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Farmers' cooperation to improve water quality under scientific uncertainty: A lab-in-the-field experiment

Simone Angioloni[1] | **Simone Cerroni**[2]

[1]Economics Research Branch, Agri-Food and Biosciences Institute, Belfast, UK

[2]Department of Economics and Management and C3A, University of Trento, Trento, Italy

Correspondence
Simone Angioloni, Economics Research Branch, Agri-Food and Biosciences Institute, 18a Newforge Lane, BT9 5PX Belfast, UK.
Email: simone.angioloni@afbini.gov.uk

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Abstract

Cooperation amongst natural resource users is key to manage ecosystems sustainably and achieve environmental goals proposed by policy and regulations. This paper focuses on the impact that livestock farming can have on the quality of a water body and investigates farmers' willingness to cooperate to preserve water quality under two different sources of uncertainty and four different degrees of uncertainty. The first source relates to the level of water quality that must be guaranteed in a river catchment to avoid irreversible deterioration of aquatic ecosystems (threshold uncertainty, i.e. with catastrophic consequences). The second source relates to the financial losses that farmers will experience in the long run if they fail to cooperate (impact uncertainty). To this end, a lab-in-the-field experiment was conducted with livestock farmers of Northern Ireland. A local public good game with threshold uncertainty was framed around an agri-environmental scheme designed to create ungrazed buffer zones for water quality preservation. Results indicate that uncertainty generally hampers farmers' cooperation and the provision of information geared to reduce uncertainty enhances it. Impact uncertainty has a milder negative impact on cooperation than threshold uncertainty. Risk preferences and probability weighting do not influence cooperation, while loss aversion has an influence on cooperation.

KEYWORDS

agri-environmental schemes, livestock farming, public good game, uncertainty, water quality

JEL CLASSIFICATION

C71, D81, Q18, Q25

1 | INTRODUCTION

Cooperation contributes to avoiding natural resource depletion. At the global scale, cooperation amongst governments is crucial to negotiate emissions reductions and achieve the greenhouse gases mitigation targets imposed by the Paris agreement (e.g. Bellelli et al., 2023). At the local scale, cooperation amongst natural resource users is pivotal to manage ecosystems sustainably and reach environmental goals as defined by transnational regulations and policy, for example the new Common Agricultural Policy 2023–2027 (CAP), Farm-to-fork strategy, and the EU's biodiversity strategy for 2030 (European Commission, 2023a).

Unfortunately, scientific uncertainty about changes required to meet minimum quantity and/or quality standards that given natural resources should satisfy hampers the identification of the users' collective effort that is needed to prevent irreversible environmental deterioration. This can hinder cooperation at the global and local scale (Milinski et al., 2008; Nguyen et al., 2022, respectively). Similarly, scientific uncertainty regarding long-term economic losses that natural resource users will experience, if the minimum quantity and/or quality requirements are not guaranteed, can prevent cooperation amongst users themselves (Barrett, 2013; Dannenberg et al., 2015). Despite this, the precautionary principle teaches us that the presence of different sources and degrees of uncertainty should not prevent any cost-effective adaptation and mitigation action (see Principle 15 of Rio Declaration on Environment and Development, United Nations, 1992).

Amongst different anthropomorphic interferences with an ecosystem, the impact of livestock activities on water bodies is capturing the attention of policymakers and the general public (Nicholson et al., 2020; USDA, 2022). The primary cause of water quality deterioration is the run-off of phosphorus and nitrogen from animal manure. An increase in the concentration of these nutrients can modify the chemical and biological characteristics of the water, and ultimately lead to eutrophication (e.g. Evans et al., 2019; Hooda et al., 2000). Several management strategies have been developed to reduce the impact of livestock farming on water quality. The most promising are riparian buffer zones where no farming activity is allowed and fencing that physically prevents cattle approaching and entering water bodies (e.g. Lowrance et al., 2002; Muirhead, 2019). These measures can be particularly suitable to mitigate the impact of livestock activities on the water quality of a lentic ecosystem, i.e. a closed aquatic ecosystem like a lake and a pond, where the limited replacement of fresh water from ground and underground sources makes them the most exposed to the run-off from animal manure (e.g. Bhateria & Jain, 2016). However, the quantification of the negative impact produced by livestock farming on water bodies is still uncertain (Graveline et al., 2012; Nicholson et al., 2020). This challenges the identification of the minimum effort required collectively to avoid an irreversible environmental damage (threshold uncertainty, i.e. with catastrophic consequences) and hence the forecasting of the long-term economic losses that farmers will incur if the damage is not prevented (impact uncertainty).

This paper studies the impact of two sources of uncertainty, and their relative degree of uncertainty on livestock farmers' cooperation to avoid the consequences of irreversible water quality deterioration in a closed aquatic ecosystem that can be considered as a local public good. The two sources of uncertainty under study are threshold and impact uncertainty. Each source is characterised by four degrees of uncertainty: full, high, low, and no uncertainty. In addition, the paper explores the influence of behavioural factors such as risk preferences, probability weighting, and loss aversion on cooperation. Previous research has demonstrated that behavioural factors can explain farmers' cooperation in public good games (Barrett & Dannenberg, 2012; McCarter et al., 2008; Schuch et al., 2021).

To this end, a lab-in-the-field experiment was conducted with 140 grazing livestock farmers in Northern Ireland (NI). The study focuses on NI, a country where the grazing livestock farming sector is the largest contributor (57%) to the total agricultural gross output (DAERA, 2021) and where this type of farm is the primary source of contamination of water bodies (NIEA and DAERA, 2019). The experiment is based on a public good game with threshold uncertainty that is framed as a farmer's decision to participate in an agri-environmental scheme (AES) promoting the use of ungrazed buffer zones. AESs are public programmes where farmers are paid to manage their land to mitigate the environmental impact of agricultural production (e.g. Krämer & Wätzold, 2018). Specifically, our design builds on an existing AES for livestock farmers that promotes the creation of ungrazed riparian buffer zones to improve water quality in NI. The scheme, called Environmental Farming Scheme Wider Option (EFS – WO), promotes the creation of buffer zones of two different sizes (2 m wide or 10 m wide) via payments to farmers that are proportional to the ungrazed area enrolled. This scheme is similar to other schemes already implemented across EU and non-EU countries (e.g. Dalgaard et al., 2014; McKergow et al., 2016). In terms of farmers' participation, 4% of all the EFS agreements in NI were signed under EFS – WO to date (DAERA, 2022a). Unfortunately, the amount of land committed is still limited, being just 0.17 km^2, to date. This datum is concerning considering that closed water basins such as lakes and ponds are abundant in NI (with an extension of approximately 562 km^2), and they register the worst status of water quality amongst all the water bodies of the region (NIEA and DAERA, 2019). Amongst them, Lough Neagh is the largest lake in the British Isles; it accounts for the 70% of all the closed water basins in NI, and it provides 40% of its water supply (NIEA and DAERA, 2019). Recently, the quality status of its waters has drastically deteriorated due to algal blooms produced, amongst other factors, by the dispersion of animal manure (e.g. Aljazeera, 2023; BBC, 2023; News Sky, 2023). An irreversible deterioration of water quality will lead to irreversible negative consequences for the entire water system and thus the livestock sector of the region.

In our study, we slightly modify the design of this EFS – WO to include a bonus that provides an extra reward to farmers if they manage to cooperate and hence succeed in avoiding catastrophic consequences. The presence of this bonus could enhance cooperation and improve the low enrolments rates that are currently observed, hence providing policy recommendations for the future design of the scheme beyond NI (e.g. Dalgaard et al., 2014; McKergow et al., 2016). The design of our experiment builds on Barrett and Dannenberg's (2012) study on climate negotiations under scientific uncertainty. While Barrett and Dannenberg (2012) focus on a global issue, the present study explores cooperation at the local scale, hence implementing a local public good game.

In the resource depletion literature, cooperation has been extensively investigated with respect to production decisions in agriculture (e.g. Fesselmeyer & Santugini, 2013; Krämer & Wätzold, 2018; Nguyen et al., 2022). However, this literature has only recently started investigating cooperation in the presence of a catastrophic threshold (de Zeeuw, 2014; Long, 2021). A catastrophic threshold indicates a tipping point after which the use of common resources is excessive and generates an irrecoverable environmental damage (e.g. Tsur & Zemel, 2021). While theoretical models were developed and simulation studies were conducted to investigate the impact of scientific uncertainty about the catastrophic threshold on cooperation amongst users of common pool resources (e.g. Miller & Nkuiya, 2016), the empirical literature has mainly focused on cooperation under strategic uncertainty, i.e. uncertainty about other users' decisions to cooperate (e.g. Rommel, Schulze, et al. (2022); Schuch et al., 2021), therefore ignoring the joint effect of different sources and degrees of uncertainty on users' willingness to cooperate.

This paper empirically investigates farmers' willingness and ability to cooperate to improve the water quality of a closed aquatic ecosystem under scientific uncertainty. Specifically, this paper fills this gap in the literature by investigating: (i) to what extent farmers' cooperation is influenced by different degrees of catastrophic threshold and impact uncertainty, and (ii) to what extent behavioural factors such as risk preferences, probability weighting, and loss aversion influence cooperation. As our experiments replicate the same design and game-theoretical conditions used by Barrett and Dannenberg (2012), we expect that cooperation decreases as impact and threshold uncertainty increase; more specifically, we expect to find the lowest level of cooperation under high uncertainty and the highest level under full certainty. In addition, we also expect threshold uncertainty to undermine cooperation more than impact uncertainty as suggested by Barrett and Dannenberg (2012). The influence of behavioural factors such as risk preferences, probability weighting, and loss aversion on cooperation in threshold public good games is not well understood in the related literature and hence the nature of the study was mainly explorative in our study.

