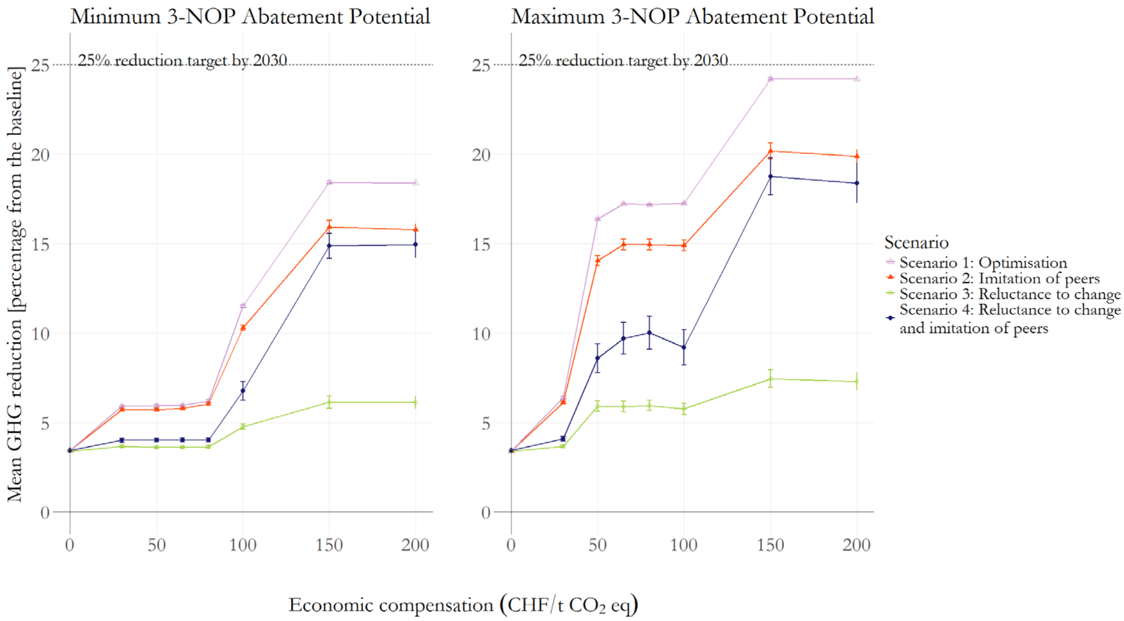

FIGURE 2 | Average GHG emission reduction by economic compensation per tonne of CO_2-equivalent in four behavioural and social scenarios with 3-NOP and replacement of imported concentrates with on-farm production of legumes. Each line represents one behavioural and social scenario, and the dashed line corresponds to the target reduction in Switzerland by 2030. The left graph corresponds to the case for which we consider 3-NOP to have a low mitigation potential (15%), and the right graph corresponds to the case for which we consider 3-NOP to have a high mitigation potential (30% for dairy and 22% beef cattle). The error bars correspond to a 95% confidence interval across all farms in the sample for 200 random price realisations.

drops by up to 17 percentage points compared to the profit maximisation scenario. In the combined scenario (Scenario 4), similar reduction levels as in the imitation scenario can be achieved, provided that the financial compensation is sufficiently high. In the following, we describe the results of the behavioural and imitation scenarios in more detail.

In Scenario 2 (imitation), we observe how the effect of imitating peers leads to emission reductions comparable to those in the optimisation scenario. The emission reductions range from 16% to 20%, reflecting an absolute decrease of 2 to 4 percentage points and a relative reduction of 11% to 17% compared to Scenario 1 (optimisation). Given that some farmers have only a few isolated links, not all farms in our sample can imitate successful adopters, thus remaining slightly below the optimisation scenario. Overall, the simulations show that peer imitation can significantly increase GHG mitigation potential. This is also confirmed by our sensitivity analysis (detailed in the ODD+D protocol in Appendix S1). The sensitivity analysis reveals that, among all the parameters considered in the simulation—including structural, behavioural and threshold values related to reference income and tolerance—social networks have the most significant impact on the total reduction of GHG emissions.

In Scenario 3 (reluctance to change), we observe how the behavioural factor of reluctance to change reduces the percentage of emissions abated. When farmers are reluctant to adopt new practices, the emissions reductions range from 6% to 7%, representing an absolute decrease of 12 to 17 percentage points and a relative decline of 67% to 71% compared to Scenario 1 (optimisation).

However, when reluctance to change is combined with peer imitation (Scenario 4), the reduction in emissions improves. We find a decrease in GHG emissions from 15% to 19%, which reflects an absolute change of −3 to −5 percentage points and a relative change of −17% to −21% compared to Scenario 1 (optimisation). This means that the reduction due to reluctance to change (Scenario 3) is offset by farmers imitating their peers (Scenario 4). As a result, when peer imitation is included, the reduction in emissions increases by an absolute range of 9 to 12 percentage points and relatively by 60% to 63% compared to the reduction observed when only reluctance to change is considered.

