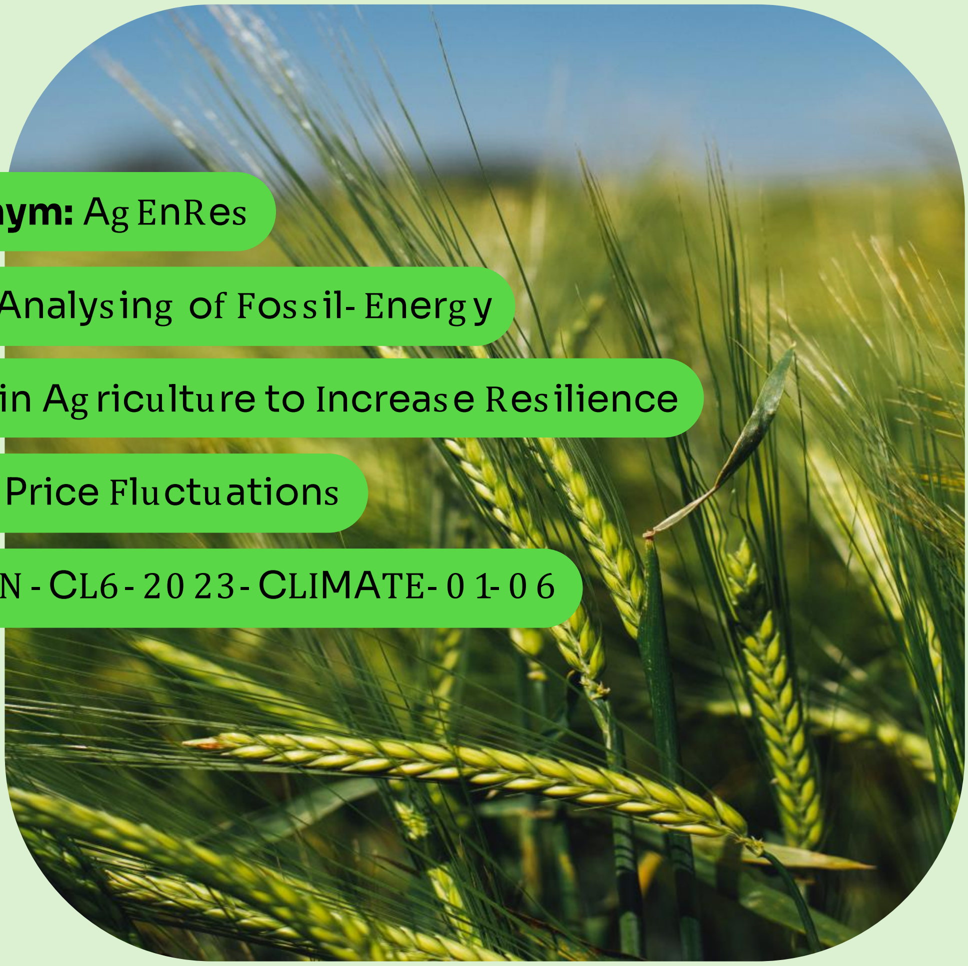
AgEnRes

D5.1 Farmers' mineral fertilizer decisions under risk



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Project title: Analysing of Fossil-Energy Dependence in Agriculture to Increase Resilience against Input Price Fluctuations

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Executive Summary

Fertilizer use in agriculture has been a cornerstone of increasing global food production over the past century. At the same time, fertilizer overuse can pollute the environment, and the energy-intensive production of mineral nitrogen fertilizer comes with significant carbon dioxide emissions. To reduce the (over-)use of fertilizers, the European Union and member states have established numerous policies in recent years that restrict fertilization at the farm level. Yet farmers' fertilizer decisions still deviate from optimality, often resulting in fertilizer underuse and overuse. Such behavior deviates from expected utility or profit maximization and standard economic theory. Overall, there remain significant gaps in the understanding of farmers' decisions about the quantity and timing of fertilizer use at farm level.

In this report, we develop a conceptual framework that explains farmers' fertilizer decisions. This framework suggests that such decisions are made under risk and uncertainty and different sources of uncertainty exist. The more pronounced are those related to the fluctuation of fertilizer and crop prices as well as crop yields. In this environment, behavioral factors related to decision making under risk and uncertainty can significantly influence farmers' behavior. In addition to risk preferences, we also consider behavioral factors underlying non-standard theories of decision making under risk and uncertainty, such as loss aversion, ambiguity preferences, and probabilistic expectations and distortions. Since farmers' fertilizer decisions have also an intertemporal component, we also consider standard (i.e. exponential) and non-standard discounting factors such as hyperbolic discounting.

To gain a better understanding of the role of behavioral factors in farmers' fertilizer decisions, this report presents the main findings from a systematic literature review, conducted using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach in high-income countries. We synthesize insights from 63 peer-reviewed articles on farmers' fertilizer decisions, behavioral factors, and methods to incorporate behavioral factors into fertilizer decision models.

Two main findings can be drawn from the literature review. First, with two exceptions, all studies investigate the role of risk preferences in an expected utility theory (EUT) framework to explain fertilizer applications. These findings indicate a substantial gap in the literature and the need to further explore whether and to what extent other behavioral drivers can explain fertilizer (over-)use. Second, most studies normatively optimize fertilizer decisions using mathematical methods in an EUT framework, while only a limited number of studies tries to investigate the relationship between behavioral drivers and farmers' actual fertilizer decision using econometric models and primary data methods such as stated preferences and experimental methods.

Based on these findings we conclude that future research should explore further the relationship between behavioral factors other than risk preferences and farmers' fertilizer decisions. Loss aversion, ambiguity preferences, probability distortions and probabilistic expectations have the potential to explain deviations from optimal fertilizer use by farmers. Stated preference methods and economic experiments can be used to elicit farmers' preferences and study in more detail their correlation with actual (over-)fertilization behavior. Furthermore, mathematical approaches could relax assumption of EUT to accommodate the incorporation of other behavioral factors (other than risk preferences) in their modelling approach when possible and not computationally demanding. This strategy would imply the incorporation of non-standard theories of decision making under risk and uncertainty into mathematical approaches (e.g., cumulative prospect theory). Findings from stated-preference studies and economic experiments could further inform mathematical models, improving their ability to predict farmers' actual behavior and deviations from optimal fertilizer use, ultimately

facilitating the design of more effective policies to reduce fertilizer consumption. Despite considerable challenges ahead, this literature review highlights the need for a more coordinated and coherent integration of behavioral research, mainly conducted using primary data methods, and research based on mathematical methods which offers a more systemic perspective.

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List of Acronyms

EUT	Expected utility theory
GPNM	Global Partnership on Nutrient Management
N	Nitrogen
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SJR	SCImago Journal Rank
SEUT	Subjective expected utility theory
UNEP	United Nations Environment Program

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1. Introduction

Fertilizer use in agriculture has been a cornerstone of increasing global food production over the past century. However, the overuse of synthetic nitrogen-based (N-based) fertilizer has raised environmental and economic concerns, threatening the sustainability and resilience of farming systems (e.g., Mozumder & Berrens, 2007). Fertilizer use accounted for 11% of agricultural greenhouse gas emissions and 2% of global emissions in 2018 (Menegat et al., 2022). At the same time, increasing price volatility of synthetic fertilizer, driven by fluctuating energy costs and political events such as Russia's invasion of Ukraine, has put farmers' incomes at risk worldwide (e.g., Alexander et al., 2022; Schaub & Benni, 2024). On the other hand, a potential under-fertilization can threaten food security (Snapp et al., 2023, Stewart & Roberts, 2012, EU Commission, 2022).

Reductions in fertilizer pollution and nutrient losses, while maintaining food security, are key elements of the agricultural policy agenda, especially in high-income countries, where N fertilizer overuse is common (Stevens, 2019). Several policies were developed and implemented in recent years to tackle the fertilization overuse issue. An example is the Global Partnership on Nutrient Management (GPNM) initiated by the United Nations Environment Program (UNEP) in 2009 (UNEP, 2009). At EU level, multiple directives on N use, nitrate pollution, water protection, and emission ceilings attempted to mitigate the problem (EU Regulation 2021/2115, 91/676/EEC, 2000/60/EC, 2016/2284/EU). However, farmers' fertilizer decisions often deviate from the optimal use of N fertilizer, making them difficult to explain using rational choice theory. Here, optimality refers to a profit maximizing fertilizer use. Overall, it appears that farmers' fertilizer decisions are poorly understood and there is a lack of knowledge about how much and when farmers decide to use fertilizer.

To fill this gap, this deliverable develops a conceptual framework that aims to synthetize the main decisions that farmers generally make regarding fertilizer usage, namely the amount and timing of fertilization. These decisions are made under conditions of risk and uncertainty.[1] Three main sources of uncertainty are contemplated: crop and fertilizer price volatility, and crop yield variations. The conceptual framework emphasizes the influence of behavioral factors on farmers' fertilizer decisions. The framework considers behavioral factors within expected utility theory (EUT), the standard economic model for decision-making under risk and uncertainty, including risk preferences and exponential time discounting. More importantly, it explicitly recognizes the need to incorporate behavioral factors from non-standard economic theories, such as loss aversion, ambiguity preferences, hyperbolic discounting, probabilistic expectations, and probability distortions. These behavioral factors are incorporated in different theories of decision making under uncertainty and ambiguity. More details are provided in the conceptual framework presented in the next section.