Results contribute to the ongoing debate about the role that scientific uncertainty plays on farmers' cooperation to fight global challenges related to climate change (e.g. Schill & Rocha, 2023; Schuch et al., 2021). This is a timely issue given the renewed attention into agricultural nutrient management such as the European Green Deal, the Farm-to-Fork Strategy (European Commission, 2023a), and the new Sustainable Farming Incentive (DEFRA, 2023). Specifically, results can provide policymakers with useful information regarding the influence that scientific uncertainty can have on farmers' participation into water protection AESs and suggestions regarding potential strategies to boost farmers' participation in such schemes (European Commission, 2023a; Kuhfuss et al., 2019). The remainder of the paper is organised as follows: Section 2 provides the literature review, Section 3 presents the case study, Section 4 describes the experimental approach, Section 5 discusses the results, and the conclusions and policy implications are presented in the last section.

2 | OVERVIEW OF THE EXISTING LITERATURE

2.1 | Farmers' cooperation under threshold and impact uncertainty

Cooperation can play an important role in preventing the over-use of shared natural resources as in the tragedy of commons (Ostrom, 1990). Farmers' cooperation has been shown to be beneficial in many contexts: greenhouse gasses reduction (e.g. Calzolari et al., 2018), irrigation decisions (e.g. Fujiie et al., 2005), habitat and species conservations (e.g. Bareille et al., 2023; Kuhfuss et al., 2022), creation of ecological corridors (e.g. Parkhurst & Shogren, 2007), fishery (e.g. Miller & Nkuiya, 2016), and land use management (e.g. Banerjee et al., 2021; Krämer & Wätzold, 2018). Unfortunately, in many instances, farmers' willingness to cooperate can be hindered by uncertainty about the collective effort required by users to avoid reaching catastrophic thresholds and about long-term economic losses due to irreversible natural resource depletion (e.g. Nguyen et al., 2022; Schill & Rocha, 2023).

A few studies developed theoretical models to describe farmers' behaviour under scientific uncertainty. For example, Fesselmeyer and Santugini (2013) developed a model describing the behaviour of fishery's users under uncertainty on the quantity (fishery growth) and quality of the catch. The model assumes that uncertainty about quantity reductions induces agents to lower extractions of the natural resource, while uncertainty about quality deterioration has the opposite effect. Other studies tested the ability of these theoretical models to explain farmers' behaviour under scientific uncertainty using simulation procedures. Miller and Nkuiya (2016) investigated the impact of catch regime shifts on fishermen's interactions and concluded that exogenous shocks (i.e. scientific uncertainty) can have mixed results on cooperation.

The empirical research investigating farmers' cooperation in the management of common pool resources has recently experienced rapid growth. However, this literature largely ignores the impact that scientific uncertainty can have on farmers' cooperation to avoid irreversible environmental damage. The catastrophic threshold and the impact generated by failure to achieve the threshold are fixed (i.e. certain) in the vast majority of the studies. Hence, the only source of uncertainty considered is strategic uncertainty, which refers to farmers' inability to know a priori other farmers' contributions. For example, Schuch et al. (2021) compared Cambodian farmers' cooperation in a public good game, where the socially optimal strategy is known in advance, and in a threshold game, where the threshold is fixed but social optimum depends on the participants' contributions. Similarly, Rommel, Schulze, et al. (2022) developed a public good game to investigate German farmers' willingness to cooperate where the source of uncertainty is due only to participants' interaction.

Other studies have investigated the impact of strategic uncertainty on farmers' cooperation in public good games contextualising the experimental tasks to resemble decision problems that farmers face in their everyday activities. Bouma et al. (2020) used a contextualised threshold public good game to study how different collective bonus rules and different threshold settings can affect participants' cooperation under strategic uncertainty. The experimental tasks mimicked the decision to join a collective agri-environmental contract. Similarly, Limbach et al. (2023) used a contextualised threshold public good game with strategic uncertainty to investigate the effect on cooperation of an unconditional subsidy (action-based payment) and a conditional subsidy (outcome-based payment). The experimental tasks resembled farmers' decisions to participate in an AES to improve water quality. Other studies have attempted to add realism to coordination games adding spatial and temporal context to the experimental tasks. For example, Janssen et al. (2010) used a dynamic public good game to test whether communication amongst participants and/or financial punishment could enhance coordination. Banerjee et al. (2014, 2021) introduced a spatial component by developing an agglomeration bonus to facilitate farmers' spatial coordination. The strengths and limitations of contextualization are much debated in experimental economics. On the one hand, contextualization could increase the external validity of experimental findings and improve participants' understanding of experimental instructions and tasks. On the other hand, it could increase the likelihood of confounding factors coming into play and hence undermine the internal validity of experimental results (Alekseev et al., 2017). More focused discussions on the pros and cons of using contextualization in experimental research involving farmers are provided by Appel and Balmann (2019), Rommel et al. (2019), and Cerroni (2020).

The only study (that we are aware of) introducing threshold uncertainty in a public good game with farmers is Schill and Rocha (2023). Specifically, this study tests the effect of different degrees of threshold uncertainty (risk, ambiguity, certainty) on cooperation with a lab-in-the-field experiment involving Colombian fishermen. Results indicated that threshold uncertainty does not increase the over-use of common pool resources, while catch inequalities and community-level factors are the main drivers of such exploitation. Our paper contributes to this research by investigating jointly the effect of different sources (threshold and impact) and degrees of uncertainty (full, high, low, and no uncertainty) on farmers' cooperation using a contextualised experiment. Table 1 summarises this literature review.

2.2 | Economic agents' cooperation under threshold and impact uncertainty

Our study is strictly related to the substantial body of research investigating economic agents' cooperation in climate change public good games.[1] Specifically, it builds on the lab experiment conducted by Barrett and Dannenberg (2012) to assess countries' willingness to cooperate in climate negotiations under two sources of uncertainty: threshold and impact uncertainty (i.e. students acted as countries in the lab). The former referred to the total emission

[1]We acknowledge the existence of a stream of experimental literature looking at economic agents' cooperation under threshold uncertainty, different initial endowment of resources, and agents' communication not specifically related to climate change issues (e.g. Budescu et al., 1995; Hackett et al., 1994; Ostrom et al., 1992)

TABLE 1 Experimental studies on public good games with/without threshold and impact uncertainty.

Study	Sample	Group threshold	Economic impact	Behavioural factors	Findings
Studies involving farmers or having an agricultural contextualisation					
Janssen et al. (2010)	165 US undergraduate students	Non-random	Non-random	None	Communication is an effective way to reduce resource harvesting and increase overall welfare; costly punishment alone is not sufficient to avoid resource depletion
Banerjee et al. (2014)	144 US students	Non-random	Non-random – proportional to the number of direct neighbours	None	Under strategic uncertainty about other players' choices, the risk-dominant strategy is selected in the long run
Bouma et al. (2020)	204 Dutch farm management students	Non-random although exogenous and endogenous	Non-random via group bonus: fixed (identical payoffs) and variable (different payoffs)	None	Exogenous thresholds work better than endogenous thresholds to promote cooperation with mixed results for group bonus
Schuch et al. (2021)	282 Cambodian farmers	Non-random	Non-random	Risk aversion elicited via one shot lottery	Risk and social capital affect cooperation in the linear public good game, not in the threshold game
Rommel, Schulze, et al. (2022)	358 German farmers	Non-random	Non-random	None	Amongst the studied treatments, nudging the social optimum is the most effective to promote cooperation
Limbach et al. (2023)	140 French students and 24 French farmers	Non-random	Non-random: constant (unconditional) and variable (conditional) subsidy	Risk aversion elicited via Holt and Laury (2022)	No difference between conditional and unconditional subsidy; farmers cooperated more than students; risk aversion does not affect cooperation
Schill and Rocha (2023)	256 Colombian fishermen	Non-random, random with fixed probability, and random in an interval with unknown probability	Non-random	None	Threshold uncertainty does not increase the over-use of common pool resources, while catch inequalities and community-level factors are the main drivers of such exploitation
Studies involving students or without an agricultural contextualisation					
Milinski et al. (2008)	180 German students	Non-random	Random with fixed probability for each treatment of losing all if the fixed group threshold is not achieved: 90% probability; 50% probability; 10% probability	None	Cooperation fails when the probability of an economic impact is low, but it prevails when it is high
Tavoni et al. (2011)	240 German students	Non-random	Random with a fixed probability of loss (50%)	None	Unequal initial endowment reduces participants' cooperation, and communication increases it

TABLE 1 (Continued)