We also observe that the smaller differences between the minimum and maximum 3-NOP efficacy scenarios are due to the fact that the carbon credits are paid per tonne of CO_2-equivalent. This means that a higher abatement potential leads to higher compensation, making the use of the feed additive 3-NOP profitable for more farms. Consequently, the effects of reluctance to change and social networks become more pronounced at higher 3-NOP reduction potentials. Comparing the minimum and maximum abatement potentials in Figure 2, the results show that for low 3-NOP effectiveness, financial compensation must exceed CHF 100 to induce a significant increase in emission reductions. In contrast, at maximum 3-NOP effectiveness, compensation levels as low as CHF 50 are sufficient to induce additional GHG reductions.

Finally, some farms in our sample also replace concentrates with legumes produced on the farm without requiring a carbon credit, suggesting that these are win–win measures that can reduce GHG emissions and increase farmers' profits. This explains why GHG emissions are reduced across all scenarios, even without carbon credit compensation. However, the effect remains very small, with only a 3% reduction in GHG emissions. Once carbon credit compensations are introduced, legumes are consistently adopted together with 3-NOP. This reflects the higher abatement potential of 3-NOP, which leads to greater compensation for farmers. Detailed adoption rates under the compensation levels of 65 and 150 CHF/tCO2eq are provided in Tables 5B–8B of Appendix S2.

5 | Discussion

Farmers' participation in voluntary carbon markets can lead to substantial GHG emission reductions, complementing public policy efforts. However, our findings show that behavioural and social factors play a critical role in shaping the actual reduction potential of these schemes. While previous ex-ante assessments have examined factors influencing farmer participation (Blazy 2021; Buck and Palumbo-Compton 2022; Chen et al. 2023; Hermann et al. 2017; Kragt et al. 2014; Kreft, Finger, and Huber 2024; Kreft, Huber, et al. 2024), they have not examined how behavioural and social factors jointly affect overall emission reductions at varying levels of economic compensation, nor how these influence the maximum abatement potential achievable through voluntary measures. Thus, our results provide quantitative support for previous findings that emphasise the importance of building trust among farmers within a community to encourage participation in voluntary programmes, particularly for those aimed at reducing GHG emissions (Chen et al. 2023; Rong and Hou 2022). Our results show that technical assessments alone may send inappropriate signals, as policymakers may rely solely on the technical potential of voluntary schemes. This approach could lead to the omission of necessary complementary policies that take into account participation influenced by behavioural and social factors (Brown et al. 2021). Moreover, drawing on the stages of technology adoption identified by Weersink and Fulton (2020), our findings suggest that voluntary mitigation tools may gain traction over time. As peer-to-peer interactions among farmers increase, they can foster wider adoption, thereby enhancing the long-term effectiveness of these policy instruments in reducing GHG emissions.

Our results also highlight the importance of specific mitigation measures such as 3-NOP and legume substitution. While previous studies have demonstrated the effectiveness of 3-NOP in reducing GHG emissions (Alvarez-Hess et al. 2019; Zerbe et al. 2025), our results show lower reductions compared to life cycle assessments such as that of Uddin et al. (2022), which reported a 31% reduction on dairy farms. This discrepancy highlights the need to consider behavioural and social barriers when assessing the implementation of mitigation measures in voluntary schemes. Assuming profit maximisation as the underlying decision-making process when evaluating voluntary programmes is likely to overestimate the true reduction potential of these initiatives. Moreover, our results align with the findings of Luke and Tonsor (2024), who demonstrated that farm structures affect the adoption of 3-NOP.

Similarly, our findings confirm the potential of legume substitution as a mitigation measure. Several studies have evaluated the potential of this measure to reduce emissions and improve farm sustainability (Eugène et al. 2021; Reckling et al. 2016). For example, Morais et al. (2018) found that growing legumes on-farm reduces emissions more effectively than using concentrates, with a reduction of 25% per kilogram of live animal weight in beef production. Other research has further emphasised the broader benefits of this mitigation measure, including reducing environmental pressure from food systems and improving human health (Stagnari et al. 2017; van Loon et al. 2023). van Loon et al. (2023) also confirmed that this approach enhances food and feed self-sufficiency.