To assess the existing research on how behavioral factors influence fertilizer decisions, we conducted a literature review following the PRISMA approach. Our review examines several behavioral factors: risk, uncertainty, and ambiguity preferences; loss aversion; exponential and hyperbolic time discounting; probability weighting; and subjective probabilities. Focusing exclusively on research from high-income countries, our systematic literature review fills a gap in the existing literature. To date, no literature reviews have specifically addressed this topic. The study closest in scope is an unsystematic

[1] Risks define outcomes with ex-ante known and meaningful probabilities, whereas uncertainties describe outcomes with unknown or irrelevant probabilities (e.g., Anger, 2020).

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review by Begho et al. (2022), which explores the relationship between risk aversion and fertilizer usage in South Asia.

The literature review provides two main findings. First, except two studies that investigate subjective probabilistic expectations and ambiguity preferences, all reviewed studies focus on the role of risk preferences in explaining fertilizer decisions. This allows us to make two further considerations. To start with, decision-making under uncertainty is mostly overlooked in current literature, although farmers' fertilizer decisions are made in the absence of objective probabilities related to future fertilizer prices and future attainable yields. In addition, farmers' fertilizer decisions are modelled and studied using a framework (EUT) that assumes rationality. This seems to be a shortcoming since non-optimal fertilizer use that is often observed at farm level does not necessarily align with expected profit maximization.

Second, our literature review reveals that two main branches of research exist that largely overlook one another. The richer branch (in terms of number of studies) relies on the use of mathematical methods to identify the optimal level of fertilizer usage by assuming rationality and expected utility maximization. One of the main focuses of this literature is the computation of optimal fertilizer usage under different levels of assumed farmers' risk aversion (e.g., Gandorfer et al., 2011). The other branch of the literature is narrower and aims to estimate or elicit risk preferences with the final goal of better understanding the potential correlation between risk preferences and fertilizer decisions. Econometric approaches estimate risk preferences based on farmers' fertilizer decisions using secondary data (e.g., Gardebroek, 2006), while stated preference surveys and economic experiments elicit risk preferences (e.g., SriRamaratnam et al, 1987; Vollmer et al., 2017). Based on this evidence, we argue that more integration between these two strands of research could lead to a better understanding of farmers' sub-optimal (i.e., over- and under-use) fertilizer decisions.

The report is structured as follows. Section 7 provides the conceptual framework for farmers' fertilizer decision under risk and uncertainty. Section 8 explains the approach used to conduct the literature review. Section 9 synthetizes evidence from the literature review, while section 10 provides conclusions.

2. Conceptual framework

Fertilizer decisions are a crucial part of farming, spanning multiple production stages throughout the season. As displayed in Figure 1, the farmer's decision-making process starts with selecting the crops to grow and ends with harvest. Before and during production stages fertilizer is applied to supply plants with sufficient nutrients to reach an expected target yield.

Our conceptual framework mainly focuses on farmer's decision-making process about fertilizer use. This process has two main interrelated components. The first is the amount of fertilizer to use and the second is the timing of fertilization. This decision-making process involves risks and uncertainties about three main variables: fertilizer price, yield, and crop price at harvesting time. Expectations about future fertilizer prices, crop prices, and yields at the end of the season differ throughout the season and thus influence fertilizer decisions. Prices of fertilizer at each time of fertilization are deterministic, whereas the future fertilizer prices are uncertain. Therefore, at the time of fertilization, the expectation about revenues (as a function of crop prices and yields) at harvest time determines the expectation about the profitability of the fertilization investments. It is also reasonable to assume that uncertainty about random crop prices and yields decreases over time, meaning that it peaks at seeding time, and it reaches the lowest level at harvesting time.

Farmers' choices regarding the amount and timing of fertilizer application are often influenced by behavioral factors rooted in diverse theories of decision-making under risk and uncertainty.

In this conceptional framework, we assume that farmers have access to objective probabilities for random variables and that their preferences can be represented by a utility function, with its curvature reflecting their level of risk aversion. In this case, determining the amount of fertilizer to apply in a production stage becomes an expected utility maximization problem (e.g., Finger, 2012).

Yet, since farmers might be in fact unaware of the actual probabilities of, for example, future fertilizer prices and the likelihood of rainfall (or other production risks) during different production stages, behavioral factors related to theories of decision making under uncertainty become relevant (e.g., Bougherara et al., 2017; Cerroni, 2020). If farmers have enough knowledge and information to form a unique and well-defined subjective probability distribution, they make decisions under uncertainty and the standard economic framework of reference becomes the subjective expected utility theory (SEUT) by Savage (1954). SEUT is equivalent to EU with the only exception that objective probabilities are replaced by subjective probabilistic expectations. If farmers lack knowledge and information, they operate in the realm of ambiguity. They can form imprecise probabilistic expectations and develop ambiguity preference that deviates from neutrality (e.g., Baillon et al., 2018; Cerroni, 2020). Multiple theories of decision making under ambiguity were developed over time that take into consideration different behavioral factors. Loss aversion and/or probability weighting characterize many reference-dependent theories, such as rank-dependent utility theory (Quiggin, 1982), cumulative prospect theory (Tversky & Kahneman, 1992), and reference-dependent utility theory (Kőszegi & Rabin, 2006, 2007). While subjective probabilities characterize the standard models for decision making under uncertainty, subjective expected utility (Savage, 1954), ambiguity preferences and/or probability insensitivity characterize models of decision making under ambiguity. Examples are smooth ambiguity (Klibanoff et al., 2005) and alpha expected utility (Ghirardato et al., 2004). These behavioral factors may have a role in explaining farmers deviations from optimal fertilizer use that we often observe at farm level. Hyperbolic discounting models were instead developed to accommodate deviations from rational choice theory and exponential discounting in intertemporal decisions (e.g., Thaler et al., 1981; see Frederick et al., 2022 for a review).

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Concluding from the above, as farmers transition from seeding to harvesting, more information that was once uncertain is revealed, and the stochastic factors driving fertilizer use become increasingly deterministic. When modeling actual fertilizer use from an ex-ante perspective, we expect that behavioral factors related to uncertainty play a significant role in earlier fertilizer applications and, as a result, in the total amount of fertilization. We therefore derive search terms in the later systematic literature review process based on the above-mentioned preferences.

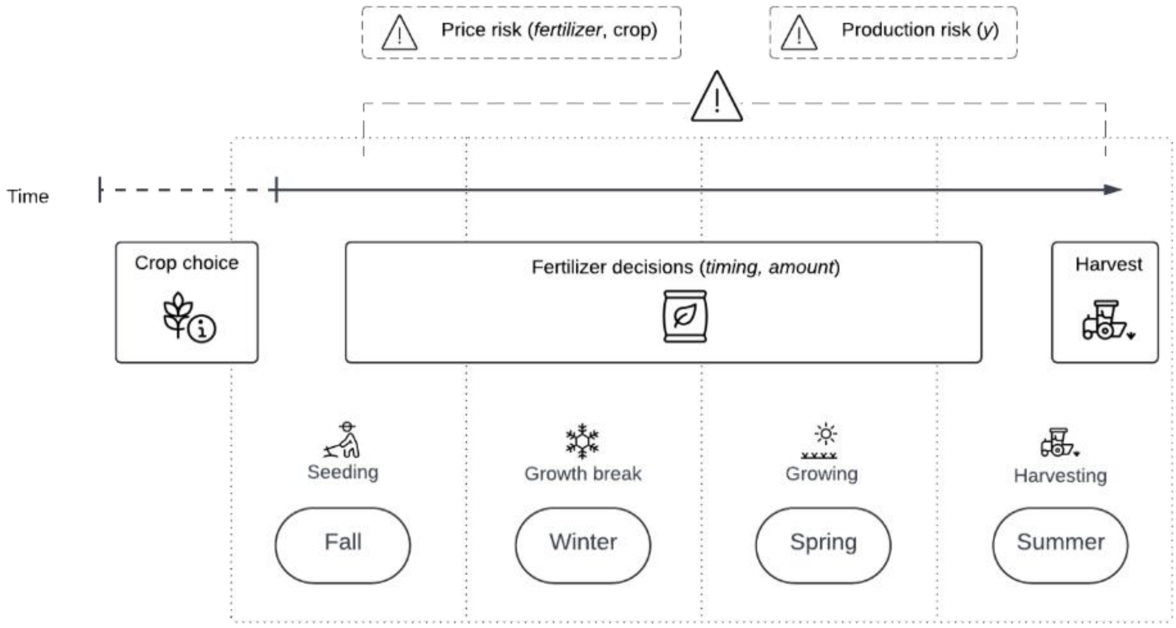

Figure 1. Farmers' production stages *(Reference: Created by the authors)*

3. Methods

Based on the PRISMA-P guidelines (Moher et al., 2015; Shamseer et al., 2015), we developed a pre-registration plan (Moritz et al., 2024). We then conducted a systematic review to synthesize findings of published studies related to our research question to transparently report the review process and findings (Page et al., 2021). Synthesizing all findings in reviewed studies reduces selection and confirmation bias, compared to a “traditional” or “narrative” literature reviews (e.g., Aromataris & Pearson, 2014). This systematic approach aims at providing a comprehensive and unbiased synthesis of current research and comprises six different steps: (1) define the main research question, (2) determine the search and selection strategy, (3) search and screen articles, (4) identify all relevant articles, (5) conduct a critical appraisal, and (6) synthesize the information gathered.