Study	Sample	Group threshold	Economic impact	Behavioural factors	Findings
Barrett and Dannenberg (2012)	400 German students	Non-random and random (uniform distribution)	Non-random and random (uniform distribution)	Risk aversion elicited via one-shot lottery	Threshold uncertainty reduces cooperation; impact uncertainty alone does not; no effect of behavioural parameter
Dannenberg et al. (2015)	180 German students	Non-random, random based on the uniform distribution (risk), and random in an interval with unknown probability distribution (ambiguity)	Non-random	Relevance of risk, safety, strategic uncertainty, and fairness in players' cooperation self-assessed at the end via multiple-option questions.	Cooperation fails under threshold uncertainty and ambiguity, and the lowest level of cooperation is attained under threshold ambiguity. Fairness more important under risk and ambiguity
Maas et al. (2017)	92 US students	Non-random and random (uniform distribution) with low and high uncertainty	Non-random	Risk aversion elicited via Likert scale	Threshold uncertainty reduces cooperation and increases the likelihood of resource depletion. No effect of risk aversion on cooperation
Ahsanuzzaman et al. (2022)	318 US students	Non-random, random-based three outcomes with the same probability (1/3; risk), and random-based three outcomes with unknown probabilities (ambiguity)	Non-random	Risk and ambiguity preferences elicited via Akay et al. (2012) lotteries	Threshold risk and ambiguity reduce cooperation, and communication improves it. Risk and ambiguity preferences do not affect cooperation
Hurlstone et al. (2022)	240 Australian students	Non-random and random (uniform distribution)	Non-random and random (uniform distribution)	Risk aversion, loss aversion, fairness, trust, altruism, and temporal discounting elicited via Likert scale	Early signals of approaching the threshold can improve cooperation, only altruism affects cooperation amongst the tested behavioural factors

reductions needed to avoid catastrophic consequences due to climate change, while the latter was related to the economic costs associated with such catastrophic consequences. In the experiment, emissions could be reduced by investing in green technologies. The experimental design consisted of four treatments: (i) full certainty, where both threshold and impact uncertainty are certain; (ii) threshold uncertainty only, where threshold is uncertain and impact is not; (iii) impact uncertainty only, where impact is uncertain, but threshold is not; and (iv) threshold and impact uncertainty combined. Results suggested that, while threshold uncertainty prevents cooperation, impact uncertainty has a limited effect on the participants' willingness to cooperate. The peculiarity of this study is that it accounts for both threshold and impact uncertainty in a public good game, while most of the related literature focuses exclusively only on one source of uncertainty at the time. For example, Maas et al. (2017) tested if threshold uncertainty affects students' cooperation with a lab experiment and confirmed that uncertainty around the tipping point reduces the level of cooperation and increases the chances of resource destruction. Similarly, Hurlstone et al. (2022) indicated that early signals of approaching climate thresholds are beneficial to increase cooperation amongst students. Dannenberg et al. (2015) explored whether cooperation was affected by the degree of threshold uncertainty. Specifically, the authors designed a lab experiment where students were exposed to three different treatments: (i) fixed threshold (certainty); (ii) random threshold distributed according to the uniform distribution (threshold uncertainty); and (iii) random threshold with unknown probability distribution (threshold ambiguity). Overall, results suggest that cooperation fails under threshold uncertainty and ambiguity, and the lowest level of cooperation is attained under threshold ambiguity. A recent study by Ahsanuzzaman et al. (2022) conducted a similar exercise and found similar results.

In contrast, in a lab experiment with students, Milinski et al. (2008) analysed how different levels of economic losses (impact uncertainty) affect their willingness to cooperate to avoid a fixed threshold. The results indicated that although cooperation fails for low levels of economic loss, it prevails when it is sufficiently high. Similarly, Tavoni et al. (2011) studied the effect of unequal endowment of resources and participants' communication on their willingness to cooperate to fight climate change. In a lab experiment, students were given an initial budget to contribute to the game by knowing that, if a fixed threshold was not achieved by all the contributors, there was a 50% chance that they would lose all their money (impact uncertainty). The results indicated that while the unequal initial endowment reduces participants' cooperation, communication increases it. Table 1 summarises the literature review on cooperative public good game under uncertainty. With respect to these studies, our research contributes to the literature by combining these two streams of research, thus exploring the impact of different sources and degrees of uncertainty on cooperation. In addition, our paper makes use of a non-student sample.

3 | CASE STUDY

We focus on grazing livestock production in Northern Ireland given the importance of this sector in the region (DAERA, 2021) and the fact that farms are still the primary source of contamination of water bodies (NIEA and DAERA, 2019). Higgins et al. (2021) analysed the contribution to phosphorous by each livestock ruminant grassland sector in NI and found that the phosphorous over-supply was more acute in dairy grassland than in other ruminant non-dairy grassland sectors due to its more intensive farming.[2] Amongst different water bodies, lakes have the worst status of water quality in the region, followed by rivers, marine waters, and ground waters (NIEA and DAERA, 2019). In 2018, 48% of lakes reported a poor or bad status of their waters against 15% of rivers, 5% of marine waters, and 0% of ground waters (NIEA and DAERA, 2019).

NI authorities are aware of the damages caused by the livestock ruminant grassland sector to the water bodies, and they have adopted a series of policy measures to mitigate this threat (NIEA and DAERA, 2019). Amongst them, the EFS – WO allows the creation, along lakes, rivers, and other water bodies, of ungrazed buffer zones of different width, by way of a stock-proof fence to prevent livestock grazing and depositing excrement near water (DAERA, 2022a).[3] The scheme aims at stimulating the creation of ungrazed buffer zones by

[2]The 50% of the dairy grassland was over-supplied with phosphorus ($p > 25$ mg Olsen-P 1 soil-1) against 25% of the beef and sheep grassland (Higgins et al., 2021).

[3]In livestock production, riparian zones provide numerous benefits to adjacent water bodies not only through the reduction of pollution, but also by stabilising streambanks, filtering of runoff, reducing of peak floods, and enhancing biodiversity (e.g. Lowrance et al., 2002). The installation of fencing to exclude cattle is also one of the most effective ways to protect riparian buffer zones (e.g. Muirhead, 2019).

paying farmers proportionally to the enrolled land. The scheme aims at improving the quality of the aquatic ecosystems alongside other policy measures defined at the same scale, for example the Lough Neagh and the River Basin Management Plans (DAERA, 2019). Unfortunately, the adoption of the scheme has been limited in terms of subscribers and enrolled land (DAERA, 2022a). For example, 4% of all the EFS agreements in NI were signed under EFS – WO, and the amount of land committed was only 0.17 km^2 to date (DAERA, 2022a).

Amongst other reasons, impact and threshold uncertainty can contribute to farmer's low uptake of the scheme. In general, the uncertainty to anticipate a change in the status of a water body is due to natural variability and knowledge-based inconsistency (Evans et al., 2019). The Water Framework Directive (WFD) is an interesting case (Nicholson et al., 2020). The WFD aims to implement new hydrological plans to improve the ecological status of water bodies and sets the guidelines that member states must follow to assess any change in its quality. Specifically, the WFD manages the uncertainty linked to the evaluation of water quality by providing results in the form of likelihoods of various outcomes (Nicholson et al., 2020). For example, the methodology adopted by DAERA under the WFD considers uncertain any change in the status of water quality below 75% confidence (NIEA and DAERA, 2019). Therefore, while the detrimental impact of livestock activities on water quality is certain, its quantification is subject to debate (Nicholson et al., 2020). In terms of farmers' cooperation, this means that there is uncertainty to fix the threshold of their collective effort to avoid the deterioration of a water body and, therefore, to assess the economic losses if that threshold is not reached. In all these cases, farmers have a collective incentive to reach the threshold (for example, to avoid possible regulatory penalties and business costs), but they also face individual incentives of free riding.

4 | MATERIALS AND METHODS

4.1 | Sample and data collection

The sample consists of 140 participants recruited from a pool of 3006 farmers that in 2017–2018 took part in the EU Exceptional Adjustment Aid (EAA) – Soil Sampling and Analysis Scheme in NI. The purpose of the scheme was to provide free testing and analysis of the soil conditions to farmers.

Recruitment and data collection were conducted by a survey company specialised in farmers' research (Social Market Research – UK and Ireland Market Research Agency). A stratified random sampling strategy was used to recruit a representative sample of the population with respect to farm size and type (i.e. dairy and non-dairy grazing livestock). Farmers who consented to participate to the study were sent a web link as the experiment was conducted online without the presence of a facilitator.[4] In total, 14 sessions with 10 farmers each were conducted between July and August 2021. The experiment was piloted with 29 farmers in June 2021.

Table 2 reports some farmer and farm characteristics. Table 2 indicates that the average age was 48 years and 11% of farmers were female. Regarding the characteristics of the farm, 34% were dairy and 48% were located in non-disadvantaged areas (lowland). The term lowland

[4]Each farmer went through the experiment independently. As reported in Appendix S1, each farmer was told that the final payoff depended on decisions made by the other nine farmers who participated in previous sessions of the study. The allocation of farmers was randomly executed. The payoff of the first farmers who participated in the study depended also on decisions made by farmers who participated in the pilot session. This procedure (i.e. cold matching) is often used in interactive games conducted in online environments.

TABLE 2 Summary statistics on farmer and farm characteristics.

Treatment group	Variable name	Mean	Standard deviation	Minimum	Maximum
Threshold uncertainty	Age (years)	49.16	11.64	22	73
	Female (1 = female)	0.10	0.31	0	1
	Environmental attitude	0.60	0.49	0	1
	Dairy farm (1 = yes)	0.24	0.43	0	1
	Lowland farm (1 = yes)	0.50	0.50	0	1
	Farm size (acres)	138.74	132.21	11	700
	AES (1 = yes)	0.33	0.47	0	1
	Farm successor (1 = yes)	0.71	0.46	0	1
Impact uncertainty	Age (years)	47.17	12.05	25	76
	Female (1 = female)	0.12	0.33	0	1
	Environmental attitude	0.66	0.48	0	1
	Dairy farm (1 = yes)	0.43	0.50	0	1
	Lowland farm (1 = yes)	0.47	0.50	0	1
	Farm size (acres)	162.71	131.33	15	800
	AES (1 = yes)	0.24	0.43	0	1
	Farm successor (1 = yes)	0.66	0.48	0	1
	Variable name	**Sample mean**		**Population mean**[a]	
Overall	Age (years)	48.16		53.20	
	Female (1 = female)	0.11		0.10	
	Dairy farm (1 = yes)	0.34		0.32	
	Lowland farm (1 = yes)	0.48		0.43	
	Farm size (acres)	150.72		131.75	
	AES (1 = yes)	0.28		0.32	
	Farm successor (1 = yes)	0.68		0.65	
	Variable name	**Variable definition**			
	Age (years)	Farmer's age in years			
	Female (1 = female)	Farmer's gender, 1 female, 0 male			
	Environmental attitude (1 = yes)[b]	1 if environmental attitude, 0 otherwise			
	Dairy farm (1 = yes)	Farm type, 1 if main activity is dairy, 0 otherwise			
	Lowland farm (1 = yes)	Land type, 1 lowland/non-disadvantaged area, 0 otherwise			
	Farm size (ha)	Farmland in hectares			
	AES (1 = yes)	1 if farmer is taking part to AES, 0 otherwise			
	Farm successor (1 = yes)	1 farmer has a farm successor, 0 otherwise			

[a]Source: DAERA (2016, 2018a, 2018b).