Nevertheless, these results have some limitations. First, we have selected two mitigation measures: using the feed additive 3-NOP and replacing concentrate feeds with on-farm-produced legumes. These measures have been proven to reduce GHG emissions while maintaining production levels and have documented abatement potential with corresponding uncertainties. Thus, they are well suited for voluntary schemes, such as voluntary carbon markets. However, challenges may arise, such as monitoring costs and the uncertainty surrounding the long-term effects of the feed additive 3-NOP (Gillenwater et al. 2007; Oldfield, Lavallee, et al. 2022; Wongpiyabovorn et al. 2022). In addition, these measures are not applicable to the entire agricultural sector, meaning that the overall contribution of these measures to the 2030 target is lower. Our simulation model also does not incorporate changes in the production structure, which may constrain the adaptability of the results.

While our simulation approach required certain assumptions with respect to 3-NOP (see Appendix S1 and S2, Section 4.4), their potential impact on the results is reflected in the lower bound of the uncertainty range for 3-NOP's mitigation potential. Furthermore, as our simulations are based on a production model only, they do not consider market feedback effects. Consequently, we cannot assess the potential land use changes or carbon leakage effects resulting from increased on-farm legume cultivation. However, we expect crop prices to remain stable due to the Swiss tariff system. Nonetheless, it remains crucial to promote these measures, even if they only apply to a portion of the sector, because the affected farms (dairy and beef) are likely to have higher emissions.

Second, the modelled results exhibit a substantial range of uncertainty. The main sources of this uncertainty are the efficacy of 3-NOP, the variability in GHG emissions reduction under varying economic compensations, and the output price uncertainty from milk and beef prices. We did not account for changes in crop prices due to the stable tariff system in Switzerland. Our sensitivity analysis (provided in Appendix S1) confirms that, in addition to social networks, the efficacy of 3-NOP and the economic compensations for GHG emissions reduction have the strongest impact on total GHG emissions reduction. However, other sources of uncertainty, such as the variability in grain and fertiliser prices, are not explicitly modelled for the reasons outlined above.

Third, we did not explicitly model a voluntary scheme such as a voluntary carbon market. (Gillenwater et al. 2007; Oldfield, Eagle, et al. 2022; Oldfield, Lavallee, et al. 2022). For instance, credible voluntary carbon markets rely on third-party verification and reporting processes, which incur transaction costs, though these may be lowered by leveraging social networks (Kreft, Huber, et al. 2024). This is where intermediaries, such as the Swiss cooperatives Mooh and Fenaco, can play a role in coordinating the verification and reporting processes.

Finally, the accuracy and validity of our simulations depend on the theoretical foundation outlined in FARMIND's conceptual framework (see, e.g., Troost et al. 2023). A key assumption in our model is that farmers who are dissatisfied and engaged in social processing may consider alternatives beyond the modelled activities and do not adopt climate change mitigation measures (opt-out strategy). This represents the idea that agents can reverse previous adoption decisions and are not locked into a measure even if they are dissatisfied with their income. We tested the robustness of this assumption by running a scenario in which dissatisfied agents following a social learning strategy could retain previously adopted measures (see Malawska and Topping 2016; Pacilly et al. 2019; van Duinen et al. 2016, for similar implementations). Allowing unsatisfied farmers to keep adopted measures increased the influence of social interactions in our simulations (see Figure 3A in Appendix S1). At equal compensation levels, engagement in social processing increased GHG mitigation by up to 6 percentage points. In this case, the results of Scenario 4—which includes both reluctance to change and imitation—approach those of Scenario 1, where farmers maximise their profits. Nevertheless, our main conclusion regarding the behavioural scenarios remains valid: adoption rates are lower when behavioural factors such as reluctance to change and imitation are taken into account. This finding holds even under different operationalisations of behavioural strategies in FARMIND, confirming the robustness of our results.

Still, the accuracy of our simulations is closely linked to the theoretical foundation established in the FARMIND conceptual framework. While our approach uniquely integrates survey data, social network analysis and farm structure information to account for a range of behavioural and social factors, the model is not directly transferable to other settings, farm types or geographical regions. In order to draw more generalisable conclusions, the modelling framework would need to be extended to include different regions, farm types and additional mitigation measures.