3.1 Search, screening, and data extraction

First, we created a list of keywords to identify relevant literature that also captures synonyms for “N fertilizer” and the behavioral factors of interest. With the help of these keywords and Boolean operators, we constructed two search strings, one for each used database: Scopus and Web of Science. After determining 43 articles as relevant literature in a preliminary search, we adjusted the search strings to include these in the final search process. Appendix Table 1 lists the final search strings that were utilized to retrieve all relevant literature in September 2024.

As shown in Figure 2, this search strategy yielded 1407 references and after the removal of duplicates, excluded document types, and excluded languages in 1114. Two independent reviewers then screened the title and abstracts of these records against defined inclusion criteria (see section 8.2) in the online software Rayyan (Ouzzani et al., 2016). 885 records were dropped in the title and abstract screening and 229 records entered the full-text assessment for eligibility, in which we dropped 171 records. For literature saturation, references of all 58 – so far – reviewed studies were scanned for relevant additions to the review (“snowball procedure”) and five records added afterwards. Finally, we discovered 63 records as relevant for our literature review.

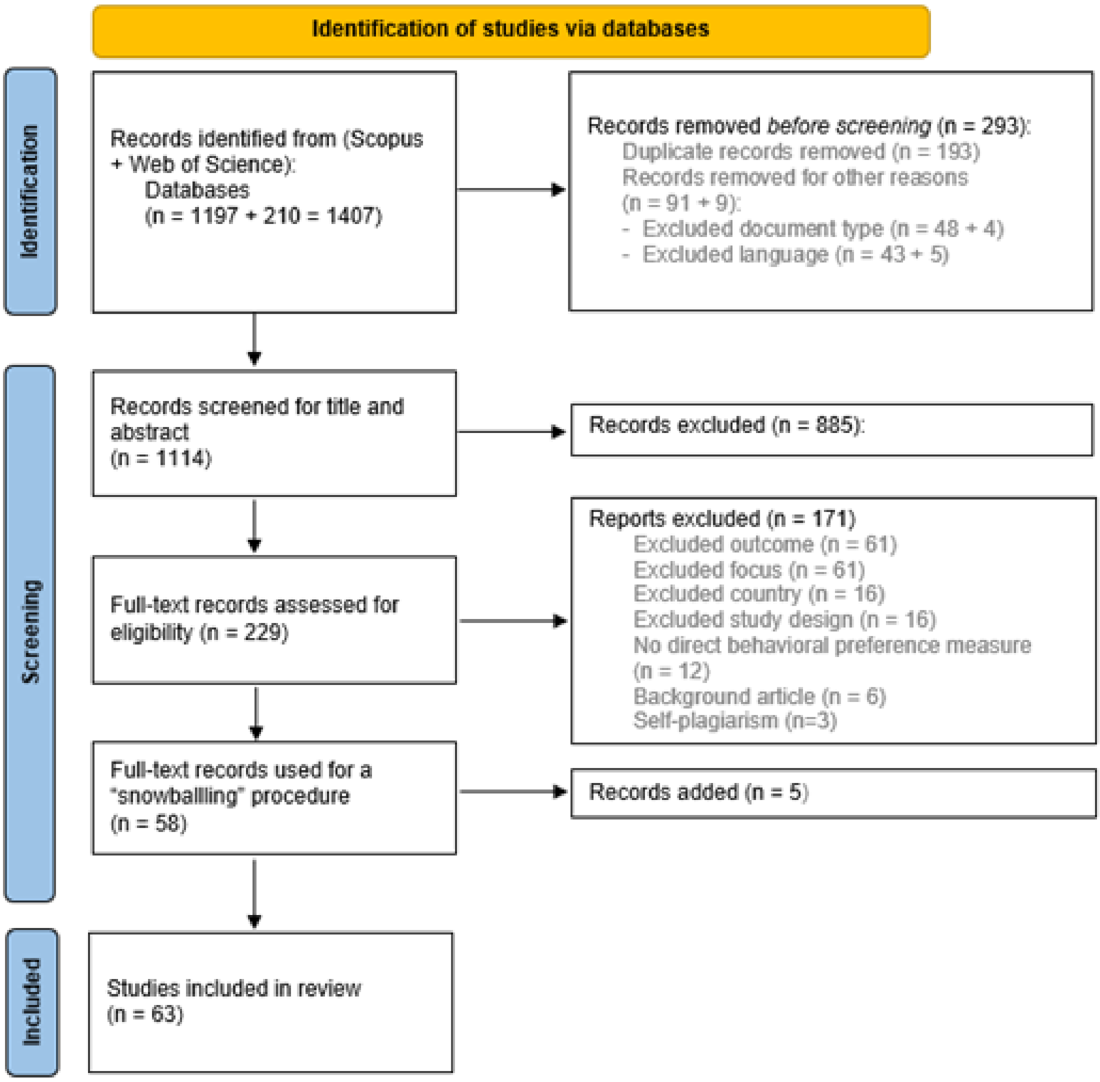

Figure 2. PRISMA flow diagram. *Note*: No automation tools were used in the identification nor screening process *(Reference: Created by the authors).*

Once we identified all relevant studies for our systematic literature review, we extracted and collected general information from these in a standardized form. Extracted metrics include general information (e.g., publication year, author(s), title), sample information (e.g., sample size), research methodology (e.g., sampling method, study design, studied behavioral factors), and key findings (e.g., direction and size effects). As the focus of this literature review is to analyze behavioral factors, methods used to study behavioral factors and their incorporation in economic modelling, and the fertilizer decision, we use these as additional categories in our extracted metrics.

Following the CASP (Critical Appraisal Skills Program) checklist for qualitative research and randomized controlled trials (Bird et al., 2019; Critical Appraisal Skills Programme, 2018, 2022; Elmiger et al., 2023), we also conducted a critical appraisal of all reviewed studies to assess their quality and scored them against four criteria: (1) clear study description, (2) appropriate comparison group/situation, (3) clear methods description, and (4) rigorous and clearly described analysis. Figure

3 presents the histogram of all quality scores that ranged between 2.5 and 4 (mean: 3.2, SD: 0.48), where "4" indicates that all four criteria are met. We do not exclude any study from this review.

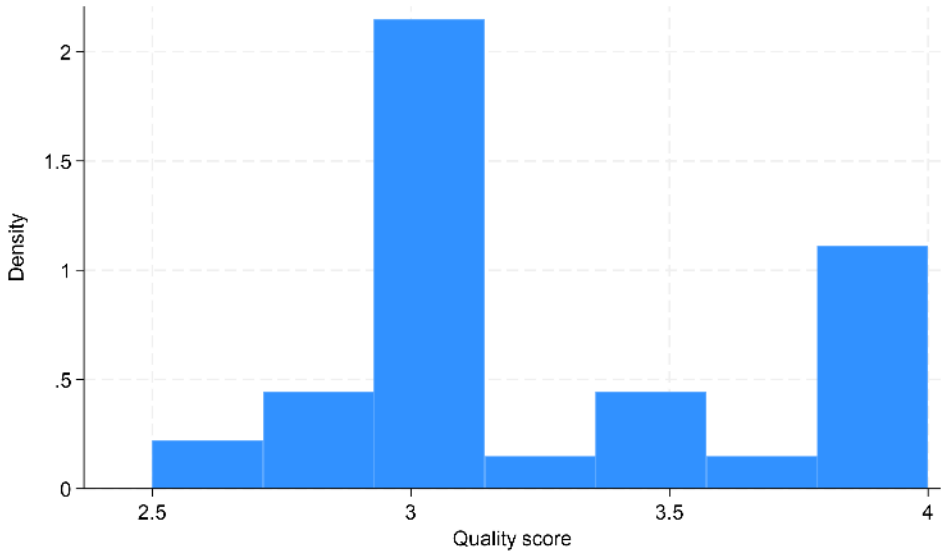

Figure 3. Distribution of quality scores across all reviewed studies *(Reference: Created by the authors).*

3.2 Eligibility criteria

We only included studies that relate farmers' behavioral factors and their N fertilizer use (including quantity, time, reduction, efficient use, optimal level, overuse). This also captures the adoption of organic farming as it directly implies limitations (reductions) in N fertilization (e.g., Krause et al., 2024). Included behavioral factors refer to the ones relevant in decision-making under risk and uncertainty: risk preferences, uncertainty preferences, ambiguity preferences, probability weighting, loss aversion, subjective probabilities, and time preferences (discounting). Included methods used to study the relationship between behavioral factors and fertilizer decisions are secondary data methods (econometric models, mathematical models), and primary data (stated preference surveys, and economic experiments).[2] Moreover, we limit this literature review to highly developed agricultural systems[3] and only include research that was published as traditional peer-reviewed literature in the English language.

[2] In this literature review, we apply a broad definition of stated preference methods that include all hypothetical studies that used stated behavioral factors and/or preferences over fertilizer management strategies. Hence, stated preference studies are not only discrete choice experiments and contingent valuation surveys.