[b]Environmental attitudes towards water conservation practices were elicited using a Likert scale with multiple items, where 1 means completely disagree and 5 completely agree with water quality improvements. The binary variable equal to 1 if the average response was larger than 4.

is used to describe those parts of the country which, because of their improved agricultural conditions, have not been designed as Areas of Natural Constraints under EU legislation (DAERA, 2021). The sample is representative of Northern Irish grazing livestock sector as shown in Table 2. Overall, the sample shows consistent similarities across treatment groups as explained in the next section.

TABLE 3 Summary of the experimental treatments.

Rounds	Treatment group: Threshold uncertainty	Treatment group: Impact uncertainty
1 Full uncertainty	High threshold uncertainty High impact uncertainty	High threshold uncertainty High impact uncertainty
2 High uncertainty	High threshold uncertainty No impact uncertainty	No threshold uncertainty High impact uncertainty
3 Low uncertainty	Low threshold uncertainty No impact uncertainty	No threshold uncertainty Low impact uncertainty
4 No uncertainty	No threshold uncertainty No impact uncertainty	No threshold uncertainty No impact uncertainty

4.2 | Experimental design

The lab-in-the-field experiment consists of three sections. In section 1, farmers participated in a multi-player farm business game where they were asked to report the number of land parcels enrolled in the AES. The purpose of the AES is to create ungrazed buffer zones to avoid the deterioration of water quality in an adjacent lake. Agricultural activity cannot be carried out on the enrolled land. Farmers were informed that if an insufficient amount of land parcels are submitted by all participants, there will be an irrecoverable deterioration of water quality with a consequent economic loss for their farms due to additional regulatory burdens. Farmers received monetary compensation depending on the amount of land that they submitted to the scheme. To facilitate participation, farmers received additional financial compensation that was calculated based on the amount of submitted land by all farmers enrolling in the AES. Hence, each farmer's payoff depends on her/his and other farmers' decisions.

Table 3 summarises the experimental design of the farm business game. Farmers were randomly allocated to two between-subject treatment groups called ‘threshold uncertainty’ (70 farmers) and ‘impact uncertainty’ (70 farmers). In the former group, farmers were exposed to scientific uncertainty about the minimum total number of land parcels that must be enrolled to avoid catastrophic consequences. In the latter group, farmers were exposed to scientific uncertainty regarding the consequent economic losses. In each treatment group, farmers were asked to enrol land parcels in four different rounds which present decreasing levels of threshold and impact uncertainty, respectively (within-subject treatments). Round 1 (full uncertainty) is equivalent in the two treatment groups, as farmers faced a high level of both threshold and impact uncertainty. Similarly, in round 4 (no uncertainty), all farmers faced no threshold and impact uncertainty, regardless of the treatment they were assigned to. In contrast, farmers assigned to the ‘threshold uncertainty’ treatment group faced no impact uncertainty, but a high and low threshold uncertainty in round 2 and round 3, respectively. Farmers assigned to ‘impact uncertainty’ treatment group experienced a symmetric situation. More details about how different degrees of uncertainty were defined will be provided in the sections below.[5]

In Section 2, farmers' risk preferences, probability weighting, and loss aversion were elicited using the approach proposed by Tanaka et al. (2010). In Section 3, farmers filled in a short questionnaire about their socio-demographic characteristics including their attitudes towards water conservation in grazing livestock farming. Before starting the experiment, farmers had the possibility to see several examples and take practice rounds to familiarise themselves with

[5]We acknowledge that our design can lead to order effects and hence it could trigger learning and/or fatigue. However, our design represents the only possible approach to investigate the impact of increasing (decreasing) levels of uncertainty on cooperation within farmers. Using a between-subject design was not an option given the hard-to-reach subject pool.

how their choices will affect their final payoff. A control question was added to improve the quality of data as shown.[6]

4.3 | Experimental business game

The description of the representative farm was based on data describing NI agriculture in 2020 (DAERA, 2021). In the experiment, farms were separated from the lake edge by an existing fence. Each farmer was asked to decide how much land to submit under a new EFS – WO by moving the fence back from the lake edge to create an ungrazed buffer zone. Farmers will receive a subsidy according to the amount of land they decide to enrol in the AES.

In the experiment, farmers are asked to enrol land in parcels of 100 m in length from their eligible farmland. They can enrol a maximum of 20 parcels as each farm has a 2 km boundary along the lake's edge. Farmers had the possibility to submit parcels under 2 options according to their width:

- Option A = 2 m wide parcel = 200 square metres per parcel of land;
- Option B = 8 m wide parcel = 800 square metres per parcel of land.

Figure 1 shows examples presented during the experiment to explain farmers how to submit parcels.

The payment level was set according to the subsidy paid by DAERA for the EFS – WO that corresponds to £355/ha (DAERA, 2022a). As the gross margin per hectare of grazing livestock farms in NI exceeded the payment/ha, farmers would incur a certain economic loss proportional to the amount of submitted land as forgone income. This was communicated to farmers with a series of numerical examples of different levels of commitment under option A, option B, and both.

To introduce the threat of a catastrophic water quality deterioration, farmers were informed that, if a collective effort was not made to take part in the AES, there was the possibility that the lake would be subject to irrecoverable environmental damage in the future. If so, voluntary measures such as those in the AES could be replaced with compulsory regulations, which will require a farmer to pay for a series of interventions mandated by the government.[7] However, due to scientific uncertainty, it was not possible to know in advance the exact number of land parcels needed to avoid the catastrophe (threshold uncertainty) and the consequent economic loss (impact uncertainty). In the experiment, a series of examples were provided to motivate each source of uncertainty (see Appendix S1).

4.4 | Game-theoretical model and parameters' calibration

The game-theoretical model assumes that there are N symmetric risk-neutral farmers, each one able to submit land by up to q^{A}_{max} under option A and by up to q^{B}_{max} under option B. The

[6]The control question is reported in Appendix S2.1. where it is also reported that 24 (17%) farmers failed to provide the correct response. These farmers were excluded from the analyses.

[7]Livestock farmers are used to mandatory intervention in NI. The most common case is the increased severity of regulations imposed via the Nitrates Action Programme (NAP), which is a legal regulation in NI. NAP was introduced in NI in 2007 and, over the years, farmers have witnessed an aggravation of compulsory regulations in response to water quality deteriorations in the region. For example, the closed period for the application of slurry was extended over the years, and this required farmers to increase slurry storage capacity and/or reduce stock numbers (DAERA, 2022b). Similarly, the imposition of margins around water bodies where a farmer is not permitted to spread slurry or chemical fertilisers has widened under NAP. Both these measures are aimed at reducing nutrient run-off into waterways and therefore improve the overall water quality.

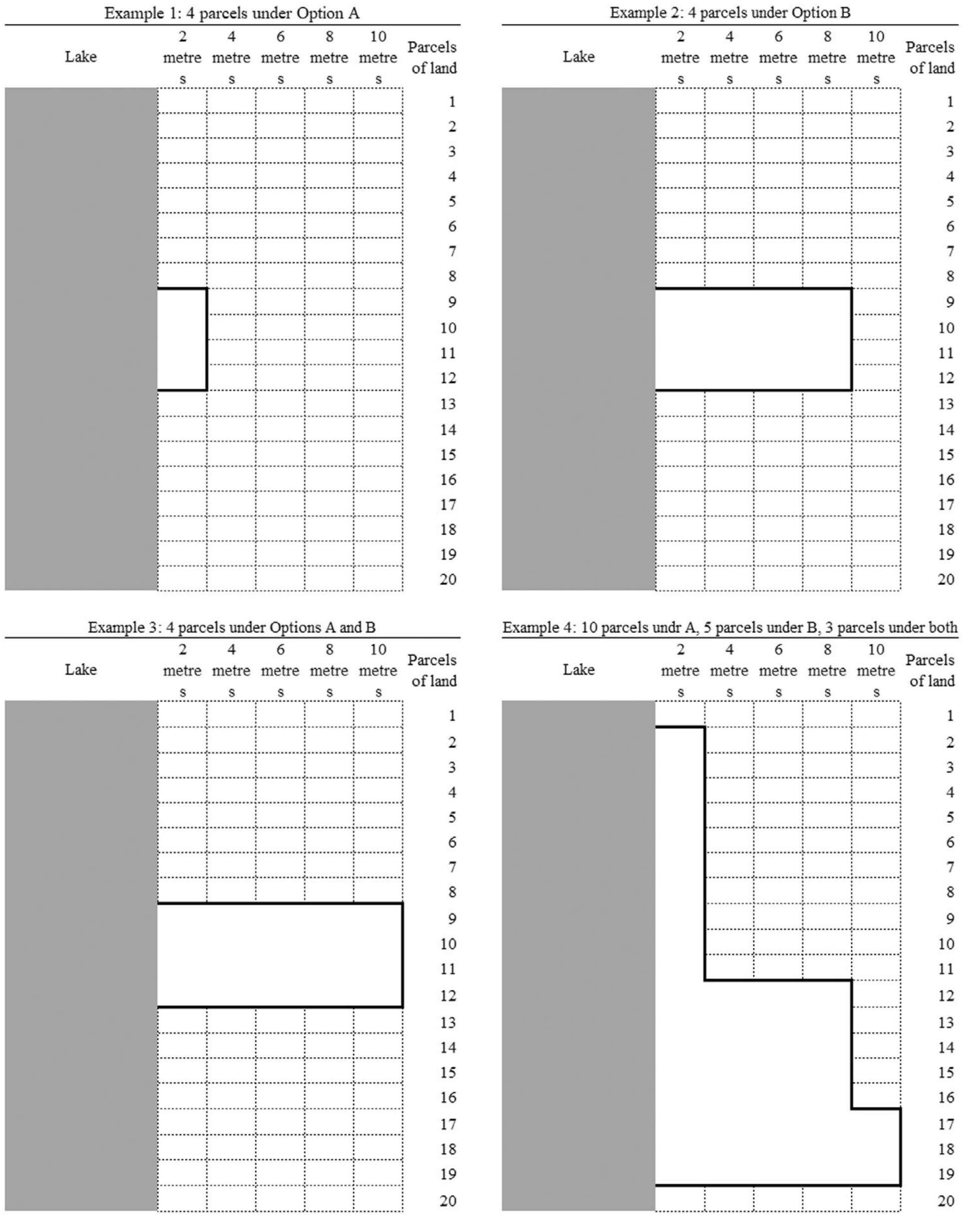

FIGURE 1 Examples of parcels and farmland enrolled in the AES under different options. A farm is distributed over a 2×0.5 km^2 plot. The bold black line delimits the land enrolled with the fence.

per-unit cost of these options is $c^A < c^B$. In Barrett and Dannenberg (2012), option A is the low-cost technology for emission reduction, while option B is the expensive technology of emission abatement. In our setting, option A allows the creation of narrower buffer zones, while option B allows the creation of wider buffer zones as in the EFS – WO programme (DAERA, 2022a). The two fencing options can be combined.