6 | Conclusion

In this paper, we explore the reductions of GHG emissions through farmers' adoption of two mitigation measures (the use of the feed additive 3-NOP and the reduction of upstream emissions by substituting imported concentrate feeds for on-farm-produced legumes) under different compensation levels. Using the bio-economic model FarmDyn with census data and the agent-based model FARMIND with survey data, we test the effect of behavioural and social factors on potential emissions reduction across four behavioural and social scenarios. Our results indicate that the adoption of these two measures under a voluntary scheme can significantly reduce GHG emissions in the agricultural sector. Assuming agents aim to maximise their incomes and considering Swiss current carbon credit prices of 70 CHF (with Fenaco prices ranging from 65 to 80 CHF per tonne of CO2-equivalent), emissions could potentially be reduced by 6%–17%, with these reductions corresponding to minimum and maximum 3-NOP efficiencies, respectively. We also find that the maximum potential reduction in emissions ranges between 18% and 24% relative to the baseline, in which no mitigation measures are adopted. However, this potential diminishes when behavioural factors are included in the simulation. Behavioural factors alone limit the maximum abatement potential to 6%–7%, which translates to an absolute reduction of 12 to 17 percentage points and a relative reduction of 67%–71% compared to the scenario where all farmers are income maximisers (i.e., optimisers). However, when peer imitation is promoted through social networks, the maximum abatement potential increases to 16%–20%, corresponding to an absolute change of −2 to −4 and a relative change of −11% to −17% in respect to the case in which farmers are optimisers.

The policy implications of our results are fourfold. First, the promotion of 3-NOP and replacement of concentrate feeds for home-grown legumes through a voluntary scheme like a voluntary carbon market can effectively contribute to achieving GHG emission reduction goals. Policymakers should consider how these schemes can complement other policies and ensure that they are accessible to farmers. Second, our results indicate that when considering behavioural and social factors, voluntary schemes alone will likely not meet GHG emission reduction targets. This means that policymakers cannot rely solely on voluntary measures but should also implement other strategies. These strategies could include other mitigation measures that may be less suitable for a voluntary programme, such as measures that might address the reduction of both the production and consumption of animal products. Third, our results show that social networks, which allow farmers to imitate successful mitigation measures, can significantly enhance the potential for GHG emission reductions. Therefore, it is crucial to design voluntary programmes by promoting and strengthening social networks, for example, through joint support groups, organisation of farm visits or events to support informal exchange to increase farmer participation in such schemes. These insights align with the findings of (Kreft, Huber, et al. 2024). Our analysis extends those by showing that payment levels also influence the effect of social networks. Their role becomes particularly significant at higher compensation levels, where the abatement potential is greater and imitation behaviour amplifies participation, helping to overcome reluctance to adopt new practices. Building on this, our results further show that the greatest GHG emission reductions are achieved at a compensation level of 150 CHF per tonne of CO_2-equivalent. Beyond this point, the emissions reductions stabilise, as there is a maximum contribution these two mitigation measures can make to the total reduction. This finding provides guidance for intermediaries or cooperatives designing a voluntary carbon market with these measures, indicating the optimal carbon credit price for maximising GHG emissions reduction. Overall, our study demonstrates how privately adopted voluntary measures can complement governmental efforts to reduce GHG emissions in agriculture.

Our analysis has implications for future research. To achieve more accurate results, transaction costs, such as those associated with monitoring, reporting and verification, should be included. Future studies could also generalise our findings to a broader sample of farms, consider different production types and explore additional mitigation measures suitable for arable production that do not necessarily maintain constant production levels. Furthermore, to better understand adoption patterns in voluntary schemes, future research could explore how these patterns, especially those shaped by peer imitation, develop over time and differ across regions. Including a reduction in the consumption of animal products to avoid carbon leakage could also be beneficial. Therefore, for a more holistic view, future research could employ a general global equilibrium model that includes both the demand and production sides while also capturing the potential carbon leakage effects from land-use changes resulting from substituting imported concentrate feeds with home-grown legumes. Given the current emergence of voluntary carbon markets in agriculture worldwide, future research should provide ex-post evidence on these initiatives, and such analysis can also be used to inform and improve ex-ante analysis (El Benni et al. 2023).

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that supports the findings of this study are available in the Supporting Information of this article, including the replication package. Moreover, once the article is published the replication package will be uploaded with a DOI at the research collection of ETH Zürich.

Endnotes

[1] It is important to note that this price refers exclusively to the Mooh and Fenaco voluntary carbon markets, which cover only a limited segment of the agricultural sector. These are two cooperatives that operate voluntary carbon schemes focused on feed additives for cattle. For further details, see Fenaco (2022) and *Mooh|Climate Program* (2022).

[2] Prospect value theory describes how individuals evaluate potential gains and losses asymmetrically, with losses typically weighing more heavily than equivalent gains (Kahneman and Tversky 1979).

[3] The cow longevity scheme aims to reduce GHG emissions by decreasing the need for replacement heifers and increasing milk yield per cow (Winter et al. 2024). Additionally, studies on the abatement costs of this measure in Switzerland indicate that it would also generate economic benefits (Huber et al. 2023; Kreft, Finger, and Huber 2024).

[4] A detailed description of the mitigation measures, including the abatement mechanisms, abatement potential, associated uncertainties and costs, and model implementation assumptions, is provided in Appendix S1.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Appendix S1. Appendix S2.**