[3] Highly developed agricultural systems are in what the International Monetary Fund (2021) defines as "advanced economies": Andorra, Australia, Austria, Belgium, Canada, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong SAR, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Macao, Malta, The Netherlands, New Zealand, Norway, Portugal, Puerto Rico, San Marino, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Taiwan, United Kingdom, United States.

3.3 General data description

This systematic literature review identifies 63 peer-reviewed studies on farmers' behavioral factors in fertilizer decision-making in high-income countries. As shown in Figure 4, the number of reviewed studies increased over time with a peak in 2015/2016. Behavioral factors in fertilizer research gained importance until the 2010s and then seems to slightly decrease in relevance in the 2020s.

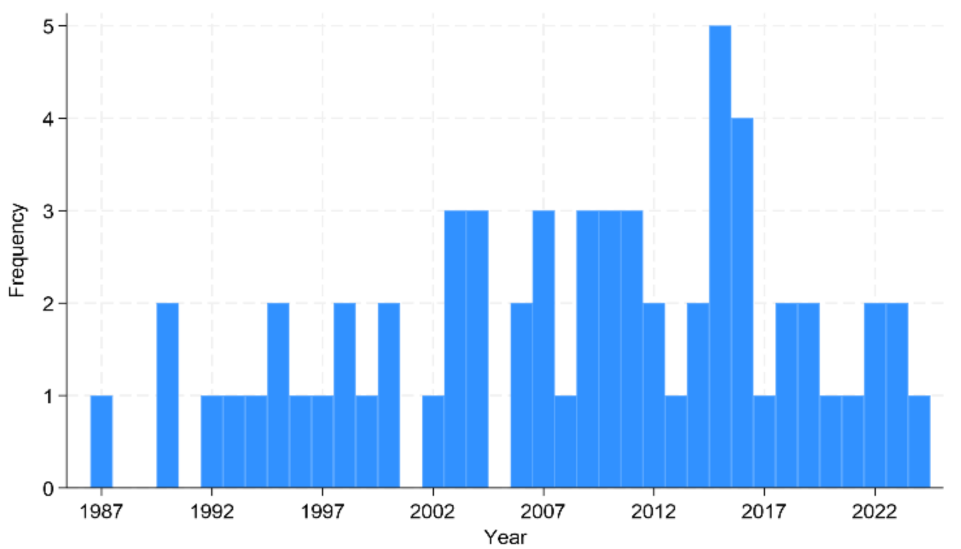

Figure 4. Publication frequency over time *(Reference: Created by the authors).*

Most reviewed articles were published in the following top journal disciplines: agronomy (36), economy (21), animal science (14), agricultural and biological science (10), renewable energy (6), sustainability and the environment (5). The journals publishing the most reviewed studies are *Agricultural Systems* (8) and *American Journal of Agricultural Economics* (7), *Journal of Sustainable Agriculture* (4), and *Agronomy Journal* (4) (see Table 1). Thus, reviewed studies are mainly located outside economic research. According to SCImago Journal Rank (SJR), reviewed articles were published in journals that ranked as the best quarter (41%) or second quarter (24%) in their discipline at the time of publication.[4]

[4] 4 Please note that the SJR ranking is missing for the year of publication in 24% of all reviewed studies.

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Table 1. Journals publishing reviewed studies *(Reference: Created by the authors).*

Journals publishing reviewed studies	
Journal	**Number of reviewed studies in this journal**
Agricultural Systems	8
American Journal of Agricultural Economics	7
Journal of Sustainable Agriculture	4
Agronomy Journal	4
Agricultural Economics	3
Canadian Journal of Agricultural Economics	2
Journal of Agricultural and Resource Economics	2
Canadian Journal of Agricultural Economics	2
Canadian Journal of Plant Science	2
Crop and Pasture Science	2
Renewable Agriculture and Food Systems	2
Sustainability (Switzerland)	2

Lastly, we observe some variation in the geographical distribution of reviewed studies (Figure 5): 51% focus on Northern America, whereas the United States alone captures 41%. Other studies address countries in Europe (41%), Australia (6%), or Israel (2%).

A summary of all reviewed studies with relevant background information is presented in Appendix Table 2.

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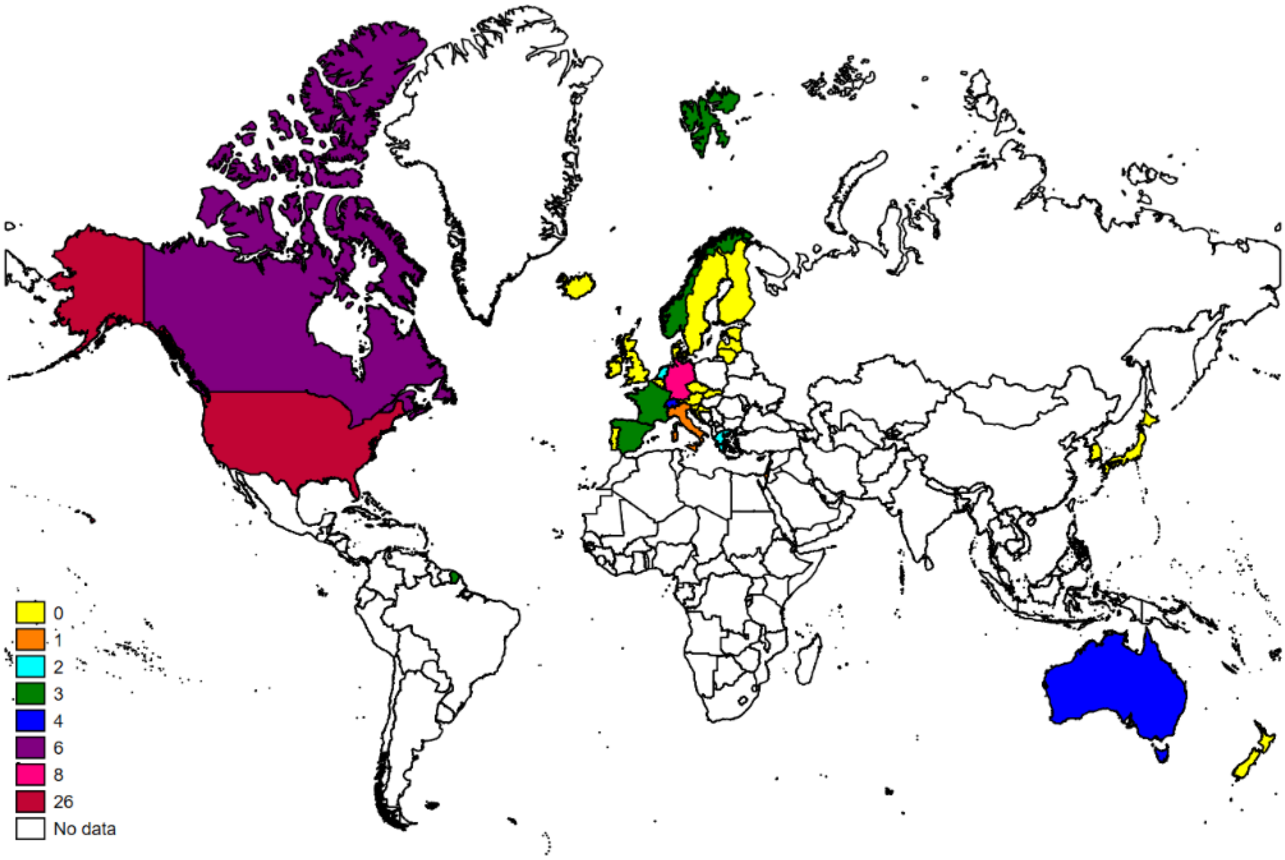

Figure 5. Geographical distribution and frequency of countries analyzed in the reviewed studies *(Reference: Created by the authors).*

4. Results and discussion

All 63 reviewed studies explore the correlation between risk preferences and decisions on the use of N fertilizer. Two studies additionally consider another behavioral factor: ambiguity preferences (Tevenart & Brunette, 2021) and subjective probabilities (SriRamaratnam et al., 1987). Therefore, this section mainly focuses on risk preferences as a driver of different N fertilizer decisions. Appendix Table 2 provides a summary of all the details discussed for each reviewed study.

4.1 Overview of applied methods and studied N fertilizer decisions

Applied methods:

We briefly provide a description of the methods used to consider behavioral factors (mainly risk preferences) in farmers' N fertilizer decisions. Following Iyer et al. (2020), we categorize these as methods (1) using secondary data: mathematical and econometric methods, and (2) methods using primary data: stated preference and economic experimental methods. Figure 6 groups these different methods and reports how often they are represented in this literature review.