In the experiment, we introduced a group bonus. The group bonus b represents the additional subsidy that each farmer would receive for every parcel of land submitted in the lake. In order to have the classical prisoners' dilemma, parameters need to be set such that $c^B > b \bullet N > c^A > b$. In our experiment, this corresponds to:

- $N = 10$ farmers
- $c^A = £23$ per parcel of land under option A
- $c^B = £92$ per parcel of land under option B
- $b = £7$ per parcel of land submitted

where c^A and c^B were determined as forgone income proportionally to the amount of land under each option.[8] The value of the group incentive b was set equal to its mean value which is £7 for every parcel of land submitted in the lake regardless of the option A or B.[9] For these parameter values, self-interest impels that each farmer would submit 0 land, whereas collectively all the farmers in the lake are better off if each submits q^A_{max} under option A, and 0 under option B.

Farmers need to submit a minimum number of parcels of land above a given threshold $\overline{Q}$. In order to avoid the irreversible deterioration of water quality, the threshold needs to be set such that farmers can avoid the catastrophe if they top up the cheap submission (option A – narrow parcels of land) with the expensive submission (option B – wide parcels of land). In this setting, as $q^A_{max} = q^B_{max} = 20$ parcels of land under each option and $N = 10$ player-farmers, $\overline{Q}$ ranges from 200 and 400 parcels.

Submission of land short of $\overline{Q}$ would result in the irreversible environmental damage and the related economic loss $\overline{X}$ (per farmer per year). As explained in the next section, the economic loss is set to exceed by a large margin the cost of submitting land under each option. Thus, farmers have an incentive to avoid environmental damage.[10] However, as the submission of land is expensive in terms of forgone income, farmers would maximise their payoff by narrowly avoiding the threshold (i.e. the optimal number of submitted parcels per farmer is 30: 20 under option A plus 10 under option B).

A final observation concerns attitudes towards risk which can play a crucial role in the analysis of collective best outcome under catastrophic climate change (Weitzman, 2009). In Barrett and Dannenberg (2012), participants of the multi-player game are assumed to be risk neutral. However, farmers are often found to be risk averse (e.g. Cerroni, 2020; Iyer et al., 2020). In this paper, we test farmers' risk neutrality and control for possible deviations.

4.5 | Sources and degrees of uncertainty

Threshold uncertainty $\overline{Q}$ presents three levels of uncertainty[11]:

- High uncertainty: $\overline{Q}$ is assumed to be distributed uniformly within its feasible range $\overline{Q} \in [\overline{Q}_{min}, \overline{Q}_{max}] = [200{,}400]$ parcels of land.
- Low uncertainty: $\overline{Q}$ is assumed to be distributed within its feasible range [200,400], but with a 50% lower variance than the case with high uncertainty.
- No uncertainty: $\overline{Q}$ is certain and set equal to 300 parcels.

[8]As the gross margin per hectare of grazing livestock farms is £1550 (DAERA, 2021) and the payment provided by the government under the EFS – WO option is £355 of ungrazed buffer hectare, the forgone income would correspond to £1150/ha or £23 under option A and £92 under option B.

[9]Given $c^A = £23, c^B = £92, N = 10$, by dividing the inequalities $c^B > b \bullet N > c^A > b$ by N implies that $b \in (£2.3, £9.2)$ or £6.75 as its mean value. This was rounded to £7 per parcel.

[10]The game has 2 Nash equilibria in pure strategy: in one, every farmer submits 0 land. In the other, farmers submit q^A_{max} under option A and $\overline{Q}/N - q^A_{max}$ under option B. As far as the economic loss $\overline{X} \geq (c^B - b) \bullet \overline{Q}/N - (c^B - c^A) \bullet q^A_{max}$, the latter equilibrium is always preferred.

[11]According to Knight (2013), it would be more appropriate to frame our decision problem under conditions of risk rather than uncertainty as the probability distributions are provided to farmers during the experiment. In the paper, we use the term uncertainty to be consistent with the related literature (e.g. Barrett & Dannenberg, 2012).

We followed the same approach for the annual economic loss/impact $\overline{X}$ that a farmer will incur in case the threshold $\overline{Q}$ is not achieved.

- High uncertainty: $\overline{X}$ was assumed to be uniformly distributed between £2400 and £4800. The central value of the economic loss as its feasible range was determined to make the co-operative equilibrium preferred.[12]
- Low uncertainty: $\overline{X}$ is assumed to be distributed within its feasible range [£2400, £4800], but with a 50% lower variance than the case with high uncertainty.
- No uncertainty: $\overline{X}$ is certain and set equal to £3600.

The Low uncertainty treatment was implemented via a triangular distribution in both the threshold and impact uncertainty groups to maintain symmetry. For example, for the threshold uncertainty group, a triangular distribution with parameters set equal to 200, 300, and 400 has 50% lower variance than a uniform distribution between 200 and 400. Low and high threshold uncertainty were communicated to farmers using Figure 2a,b, respectively. Similarly, low and high impact uncertainty levels were communicated to farmers via Figure 2c,d, respectively.[13,14]

4.6 | Monetary incentives

Participants received an e-voucher on completion of the online experiment made by a fixed participation fee (£18) and a variable additional payment which could be up to £43.60 depending on famers' decision during the experiment. The variable component consists of two elements. The first is based on farmers' decisions in each experimental session and could be up to £9.60 per farmer. At the beginning of the game, farmers were informed that they had a budget of £7000 and that no farmer could be left out of pocket at the end of the game even in case of maximum economic loss, maximum individual commitment, and no cooperation from the other participants. Farmers were also informed that their final payoff was calculated based on farmers' decisions in one of the four land parcel allocation rounds that they face during the game. The binding round is randomly selected at the end of the experiment. If, in the selected binding round, threshold and/or impact are characterised by high uncertainty, then the threshold and/or impact determining the payoff will be randomly drawn from the uniform distributions presented in Section 4.5. Similarly, if, threshold and/or impact are characterised by low uncertainty, the triangular distribution presented in Section 4.5 will be used. The payoff is the final budget left in their account divided by £1000 (i.e. a budget of £1000 is equivalent to a payoff of £1).

The second element was calculated by randomly selecting one of the decision problems (i.e. row) presented in Tanaka et al. (2010). Original payoffs used by Tanaka et al. (2010) were divided by 50, so that the minimum payoff is −£420 and the maximum is £34,000. The payoff is then divided by £1000 (i.e. a gain of £1000 is equivalent to a payoff of £1). Payoff obtained from the farm business game and Tanaka et al.'s multi-price list format was disclosed at the end of the experiment.

[12]As $\overline{X} \geq \left(c^{B} - b\right) \bullet \overline{Q} / N - \left(c^{B} - c^{A}\right) \bullet q^{A}_{max}$, the economic loss cannot be smaller than £2020 in order to make the cooperative equilibrium preferred even in case of highest threshold value ($\overline{Q} = 400$). The range of the economic loss was set proportionally to the game budget as in Barrett and Dannenberg (2012).

[13]Farmers were exposed to the spinning wheels in Figure 2 before starting the business game. They participated in a practice round where they could spin the wheels as many times as they wanted and check how their final payoff would change.

[14]An in-depth explanation of how the spinning wheels were generated is provided in Appendix S2.2.

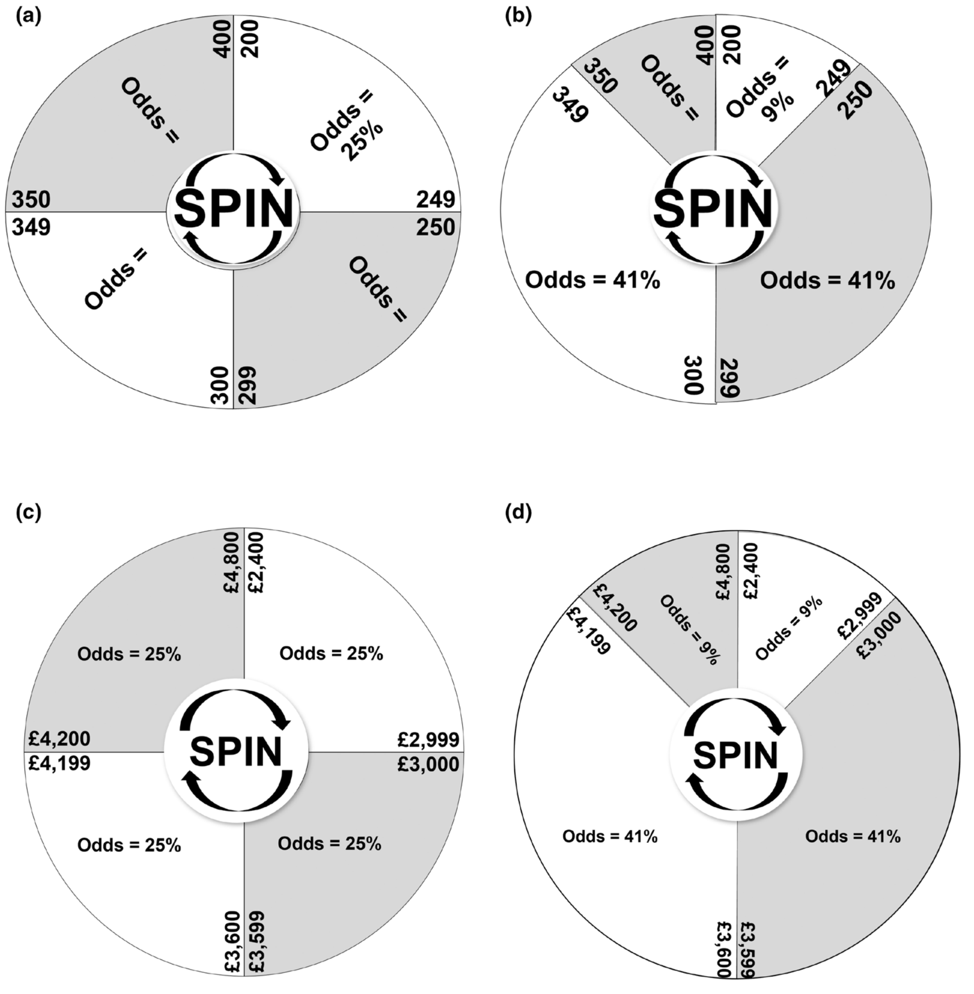

FIGURE 2 Spinning wheels under high threshold uncertainty (a), low threshold uncertainty (b), low impact uncertainty (c), and high impact uncertainty (d). See Appendix S2.2 for a discussion on how the spinning wheels were designed.

5 | ECONOMETRIC ANALYSES AND RESULTS

5.1 | The farm business game: Qualitative analysis

Figure 3 shows the average number of parcels of land submitted by a farmer by treatment and round. Three main preliminary conclusions can be reached based on these results. First, the lowest and highest levels of cooperation are achieved under full uncertainty and no uncertainty respectively. Second, farmers' cooperation increases as uncertainty decreases. Third, farmers in the impact uncertainty group submitted more land than those in the threshold uncertainty group. Figure 3 also shows the percentage of farmers' groups that submitted a number of parcels equal or larger than the equilibrium values. These percentages suggest that group performances do not improve when threshold uncertainty decreases unless this source of uncertainty is totally removed (no uncertainty). In contrast, group performances constantly improve when impact uncertainty decreases. In addition, group performances under impact uncertainty are constantly better than those under threshold uncertainty.

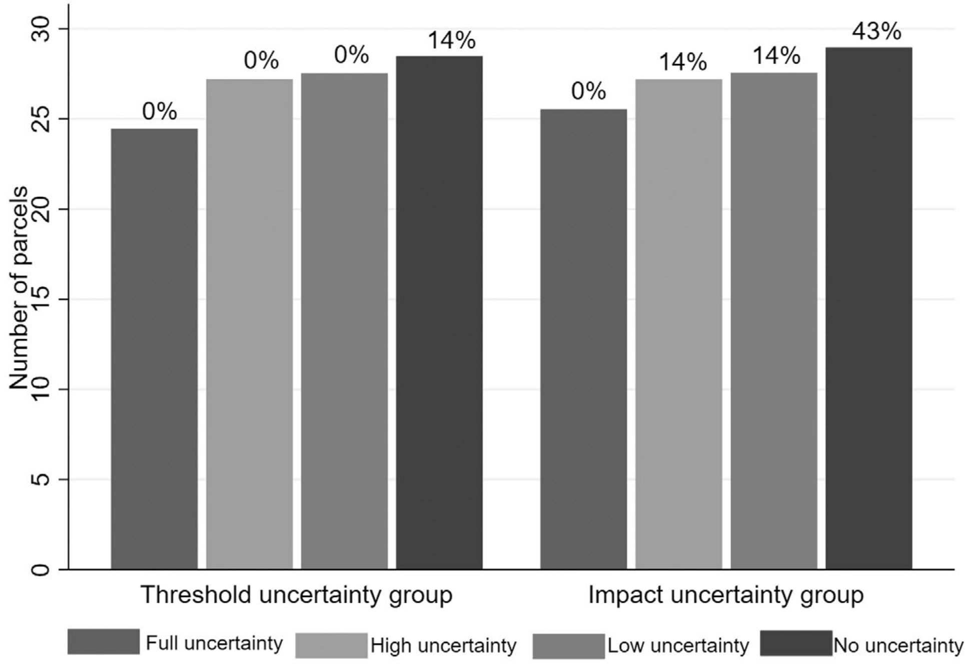

FIGURE 3 Average number of parcels of land submitted by a farmer. The percentages on the bars indicate the fraction of farmers' groups that submitted a number of parcels equal or larger than the cooperative equilibrium value (30 parcels per farmer).

5.2 | The farm business game: Econometric analysis

Two regression models were estimated to explore the impact of different sources and degrees of uncertainty on farmers' cooperation. Specifically, for each source of uncertainty (i.e. threshold and impact), the number of enrolled parcels (Model 1 – Basic) and the amount of enrolled land in hectares (Model 2 – Basic) are regressed on four fixed effects denoting the level of uncertainty faced by the farmer in each round (i.e. full uncertainty, high uncertainty, low uncertainty, and no uncertainty). The number of land parcels (Model 1 – Basic) is modelled using a generalised linear model (GLM) for binomial response data to reflect the fact that the outcome is an integer number limited between 0 and 40 parcels (Blizzard & Hosmer, 2006). The amount of enrolled land (Model 2 – Basic) is modelled using a fractional probit model after normalising the dependent variable to 0–1 (Papke & Wooldridge, 1996).[15] A set of *F*-tests is used to compare each pair of coefficients associated with the four fixed effects and, hence, to explore the impact of different sources and degrees of uncertainty on farmers' participation in the AES. Table 4 reports the regression results, while Table 6 shows the relative *F*-tests.

These results indicate three interesting cooperation patterns. First, the lowest level of cooperation is consistently reached when farmers face full uncertainty (i.e. high uncertainty linked to both threshold and impact). Specifically, Table 6 indicates that cooperation under high (round 2), low (round 3), and no uncertainty (round 4) is statistically higher than under full uncertainty (round 1). Second, while farmers' cooperation increases if one source of uncertainty

[15]In Appendix S2.3, we present results from non-parametric tests. These are consistent with results from the estimation of our econometric models. In addition, to consider potential session-level effects, in Appendix S2.4, we show the results obtained from models where standard errors were clustered at group rather than at the farmer's level. No main differences were detected in the results.

TABLE 4 Regression results from the estimation of basic models[a].

Treatment group	Variable	Parcels[b] (model 1) Coefficient	Standard error	Land[c] (model 2) Coefficient	Standard error
Threshold uncertainty	1: Full uncertainty	0.45***	0.12	0.03	0.08
	2: High uncertainty	0.75***	0.13	0.25***	0.09
	3: Low uncertainty	0.79***	0.14	0.31***	0.09
	4: No uncertainty	0.91***	0.13	0.38***	0.09
	Observations	232		232	
	Log-likelihood	−1536.47		−115.99	
Impact uncertainty	1: Full uncertainty	0.57***	0.11	0.11	0.08
	2: High uncertainty	0.75***	0.12	0.25***	0.08
	3: Low uncertainty	0.80***	0.12	0.32***	0.08
	4: No uncertainty	0.97***	0.13	0.44***	0.09
	Observations	232		232	
	Log-likelihood function	−1379.59		−113.83	

Note: ***, **, * indicates statistical significance at the 1%, 5%, and 10% level.

[a]Robust standard errors clustered at the farmer level.

[b]Generalised linear regression model for binomial response data.

[c]Fractional probit model.

is fully removed, it does not substantially change when uncertainty is reduced from high (round 2) to low (round 3). This result signals that farmers are not sensitive to reductions in the degree of uncertainty. The pairwise comparisons in Table 6 indicates that the difference between high uncertainty (round 2) and no certainty (round 4) is statistically significant at the 1%–5% level for parcels and land in each treatment group. In contrast, no statistical significance between high and low uncertainty (rounds 2 and 3) was found across treatments, parcels, and amount of enrolled land.

Third, farmers are slightly more sensitive to reductions in impact uncertainty than those related to threshold uncertainty. Table 6 shows that while farmers' cooperation increases when impact uncertainty is reduced from low (round 3) to none (round 4), this does not happen for the threshold uncertainty group. These results are consistent regardless of whether we measure cooperation in terms of parcels (Model 1 – Basic) or amount of enrolled land (Model 2 – Basic) and suggest that farmers are more responsive to impact uncertainty than threshold uncertainty reductions. If threshold uncertainty is interpreted as the probability that given negative consequences will be triggered, then the results imply that farmers are rather insensitive to probability changes. This finding is consistent with empirical evidence demonstrating that economic agents, including farmers, can be rather insensitive to changes in the probability of a risk occurring (e.g. Čop et al., 2023; Hammitt & Graham, 1999). Hence, farmers' response to risks often deviates from rational choice theory (i.e. expected utility theory, e.g. Bocquého et al., 2014; Rommel, Schulze, et al., 2022) and it is driven by the use of heuristics (e.g. Menapace et al., 2013).

Two additional models were estimated that incorporate a set of covariates controlling for farm and farmer's characteristics (Model 1 – Extended and Model 2 – Extended). Table 2 reports the covariates included in Models 2. Results from the estimation of these models are shown in Tables 5 and 6. Farmers' cooperation in response to uncertainty follows the same pattern that was found when estimating the basic models (i.e. without covariates). However,

TABLE 5 Regression results from the estimation of extended models[a].