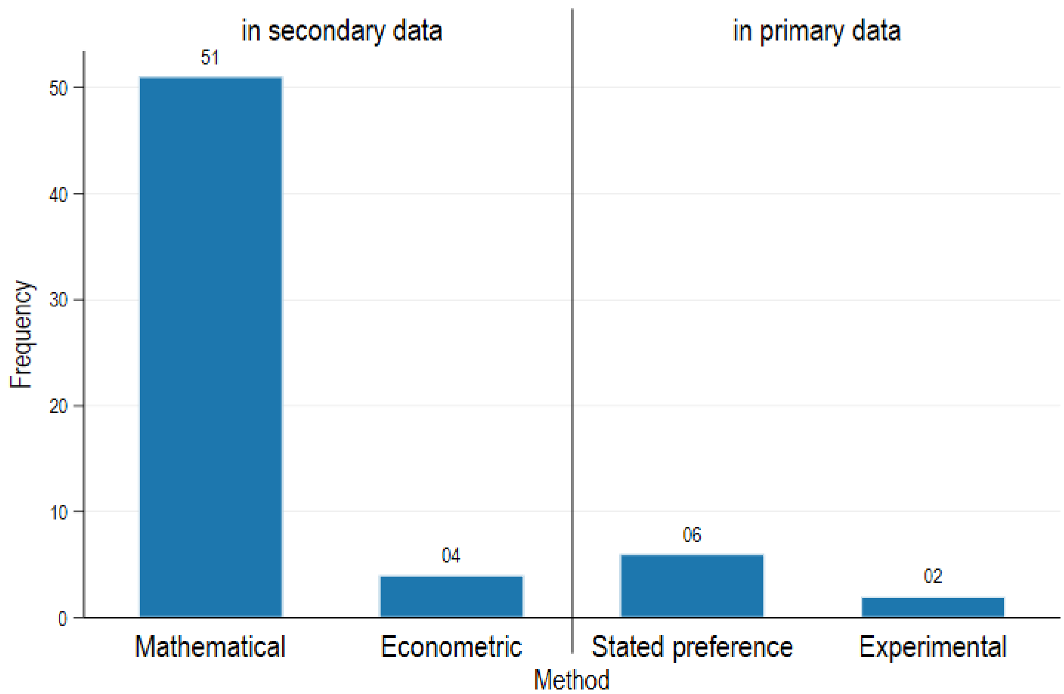

Figure 6. Categorization of methods to incorporate behavioral factors in fertilizer decision modelling in high-income countries *(Reference: Created by the authors).*

Secondary data methods rely on existing data to explore the relationship between optimal use of N fertilizer and risk preferences in *mathematical methods*, and to elicit risk preferences in *econometric methods*.

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Mathematical methods study the relationship between risk preferences and the optimal N fertilizer usage assuming expected utility maximization. In this category, mathematical programming identifies the optimal N fertilizer usage, given specific constraints, and by simulating (i.e. assuming) different risk preferences, such as different degrees of risk aversion (e.g., Babcock & Hennessy, 1996; Finger, 2012; Finger et al., 2014). In some instances, studies using mathematical programming aim to investigate the inter-temporal optimal N fertilizer usage (e.g., Bontems & Thomas, 2006; Zentner et al., 1992). Stochastic dominance, instead, provides a decision rule to identify the optimal N fertilizer usage by comparing probability distributions related to uncertain outcomes (e.g., yields) under different risk preference assumptions (e.g., Roosen & Hennessy, 2003; Schaub & Benni, 2024). Table 2 in the Appendix provides the full list of reviewed papers using mathematical programming and stochastic dominance.

Econometric methods estimate farmers' risk preferences within an EUT framework. Reviewed studies apply structural and non-structural approaches. Structural approaches imply the use of a specified functional form for the utility function to estimate risk preferences (e.g., Saha, 1997). Non-structural approaches do not directly define the utility function and estimate moments of the distribution of a random variable (e.g., profits) that are related to changes in expected utility (e.g., Antle, 1989). Appendix Table 2 provides the full list of reviewed papers using econometric methods.

Primary data methods generally elicit risk preferences using *stated preference surveys and economic experiments*. Many studies then test the correlation between elicited risk preferences and farmers' intended or real decisions regarding fertilizer application using different statistical approaches.

Stated preference surveys elicit risk preferences asking farmers to directly state their attitudes towards risk or risky scenarios using Likert Scales (e.g., Dohmen et al., 2011; Finger et al., 2023). Alternatively, stated preference methods can also ask farmers to make choices between hypothetical risky prospects that can be then used to infer farmer risk preferences (e.g., Menapace et al., 2013). Table 2 in the Appendix provides the full list of reviewed papers using stated preference methods.

Economic experiments use incentive-compatible and incentivized lottery tasks to elicit farmers risk preferences (e.g., Rommel et al., 2023; Tanaka et al., 2010). Incentive compatibility is achieved when a proper monetary incentive scheme is included that induces participants to provide truthful responses (Cummings et al., 1997; Smith, 1986). It is important to note that incentive compatibility is a theoretical property and incentive-compatible methods do not necessarily elicit truthful preferences and beliefs in practice. For an in-depth discussion of pros and cons of economic experiments, we refer to Cerroni et al. (2023), Danz et al. (2022, 2024) and Harrison et al. (2004). Appendix Table 2 provides the full list of reviewed papers using economic experiments.

As illustrated in Figure 6, 87% studies (55 of 63 studies) in this literature review incorporate behavioral factors in fertilizer decision modelling using secondary data. Of these, 94% (51 studies) apply mathematical methods and 8% (4 studies) econometric methods. Seminal work of secondary data methods in our literature review include Babcock and Hennessy (1996), Bontems and Thomas (2006), Gardebroek (2006), Isik and Khanna (2003) and Serra et al. (2008). Primary data methods receive less attention, accounting only for 13% (8 of 63) of reviewed studies. Of these, 75% (6 of 8 studies) use stated-preference methods and 25% (2 of 8 studies) economic experiments. We consider Kallas et al. (2010), SriRamaratnam et al. (1987), and Vollmer et al. (2017) as seminal work for primary data methods.

Studied N fertilizer decisions:

We now provide a brief description of the fertilizer decisions that are studied in the reviewed articles. These are categorized as follows: *Optimal N fertilizer* refers to the optimal amount of N fertilizer that is used by farmers at specific time during the production process. *Applied N fertilizer* is the actual amount of N fertilizer that is used by farmers at specific time during the production process. *Overuse of N fertilizer* refers to the difference between optimal and applied N fertilizer. *Organic fertilizer* refers to the use of organic fertilizer by farmers. This category is included since the use of synthetic fertilizer is limited in organic agriculture and N fertilizer application reduced (e.g., Krause et al., 2024).

Figure 7 indicates that 62% (39 of 63 studies) explore the optimal N fertilizer application behavior. 24% of all studies in this review (15 of 63) analyze organic fertilizer behavior. Less attention receives the actual (overuse) fertilization behavior. Only 10% (6 of 63 studies) examine the actual quantity of N fertilization and 5% (3 of 63 studies) focus on overuse. Across all studied fertilizer decisions, different time dimensions are included in twelve studies (19%). When modelling the optimal N fertilizer decisions, eight studies differentiate between the first and total amount of N fertilization. Of these, five explore the optimal N fertilizer amount conditional on the probability of failing to apply it in the growing season. Another study only focuses on optimal N fertilization in the first application. In research on the reported amount of N fertilizer used by sampled farmers, one study differentiates between the initial and total quantities applied. In the context of organic fertilizer adoption, two studies address the time required for the farm to transition from conventional to organic farming. Table 2 in the Appendix provides the full list of reviewed papers focusing on each of the listed fertilizer decisions.

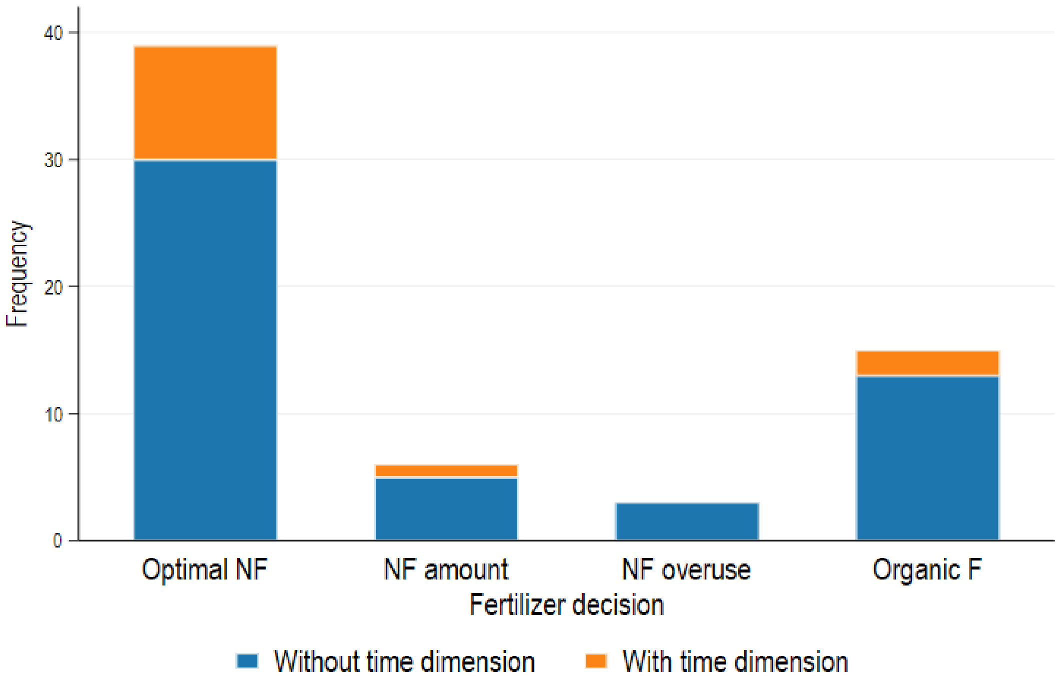

Figure 7. Frequencies of studied fertilizer decisions *(Reference: Created by the authors).*

4.2 Results and findings

We now present results about the relationship between risk preferences and N fertilizer usage regarding the main fertilizer decision groups presented above. We further provide considerations regarding the methods used to study such relationships.

Figure 8 displays the number of studies focusing on each fertilizer decision and the number of studies within each fertilizer decisions using different methodological approaches. Studies that focus on optimal N fertilizer use mainly use mathematical methods (97% - 38 of 39 studies), while only one study employs econometric methods. This is not surprising as mathematical methods are particularly suited to investigate optimal N fertilizer use. When the study focus is on the actual N fertilizer amount, 67% (4 of 6 studies) use mathematical methods and the remaining two stated preference surveys. Research that studies N fertilizer overuse is scant. 67% (2 of 3 studies) of this research uses mathematical methods, while the remaining study employs an econometric approach. We observe more method heterogeneity in research on organic fertilizer: 47% (7 of 15 studies) use mathematical methods, 27% (4 of 15 studies) apply stated preference techniques, and 13% each (2+2 studies of 15) employ econometric methods and conduct economic experiments, respectively.

Next, we turn our attention to the correlations between behavioral factors (mainly risk preferences) and the different fertilizer decisions. We categorize the correlation findings for each fertilizer decision separately as reported in Table 2 that provides a graphical mapping of main results.

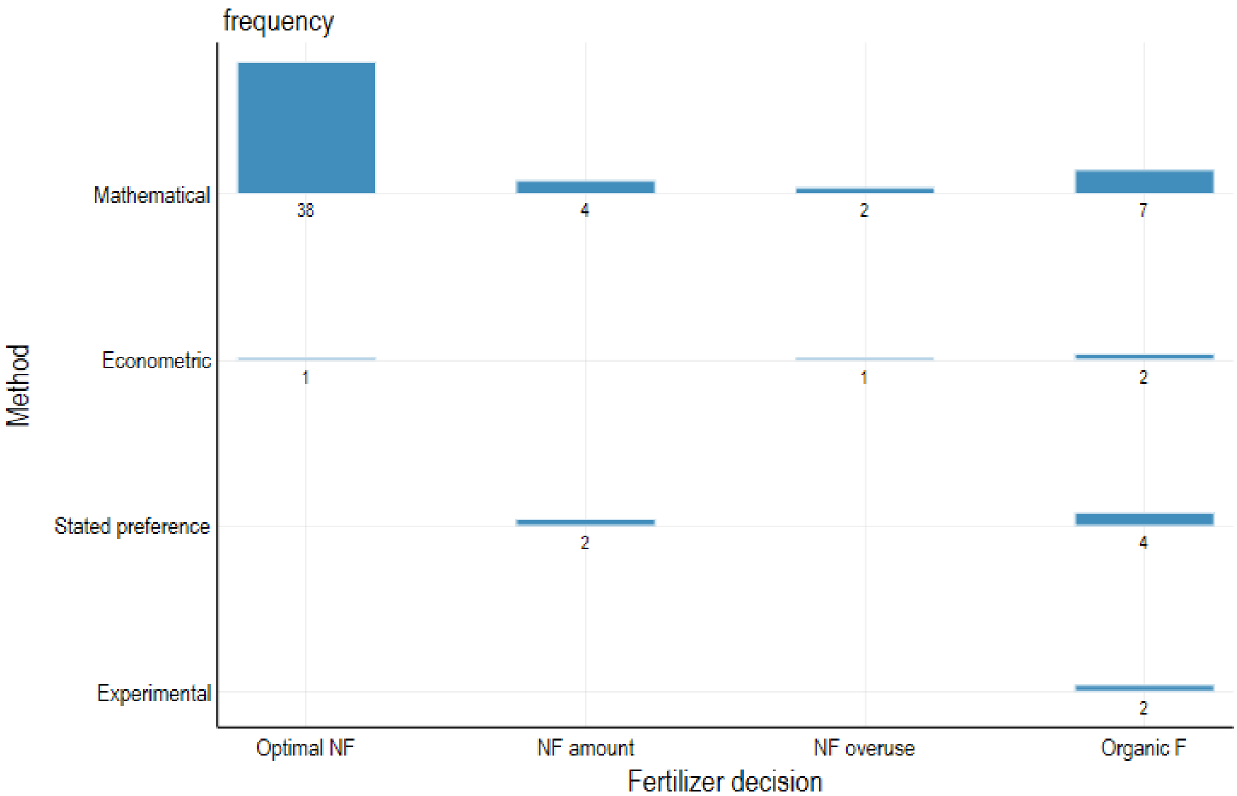

Figure 8. Interaction frequencies of studied fertilizer decisions and applied methods to incorporate behavioral factors. *Note*: “NF” refers to nitrogen fertilizer *(Reference: Created by the authors).*

<u>Optimal N fertilization (39 studies):</u>

As expected, the vast majority of studies focusing on optimal N fertilizer use mathematical methods (38 of 39). Theoretical models predict that the optimal amount of N fertilizer is lower for risk-averse farmers, compared to risk-neutral and risk-seeking farmers. This prediction holds if farmers perceive the use of N fertilizer as risk-increasing for production (e.g., Isik, 2002; Roosen & Hennessy, 2003). Such perception can be driven by adverse production and market conditions (Asci et al., 2015).

Among the 38 studies using mathematical methods, 68% (26 of 38 studies) identify that the optimal rate of N fertilizer is lower for farmers with higher risk aversion (i.e., negative correlation), supporting theoretical predictions. Several studies find that farmers with extremely or very high risk aversion tend to have a lower optimal N rate compared to risk-neutral farmers (e.g. Asci et al., 2015; Boyer et al., 2015, 2018; Cox et al., 2010; Lambert, 1990; Meyer-Aurich et al., 2009, 2016, 2020; Meyer-Aurich & Karatay, 2019; Monjardino et al., 2013, 2015, 2019; Pendell et al., 2007; Smith et al., 2012, 2015; Walburger et al., 2004). Other studies indicate that this finding also holds for more moderate levels of farmers' risk aversion (Chen et al., 2024; Finger, 2012; Finger et al., 2014; Isik, 2002; Roosen & Hennessy, 2003), and when various contextual conditions vary: soil nitrate level (Paulson and Babcock, 2010), rainfall level (Regev et al., 1997), the introduction of crop or revenue insurance coverage (Babcock & Hennessy, 1996), and the implementation of N taxes (Finger, 2012).

However, 18% (7 of 38) of reviewed studies find a positive effect of risk aversion on the optimal N fertilizer amount (e.g., Anderson & Kyveryga, 2016), 8% (3 of 38 studies) present mixed results (e.g., Bontems and Thomas, 2006), and two studies null effects (e.g., He et al., 2022).

Yet, when including the time of fertilizer application, general evidence changes. Using mathematical methods to study optimal N fertilizer applications, 63% (5 of 8 studies) then show a positive correlation between risk aversion and N fertilizer application. This correlation pattern is particularly evident when fertilization during the growing season may not be feasible (Feinerman et al., 1990; Huang et al., 1993, 1994, 1998, 2000). The remaining mathematical method studies that consider the timing of optimal N fertilizer find either mixed results (Bontems & Thomas, 2006; Huang et al., 1995) or a negative correlation between risk aversion and N fertilizer amounts (Zentner et al., 1992). The only study that focuses on optimal amount and timing using econometric approaches suggests that the optimal N fertilizer amount increases with higher risk aversion (Dequiedt et al., 2023).

<u>Quantity of N fertilization (six studies):</u>

When using mathematical methods, 50% (2 of 4 studies) indicate that actual N fertilization application is lower when farmers are more risk averse, suggesting a negative correlation between the amount of N fertilizer used and risk aversion (Larson et al., 1998; Schaub & Benni, 2024). Lu et al. (1999) find the oppositive effect, while Paudel et al. (2000) take a different approach and compare fertilization amounts of risk-minimizing and regret-minimizing farmers. Paudel et al. (2000) conclude that regret-minimizers apply more N fertilizer than risk-minimizers.

The two studies based on stated preference surveys provide mixed evidence. SriRamaratnam et al. (1987) find that farmers are risk neutral or moderately risk averse, and risk aversion (slightly) increases N application, while Tevenart and Brunette (2021) discern that the majority of farmers are risk averse and find that risk-averse farmers use lower total annual quantities of N fertilizer (compared to the others), consistently with findings from studies using mathematical methods.

SriRamaratnam et al.'s study (1987) is the only study eliciting subjective probabilities about yield expectation under different levels of N fertilizer usage. Interestingly, they explore farmers belief updating after receiving objective information from agronomic experiments and observe that farmers with little previous experience on a particular N level of fertilizer usage are overoptimistic about the N-response in yield and revise their probabilistic beliefs. Farmers with historical experience only slightly revise and their beliefs are already quite accurate.