		Parcels[b] (model 1)		Land[c] (model 2)	
Treatment group	**Variable**	**Coefficient**	**Standard error**	**Coefficient**	**Standard error**
Threshold uncertainty	1: Full uncertainty	2.10***	0.61	1.05**	0.42
	2: High uncertainty	2.42***	0.63	1.27***	0.43
	3: Low uncertainty	2.46***	0.63	1.34***	0.43
	4: No uncertainty	2.57***	0.62	1.41***	0.43
	Female	−0.22	0.35	−0.10	0.25
	Age	−0.03**	0.01	−0.02**	0.01
	Env. attitude	0.25	0.22	0.16	0.15
	Dairy farm	−0.06	0.27	−0.09	0.19
	Lowland farm	−0.37	0.23	−0.11	0.15
	Farm size (acres)	0.00	0.00	0.00	0.00
	AES membership	0.33	0.20	0.16	0.15
	Farm successor	−0.49**	0.21	−0.25	0.17
	Observations	232		232	
	Log-likelihood	−1339.57		−111.19	
Impact uncertainty	1: Full uncertainty	1.70***	0.52	0.90***	0.33
	2: High uncertainty	1.89***	0.52	1.05***	0.33
	3: Low uncertainty	1.93***	0.52	1.12***	0.33
	4: No uncertainty	2.11***	0.53	1.25***	0.34
	Female	−0.23	0.44	−0.13	0.29
	Age	−0.02*	0.01	−0.01**	0.01
	Env. attitude	−0.09	0.24	−0.14	0.14
	Dairy farm	0.16	0.25	0.01	0.17
	Lowland farm	0.33	0.24	0.21	0.15
	Farm size (acres)	0.00	0.00	0.00	0.00
	AES membership	0.33	0.24	0.40**	0.17
	Farm successor	−0.61***	0.20	−0.36**	0.14
	Observations	232		232	
	Log-likelihood	−1231.68		−107.83	

Note: ***, **, * indicates statistical significance at the 1%, 5%, and 10% level.

[a]Robust standard errors clustered at the farmer level.

[b]Generalised linear regression model for binomial response data.

[c]Fractional probit model.

results presented in Table 5 provide insights regarding the influence of farmer and farm's characteristics on cooperation.

First, young farmers cooperate more than old farmers. In Table 5, the coefficient of age is negative and statistically significant across treatments ($p \leq 5\%$). Previous research provides mixed results on this. While Peth et al. (2018) find that farmers' compliance with water protection rules in Germany increases with age, Valdivia and Poulos (2009) show that older farmers in Missouri are less willing to adopt riparian buffer zones. Rommel, Schulze, et al. (2022) do not find any significant effect of farmers' age on their collective engagement in Germany.

TABLE 6 *F*-tests on the pairwise differences across levels of uncertainty (*p*-value).

Treatment group	Round	Round	Parcels[a] (model 1 – basic)	Land[b] (model 1 – basic)	Parcels[a] (model 2 – extended)	Land[b] (model 2 – extended)
Threshold uncertainty	1: Full uncertainty	2: High uncertainty	0.00	0.00	0.00	0.00
	1: Full uncertainty	3: Low uncertainty	0.00	0.00	0.00	0.00
	1: Full uncertainty	4: No uncertainty	0.00	0.00	0.00	0.00
	2: High uncertainty	3: Low uncertainty	0.43	0.11	0.43	0.12
	2: High uncertainty	4: No uncertainty	0.04	0.02	0.04	0.02
	3: Low uncertainty	4: No uncertainty	0.11	0.16	0.10	0.16
Impact uncertainty	1: Full uncertainty	2: High uncertainty	0.03	0.00	0.03	0.00
	1: Full uncertainty	3: Low uncertainty	0.01	0.00	0.01	0.00
	1: Full uncertainty	4: No uncertainty	0.00	0.00	0.00	0.00
	2: High uncertainty	3: Low uncertainty	0.49	0.19	0.49	0.20
	2: High uncertainty	4: No uncertainty	0.02	0.00	0.02	0.00
	3: Low uncertainty	4: No uncertainty	0.02	0.00	0.02	0.00

[a]Generalised linear regression model for binomial response data.

[b]Fractional probit model.

TABLE 7 Farmers' behavioural factors.

	Sample	Threshold uncertainty group	Impact uncertainty group
Average			
σ	0.53	0.56	0.50
α	0.67	0.63	0.73
λ	3.39	2.88	3.95
% farmers			
Risk averse: $\sigma < 1$	93%	93%	93%
Inverted S-shaped: $\alpha < 1$	86%	93%	78%
Loss averse: $\lambda > 1$	67%	64%	72%
t-test: H_0	*p*-value	*t*-test: H_0	*p*-value
$\sigma < 1$	0.00	$\sigma_A = \sigma_B$	0.41
$\alpha < 1$	0.00	$\alpha_A = \alpha_B$	0.17
$\lambda > 1$	0.00	$\lambda_A = \lambda_B$	0.16

Second, farmers with a farm successor committed fewer parcels and less land than farmers without a successor; the coefficients of farm successor are negative and statistically significant ($p \leq 5\%$) in 3 out of 4 cases. Although sustainable farming is linked to long-term goals that require continuity of action and thus an intergenerational approach (Duesberg et al., 2017), studies have indicated that multigenerational farm businesses (i.e. farms managed by later generations) tend to be less innovative indicating that the adoption of environmental practices may decrease as the number of successions increases (Block, 2012; Suess-Reyes & Fuetsch, 2016).[16]

5.3 | Accounting for risk preferences, probability weighting, and loss aversion

Risk preference (σ), probability weighting (α), and loss aversion (λ) parameters elicited using Tanaka et al. (2010) was used as additional controls in our regression models. We employed the mid-point method to retrieve σ, α, and λ. This method requires that a participant switches only once for each row of Tanaka et al. (2010) multi-price list. Thus, we dropped 12 observations from the threshold uncertainty group and 17 from the impact uncertainty group due to multiple switchers. This reduced the sample size to 176 observations for the threshold uncertainty group and to 156 for the impact uncertainty group.[17]

Table 7 shows that, on average, farmers are risk averse ($\sigma = 0.53$), weigh probability according to an inverse S-shaped probability weighting function ($\alpha = 0.67$), and are loss averse ($\lambda = 3.39$). These values are consistent with existing empirical evidence (e.g. Bocquého et al., 2014; Bonjean, 2022; Cerroni, 2020; Finger et al., 2023; Rommel, Schulze, et al., 2022).

[16]To test the robustness of our results, we also estimated other model specifications. First, we estimated a continuous regression model for left and right censored data (Model 3) to analyse the amount of enrolled land. Results are presented in Appendix S2.5. Second, we estimated models where a constant is included in the extended Models 1 and 2 and the full uncertainty level is used as reference to measure the impact on cooperation of other levels of uncertainty. Results are presented in Appendix S2.6.

[17]Appendix S2.7 provides the details of the method employed to retrieve σ, α, and λ. To test the robustness of our findings, we estimated basic and extended specifications of Models 1 and 2 using the same sub-sample of respondents used in the analyses regarding the impact of behavioural factors on cooperation. Results are presented in Tables B.7.1 and B.7.2 in Appendix S2.7, and they do not diverge from those reported in Tables 4 and 5 suggesting that our results are robust. In addition, we acknowledge the possibility of using alternative methods that allos retrieving σ, α, and λ in presence of multiple switchers. A noticeable example is provided in Rommel, Sagebiel, et al. (2022).

A series of two-sided t-tests indicate there are no significant differences between elicited behavioural factors in the threshold and impact treatment groups (Table 7).

Table 8 reports the regression results obtained after including the elicited behavioural factors in the extended regression models presented in Section 5.2. More specifically, the categorical variable *risk averse* indicates risk-averse farmers ($\sigma < 1$), the categorical variable *inverted*

TABLE 8 Regression results from the estimation of models including categorical behavioural factors[a].

		Parcels[b] (model 1)		Land[c] (model 2)	
Treatment group	**Round**	**Coefficient**	**Standard error**	**Coefficient**	**Standard error**
Threshold uncertainty	1: Full uncertainty	3.42***	1.20	1.81***	0.68
	2: High uncertainty	3.77***	1.22	2.07***	0.69
	3: Low uncertainty	3.82***	1.22	2.13***	0.69
	4: No uncertainty	3.90***	1.22	2.19***	0.69
	Female	−0.20	0.39	−0.04	0.27
	Age	−0.03**	0.01	−0.02**	0.01
	Env. attitude	0.36	0.27	0.18	0.18
	Dairy farm	−0.31	0.28	−0.24	0.17
	Lowland farm	−0.32	0.25	−0.03	0.16
	Farm size (acres)	0.00	0.00	0.00	0.00
	AES membership	0.50*	0.26	0.22	0.17
	Farm successor	−0.37	0.29	−0.05	0.19
	Risk averse	−0.88	0.87	−0.30	0.57
	Inverted S-shaped	−0.37	0.37	−0.40	0.25
	Loss averse	−0.31	0.30	−0.39**	0.19
	Observations	176		176	
	Log-likelihood	−955.91		−81.24	
Impact uncertainty	1: Full uncertainty	1.43*	0.82	0.76	0.55
	2: High uncertainty	1.68**	0.80	0.93*	0.53
	3: Low uncertainty	1.73**	0.80	1.04**	0.54
	4: No uncertainty	1.99**	0.81	1.21**	0.54
	Female	−0.61	0.49	−0.37	0.32
	Age	−0.02	0.01	−0.02**	0.01
	Env. attitude	0.08	0.31	−0.15	0.20
	Dairy farm	−0.06	0.33	−0.20	0.21
	Lowland farm	0.15	0.30	0.16	0.20
	Farm size (acres)	0.00	0.00	0.00	0.00
	AES membership	0.47*	0.29	0.46**	0.21
	Farm successor	−0.65**	0.26	−0.28	0.19
	Farm successor	0.12	0.28	0.00	0.31
	Risk averse	0.21	0.35	0.25	0.24
	Inverted S-shaped	−0.11	0.32	−0.02	0.20
	Observations	156		156	
	Log-likelihood	−786.71		−70.99	

Note: ***, **, * indicates statistical significance at the 1%, 5%, and 10% level.