Tevenart and Brunette's study (2021) is also the only attempt to elicit ambiguity preferences and link these to farmers' fertilizer usage. The study concludes that farmers are predominately ambiguity-neutral, but ambiguity preferences have little effect on N fertilization decisions (only in the first splitting).

Overuse of N fertilization (three studies):

Only three studies look at the overuse of N fertilization, which represents a sub-optimal choice assuming an expected utility framework. In this category, Rajsic et al. (2009) and Rosas et al. (2015) converge on the result that more risk-averse farmers reduce the overuse of N fertilizer using mathematical methods. Isik and Khanna (2003), using econometric methods, suggest that risk-averse farmers have a lower probability to adopt site-specific technologies (SST) to apply adequate fertilizer rates (reduce overfertilization).

Organic fertilization (15 studies):

In the context of organic farming, studies using mathematical 13% (2 of 15 studies) report that risk-averse farmers tend to use more organic fertilizer and reduce N fertilizer amounts (Lu et al., 2003; Zentner et al., 2011). Both studies employ mathematical approaches.

However, there is more evidence for the opposite effect: 47% (7 of 15 studies) observe a positive correlation between higher risk aversion and conventional farming associated with higher N fertilizer use. This evidence is found in various methods to incorporate risk preferences into the fertilizer model: mathematical methods (Acs et al., 2009; Liontakis & Tzouramani, 2016), econometric methods (Gardebroek, 2006), and stated preference methods (Kallas et al., 2010; Koesling et al., 2004; Parra-Lopez et al., 2007).

Lastly, the remaining 33% (5 of 15 studies) present evidence of a null effect between risk preferences and organic fertilization in various methodological approaches: mathematical methods (Flaten & Lien, 2007; Tzouramani et al., 2011), econometric methods (Serra et al., 2008), and in experimental studies (Hermann et al., 2016; Vollmer et al., 2017).

Overall conclusions:

Empirical evidence from studies using mathematical methods partially supports the theoretical prediction that risk-averse farmers apply less N fertilizer compared to their risk-neutral or risk-seeking counterparts. This indicates that N fertilizer decisions can deviate from rational behavior but reasons for this remain unclear.

Evidence on the relationship between risk preferences and actual fertilizer use or overuse is mixed. This inconsistency may arise from the contextual of risk preferences, as well as the different methodological approaches employed in these studies.

Regarding organic farming, we find mixed evidence on how risk preferences affect the use of organic fertilizer that also seems to be method-dependent. Yet, results in the organic farming context should be treated more cautiously as a conversion to organic farming is a complex decision that has important consequences on crop management practices, soil health improvements, pest control methods, and compliance with certification standards.

Table 2. Synthesis of the evidence of risk preferences on fertilizer decisions across different methods *(Reference: Created by the authors).*

Synthesis of the evidence of risk preferences on fertilizer decisions across different methods					
Method / **Fertilizer decision**	**Mathematical methods** (51 studies)	**Econometric methods** (4 studies)	**Stated preference methods** (6 studies)	**Economic experiments** (2 studies)	**Overall assessment**
Optimal N fertilizer (39 studies)	*38 studies*: often detailed analysis of different degrees of risk aversion but neglect risk-seeking preferences; mostly: risk aversion ↓ optimal N rate. 9 studies consider fertilizer timing.	*1 study*: all risk preferences; risk aversion ↑ optimal N rate.	/	/	Quite good general evidence, little knowledge on the role of risk affinity, little knowledge on method sensitivity, correlation effect seems method-dependent. Little evidence on fertilization decision over time.
Actual quantity N fertilizer (6 studies)	*4 studies*: mostly: risk-neutral vs. risk-averse analysis; mostly: risk aversion ↓ N rate.	/	*2 studies:* different risk preferences; mixed results. 1 study considers fertilizer timing.	/	Little general evidence, little knowledge on the role of risk affinity, little knowledge on method sensitivity, correlation effect seems method-dependent. Little evidence on fertilization decision over time.
Overuse (3 studies)	*2 studies:* similar methods; different risk aversion levels; risk aversion ↓ overuse	*1 study*: all risk preferences; risk aversion ↑ N overuse.	/	/	Overall, very limited knowledge on everything!
Organic fertilizer (15 studies)	*7 studies*: often detailed analysis of different degrees of risk aversion but neglect risk-seeking preferences; rather mixed correlation results.	*2 studies*: all risk preferences; risk aversion ↓ organic fertilizer adoption.	*4 studies:* risk aversion vs. risk affinity; risk aversion ↓ organic fertilizer adoption. 2 studies consider adoption duration.	*2 studies*: all risk preferences; no significant effects.	Good general evidence, good knowledge on different risk preferences and method sensitivity, correlation effect seems method-dependent. Little evidence on organic fertilization over time.

5. Conclusions

The use of fertilizer in agricultural production is key for the economic resilience of farming systems but also to guarantee food security worldwide. Deviations from an optimal use of N-based fertilizer can have important consequences on the economic, social and environmental sustainability of food systems. On the one hand, the excessive application of synthetic nitrogen-based (N-based) fertilizer has raised both environmental and economic concerns due to price volatility, posing risks to the sustainability and resilience of farming systems. On the other hand, inadequate fertilizer use can threaten food security.

Deviations from an optimal use of N fertilizer represent departures from standard economic theory and expected utility or profit maximization. To gain a deeper understanding of these deviations, this deliverable presents a conceptual framework outlining the key decisions farmers typically make regarding fertilizer use, namely the quantity applied and the timing of application. These decisions are made under conditions of risk and uncertainty regarding three main random variables: crop prices, fertilizer prices, and yields. The conceptual framework accommodates deviations from utility and profit maximization by acknowledging the influence of behavioral factors that underly non-standard economic theories. Examples of such behavioral factors are: loss aversion, ambiguity preferences, hyperbolic discounting, probabilistic expectations, and probability distortions.

To gain better understanding of the literature studying the role of behavioral factors in fertilizer decision-making in high-income countries, we conducted a literature review following the PRISMA approach. Three main findings that could stimulate interesting considerations for further research emerge from our literature review.

First, nearly all studies, with only two exceptions, examine the influence of risk preferences on fertilizer application within the framework of expected utility theory. The remaining two investigate other behavioral factors: ambiguity preferences (Tevenart & Brunette, 2021) and subjective probabilities (SriRamaratnam et al., 1987). This highlights that, although farmers' fertilizer decisions often deviate from optimal levels at the farm level (i.e., under- and overuse of N fertilizer), the scientific community mostly ignores this phenomenon and its causes. Science continues to interpret and model fertilizer decisions in a standard utility maximization framework that assumes no deviation from rationality. In addition, while most of farmers' fertilization decisions imply, at least, some level of uncertainty about fertilizer and output prices as well as crop yields, current research predominantly ignores theories of decision making under uncertainty and ambiguity. This disregards related behavioral factors such as loss aversion, subjective probabilistic expectations and probability weighting, ambiguity preferences and non-standard discounting like hyperbolic discounting. Theories that could explain some aspects of non-optimal farmers' fertilizer decisions are reference-dependent theories, rank-dependent utility theory (Quiggin, 1982), cumulative prospect theory (Tversky & Kahneman, 1992), reference-dependent utility theory (Kőszegi and Rabin, 2006; 2007), subjective expected utility theory (Savage, 1954), smooth ambiguity theory (Klibanoff et al., 2005), and alpha expected utility theory (Ghirardato et al., 2004).

Second, and related to the first finding, our literature review highlights that most of the research overlooks the main problem related to farmers' fertilization decisions, that is fertilizer overuse. The vast majority of the reviewed studies aim at understanding the extent to which optimal fertilizer decisions vary assuming different degrees of risk aversion using mathematical approaches based on mathematical optimization procedures or stochastic dominance. Only a limited number of studies focus on the relationship between risk preferences and actual N fertilizer use or overuse, and results from these studies are mixed. This suggests that future research is needed to shed light on the correlation between risk preferences and other behavioral factors that relax strict rationality assumptions behind expected utility or profit maximization,

Third, and related to the previous points, our literature review suggests that strands of research using different methodological approaches mainly ignore each other. Research conducted using mathematical models is largely detached from research estimating risk preferences using econometric approaches or research eliciting risk preferences using stated preference surveys and economic experiments. A first step to bridge this gap would be to incorporate qualitative risk preferences measures (qualitative judgements) elicited in stated preference surveys in mathematical models. Alternatively, one could also use quantitative risk preferences coefficients estimated via econometric approaches or elicited using economic experiments in mathematical methods based on optimization procedures. This relatively small step already presents some fundamental challenges such as the feasibility of incorporating qualitative judgments into formal economic models or the endogeneity that could be generated by measurement errors arising when eliciting quantitative risk preference coefficients using economic experiments (see Cerroni, 2020; Cerroni et al., 2023 for a discussion). There is a large amount of empirical evidence that risk preferences elicited using hypothetical and incentivized lottery tasks are unstable across methods and time (e.g., Finger et al., 2023; Reynaud & Couture, 2012).