[a]Robust standard errors clustered at the farmer level.

[b]Generalised linear regression model for binomial response data.

[c]Fractional probit model.

s-shaped indicates farmers who overweight small probability gains and underweight high probability gains (i.e. probabilistically risk-averse farmers) ($\alpha < 1$), and the categorical variable *loss aversion* indicates loss-averse farmers ($\lambda > 1$). Table 7 indicates that 93% of our sample is risk averse ($\sigma < 1$), 86% behaves according to an inverse S-shaped probability weighting function ($\alpha < 1$), and 67% is loss averse ($\lambda > 1$).

Overall, Table 8 indicates that farmers' risk preferences and probability weighting do not influence cooperation, while loss aversion has a weak impact on cooperation; specifically, loss-averse farmers are less likely to cooperate than others. The impact of loss aversion is only significant when cooperation is measured in terms of amount of land enrolled in the AES (not number of parcels) and under threshold uncertainty (not impact uncertainty) ($p \leq 5\%$). While the impact of probability weighting and loss aversion on cooperation in public good games under uncertainty has not been investigated before, previous research has shown that risk aversion has no or little influence on economic agents' degree of cooperation in this type of game (e.g. Barrett & Dannenberg, 2012; Schuch et al., 2021). The impact of including these behavioural factors in our models does not overturn the results from pairwise comparison conducted to test the impact of variations in the degree and type of uncertainty on cooperation.[18,19] Given the small sample sizes, we acknowledge the possibility of false negative (Type II error), and hence, we recommend caution in the interpretation of the results.[20]

We acknowledge that our experiment implies multiple hypotheses testing. To this end, a standard Bonferroni correction to control for family-wise error rates was performed. Results are available in Appendix S2.10 and confirm that caution should be used when assessing changes in farmers' cooperation in response to intermediate reductions in the level of uncertainty.

6 | CONCLUSIONS

The impact that livestock farming can have on biodiversity, land regeneration, and air and water quality has recently captured the attention of academics, policymakers, and the general public (e.g. Hooda et al., 2000; Nguyen et al., 2022). Cooperation amongst livestock farmers is often pivotal to reduce the negative externalities generated by farming activity on natural resources and hence comply with increasingly stringent environmental regulations (e.g. DAERA, 2023; DEFRA, 2023; European Commission, 2023b).

This paper focuses on the impact that phosphorous and nitrogen run-off can have on the water quality of a lake and the ability of farmers to cooperate to avoid catastrophic consequences due to an irreversible deterioration of water quality. Farmers' cooperation can be hindered by many drivers. Amongst others, there is uncertainty around the minimum water quality standard that should be guaranteed to avoid catastrophic consequences (i.e. threshold

[18]To test the robustness of our results, we also estimated models with behavioural factors included as continuous variables. Results presented in Appendix S2.8 show that the impact of behavioural factors on decision making is consistent regardless of whether these are modelled as continuous or discrete variables.

[19]In Appendix S2.9, we present results from the estimation of extended models that allow the investigation of the influence of behavioural factors on decision making differentiated by level of uncertainty. We thank an anonymous Referee for the advice.

[20]A power analysis was conducted and reported in Appendix S2.11. Specifically, Figure B.11.1 plots the power curves given a range of sample sizes for the two-sided test (5% statistical significance) on the difference in the number of parcels submitted by a farmer between two uncertainty rounds. For a sample size of 50 farmers per treatment group, the power of the test is above the conventional levels (0.80) in all cases apart from when the difference in the level of uncertainty between rounds is limited, specifically 'High uncertainty – No uncertainty' for the threshold treatment group and 'Full uncertainty – High uncertainty' for the impact treatment group. Similar observations can be drawn from Figure B.11.2 which plots the minimum detectable difference (5% statistical significance) in the number of parcels submitted by a farmer in two uncertainty rounds (80% statistical power). Overall, this suggests that caution should be adopted in interpreting the results across intermediate levels of uncertainty.

uncertainty) and the uncertainty regarding the long-term economic losses that such catastrophic consequences imply (i.e. impact uncertainty) (e.g. Graveline et al., 2012; Nicholson et al., 2020).

In this paper, we conduct a contextualised lab-in-the field experiment with 140 livestock farmers in Northern Ireland to disentangle the influence that different sources of uncertainty and different degrees of uncertainty have on farmers' ability to cooperate. Two sources of uncertainty are considered: threshold and impact uncertainty. Four levels of uncertainty are examined: full, high, low, and no uncertainty. Farmers are split into two treatment groups, one for each source of uncertainty. Farmers in each group are exposed to the four levels of uncertainty. All farmers are asked to play a farm business game which consists of a local public good game that is framed as a farmer's decision to participate in an AES promoting the use of ungrazed buffer zones (EFS – WO). Farmers' risk preferences, probability weighting, and loss aversion are elicited using Tanaka et al. (2010). All tasks are incentive compatible and incentivised.

Results indicated that uncertainty limits farmers' cooperation to avoid the irreversible deterioration of water quality. This is not far from reality: AESs operate on a voluntary basis, and a limited number of participants usually enrol to these schemes (e.g. Kuhfuss et al., 2019). To date, farmers committed 0.2% of their total farmland to the current AES in place in NI (EFS – WO) (DAERA, 2022a). However, our results suggest that reducing uncertainty about the level of cooperation required to avoid catastrophic consequences (i.e. threshold uncertainty) and about the magnitude of the long-term economic losses due to such catastrophic consequences (i.e. impact uncertainty) facilitates cooperation amongst farmers. Interestingly, farmers respond differently when exposed to different sources of uncertainty. Farmers' cooperation is more sensitive to reductions in impact uncertainty than those related to threshold uncertainty. If threshold uncertainty is interpreted as the probability that catastrophic consequences will occur, this result becomes consistent with a stream of the literature suggesting that economic agents, including farmers, can be rather insensitive to probability variations (e.g. Čop et al., 2023; Robinson & Botzen, 2019). Findings related to variations in the level of farmers' cooperation between intermediate levels of threshold and impact uncertainty should be treated with caution. The size of our sample may not be sufficient to detect differences in cooperation across intermediate levels of uncertainty, thus generating type II errors. Our results also suggest that behavioural factors such as risk aversion, probability weighting, and loss aversion have little impact on farmers' cooperation.

These findings highlight the need for action. A mix of policy interventions could be implemented to facilitate farmers' cooperation. The lever that is generally used to promote farmers' participation in AES is subsidisation. For example, compensation for costs incurred and income forgone to comply with the actions required by the AES was the financial lever used in the CAP 2014–2020 (Dupraz & Guyomard, 2019). The latest CAP reform 2023–2027 has introduced the so-called eco-schemes that have a more incentivising premise, with compensation higher than the cost incurred and foregone income (DEFRA, 2023; European Commission, 2023c). An example of a financial lever could be the introduction of group bonus (an extra financial reward for farmers) when a given cooperation goal is reached (i.e. amount of land enrolled). Our business game introduces the presence of such an instrument and results appear to be encouraging. If the current level of total farmland committed to the EFS – WO is currently 0.2%, our results show that our farmers enrolled more than 1% of their total farmland in our business game under full uncertainty. Full uncertainty is the scenario that more closely resembles the current (awareness/knowledge) environment in which NI farmers make their decisions to join the EFS – WO. While these results are consistent with previous empirical evidence showing that the use of group bonus can promote farmers' commitment to preserving common pool resources (e.g. Kuhfuss et al., 2019), they should be treated with caution as farmers' behaviour in an experimental setting can deviate from their behaviour in real life due to many biases (e.g. experimenter demand effect). Another financial lever could be increasing the cost of uncooperative behaviours with respect to the gains from free riding including making cooperation compulsory in case of urgent action. However, punishing interventions are less likely to be proposed and implemented especially when these could lower the competitiveness of farming in more marginal rural areas and further exacerbate inequalities.

The results also highlight that information-based interventions must be part of the policy mix. Policymakers and involved stakeholders should pay particular attention to communication of uncertainty associated with environmental outcomes to farmers. First, farmers should be instructed about one of the key principles of the environmental protection legislation, the precautionary principle. Farmers should be aware that scientific uncertainty regarding the negative externalities produced by agriculture on natural resources should not prevent them from taking more responsibility. In addition, it is pivotal that communication and educational campaigns use methods and approaches that make farmers more conscious about the possibility that their actions could generate long-term farm income losses. Marx et al. (2007) indicated that, in the case of climate change, individuals process information not just analytically, but also through an experiential processing system. Translation of scientific information into concrete experience can facilitate understanding of both probabilities and the consequences of their incremental changes. Sharing experiences in group discussions can be beneficial to boost environmental awareness. From this point of view, peer-to-peer discussion groups designed to involve farmers from a specific site such as a lake and other aquatic sites could help to understand different sources of uncertainty and promote their cooperation (Burton & Paragahawewa, 2011; Speelman et al., 2014). These initiatives can help overcoming educational barriers that hinder long-term behavioural change (Angioloni et al., 2023). Future research could test whether these approaches are efficient in promoting farmers' cooperation in the light of scientific uncertainty.

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DATA AVAILABILITY STATEMENT

The data and software codes that support the findings of this study are available in the supplementary material of this article.

ORCID

Simone Angioloni https://orcid.org/0000-0001-9549-4055
Simone Cerroni https://orcid.org/0000-0001-9231-1591

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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