Relaxing the rationality assumption by incorporating elements of non-standard economic theories would be ever more challenging. This approach will introduce additional complexities and probably raise the estimation computational burden of mathematical optimization procedures. The most realistic step would be the incorporation of cumulative prospect theory's behavioral factors such as loss aversion and probability weighting into agent-based models. This would be facilitated by the large amount of empirical work aiming at eliciting such behavioral factors from farmers. Meta-analysis and replication studies are available in the literature (e.g., Garcia et al., 2024; Rommel et al., 2023). In addition, there are attempts to incorporate behavioral insights in agent-based model at farm level (e.g., Appel & Balmann, 2019; Huber et al., 2022, 2023). Extensions incorporating other models of decision making under uncertainty and ambiguity would be challenging in the near future. One barrier is the lack of the empirical evidence about farmers' ambiguity preferences. Only few studies have been attempted the elicitation of farmers uncertainty and ambiguity preferences, and research is not yet consolidated in this area (e.g., Bougherara et al., 2017; Cerroni, 2020).

A limitation of this deliverable is that we only consider N fertilizer (and organic fertilizer), ignoring other types of fertilizer. The main focus on N fertilizer is due to the fact that these are the most commonly used fertilizers and their impact on the environment is well documented.

While we acknowledge that the incorporation of behavioral insights into complex optimization models is a considerable challenge, we also believe this scientific approach is the way forward to achieve a comprehensive understanding of farmers' fertilization behaviors and design policy instruments that can improve the sustainability and resilience of farming and food systems.

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APPENDIX

Table A1. Final search strings *(Reference: Created by the authors).*

Final search strings		
Database	**Search string**	**Hits**
Scopus	TITLE-ABS-KEY ((fertilizer OR "agricultural fertilization" OR "nutrient management" OR "nitrogen application" OR "N application" OR "nitrogen management" OR "N management" OR organic) AND (farm* OR produc* OR grower)) AND ALL (("uncertainty preference" OR "uncertainty attitude" OR "uncertainty consideration" OR "uncertainty avers*" OR "risk preference" OR "risk attitude" OR "risk consideration" OR "risk avers*" OR "ambiguity preference" OR "ambiguity attitude" OR "attitude consideration" OR "ambiguity avers*" OR "probability weighting" OR "loss avers*" OR "subjective probability" OR "time preference" OR "temporal preferences" OR "hyperbolic discounting" OR "delay discounting"))	1197
Web of Science	AB = ((fertilizer OR “agricultural fertilization” OR "nutrient management" OR "nitrogen application" OR "N application" OR "nitrogen management" OR "N management" OR organic) AND (farm* OR produc* OR grower)) AND ALL = ("uncertainty preference" OR "uncertainty attitude" OR "uncertainty consideration" OR "uncertainty avers*" OR "risk preference" OR "risk attitude" OR "risk consideration" OR "risk avers*" OR "ambiguity preference" OR "ambiguity attitude" OR "attitude consideration" OR "ambiguity avers*" OR "probability weighting" OR "loss avers*" OR "subjective probability" OR “time preference” OR “temporal preferences” OR “hyperbolic discounting” OR “delay discounting”)	210

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Table A2. Study overview *(Reference: Created by the authors).*

Study overview								
Study	**Behavioral factor (BF)**	**Method to incorporate BF**	**Assumed utility function**	**Assumed/ measured/ estimated BF preference**	**Fertilizer (F) decision**	**Finding of BF on N application**	**Year of analysis**	**Country**
Acs et al. (2009)	Risk preferences	Mathematical	Negative exponential	CARA (0 - 0.0000048)[b]	Organic adoption	RA increase	n/a	Netherlands
Anderson & Kyveryga (2016)	Risk preferences	Mathematical	n/a	Risk-tolerant, risk-neutral, risk-averse (own definition)	Optimal N F amount[+]	RA increase	2006 - 14	USA
Asci et al. (2015)	Risk preferences	Mathematical	n/a	RRAC (0 vs. 2)[b]	Optimal N F amount	RA decrease	1952 - 2010	USA
Babcock & Hennessy (1996)	Risk preferences	Mathematical	Negative exponential	CARA (0-0.01)[b]	Optimal N F amount	RA decrease	1986 - 91	USA
Bontems, & Thomas (2006)	Risk preferences	Mathematical	vNM	CRRA (0-5)[b]	Optimal N F amount & timing	Mixed	1994	France
Boyer et al. (2015)	Risk preferences	Mathematical	Power UF: $U = \frac{\pi_i^{1-r}}{1-r}$	RRAC (0-3)[b]	Optimal N F amount[+]	RA decrease	2006 - 12	USA
Boyer et al. (2018)	Risk preferences	Mathematical	Negative exponential	ARAC (0-0.03)[b]	Optimal N F amount	RA decrease	1984 - 2012	USA
Capitanio et al. (2014)	Risk preferences	Mathematical	Negative exponential	DARA (1 vs. 3, low vs. high RA)	Optimal N F amount	RA decrease	2003 - 08	Italy
Chen et al., (2024)	Risk preferences	Mathematical	Negative exponential	CARA (0-0.008)[d]	Optimal N F amount	RA decrease	2018 - 22	USA

Choi & Feinerman (1995)	Risk preferences	Mathematical	CRRA UF: $U = -\pi^{1-R}$	CRRA (0 vs. 123)[b]	Optimal N F amount in early application	RA increase	1969 - 70	Israel
Cox et al. (2010)	Risk preferences	Mathematical	Negative exponential	CARA (0-0.02)[b]	Optimal N F amount[+]	RA decrease	1995 - 98	Australia
Dequiedt et al. (2023)	Risk preferences	Econometric	Negative exponential	CARA (%risk-loving > %risk-averse > %risk-neutral)	Optimal N F amount	RA increase	2010 - 13	France
Feinerman et al. (1990)	Risk preferences	Mathematical	Bounded exponential (CARA): $1 - e^{-\gamma\pi}$ Power (CRRA): $U = -\pi^{1-R}$	CARA (0-0.0005), CRRA (0-20)[b]	Optimal N F amount & timing	RA increase	1955 - 87	USA
Finger (2012)	Risk preferences	Mathematical	(Follow Di Falco et al. (2007) to calculate risk premium and then max CE)	CRRA (0 vs. 2)[c]	Optimal N F amount	RA decrease	1981 - 2006	Switzerland
Finger et al. (2014)	Risk preferences	Mathematical	Following Chavas et al. (2009), power UF: $U = (1-\tau)^{-1}\pi^{1-\tau}$	ARAC (0-3)[c]	Optimal N F amount	RA decrease	1993 - 2002, simulate 2071 - 2100	Switzerland

Flaten et al. (2005)	Risk preferences	Stated preference	-	Risk aversion	Organic adoption	RA increase ($RA_{organic}$ < $RA_{convetional}$)	2002 - 03	Norway
Flaten & Lien (2007)	Risk preferences	Mathematical	Negative exponential	CARA (0-0.000003)[b]	Organic adoption	Zero	2003 - 04	Norway
Gandorfer et al. (2011)	Risk preferences	Mathematical	CRRA UF: $U = c + dW_t^{1-R}$	RRAC (0-4)[b]	Optimal N F amount[+]	Zero	1994 - 2006	Germany
Gardebroek (2006)	Risk preferences	Econometric	"is not explicitly defined"	CARA measure	Organic adoption	RA increase ($RA_{organic}$ < $RA_{convetional}$)	1990 - 99	Netherlands
Harmon et al. (2018)	Risk preferences	Mathematical	Power UF: $U = \frac{\pi_{ij}^{1-r}}{1-r}$	ARAC (0-3)[b]	Optimal N F amount[+]	RA decrease	1981 - 2012	USA
He et al. (2022)	Risk preferences	Mathematical	Negative exponential	ARAC (0-0.0017)[b]	Optimal N F amount	Zero	2016 - 18	USA
Hermann et al. (2016)	Risk preferences	Experimental	-	Holt & Laury (2002) values	Organic adoption	Zero	2013	Germany
Huang et al. (1993)	Risk preferences	Mathematical	Power UF: $U = \frac{\pi^{1-R}}{1-R}$	CRRA (0 vs. 1.5)[c]	Optimal N F amount & timing	RA increase	1989	USA
Huang et al. (1994)	Risk preferences	Mathematical	Power UF: $U = \frac{\pi^{1-R}}{1-R}$	CRRA (0 vs. 1.5)[c]	Optimal N F amount & timing	RA increase	1989	USA
Huang et al. (1995)	Risk preferences	Mathematical	Power UF: $U = \frac{\pi^{1-R}}{1-R}$	CRRA (0 vs. 1.5)[c]	Optimal N F amount & timing	mixed	1989	USA
Huang et al. (1998)	Risk preferences	Mathematical	n/a	ARAC (0-0.02)[b]	Optimal N F amount & timing	RA increase	1991	
Huang et al. (2000)	Risk preferences	Mathematical	n/a	ARAC (0-0.02)[b]	Optimal N F amount & timing	RA increase	1996	USA

Isik (2002)	Risk preferences	Mathematical	Flexible	ARAC (0.26 vs. 0.36), RRAC (1.74 vs. 2.74) = low vs. moderate RA	Optimal NF amount	RA decrease	1975 - 99	USA
Isik & Khanna (2003)	Risk preferences	Econometric	Flexible	Find DARA & IRRA	NF overuse	RA increase	1993 - 94	USA
Kallas et al. (2010)	Risk preferences	Stated preference	-	RA	Organic adoption & adoption time	RA increase ($RA_{organic} < RA_{convetional}$) [for both]	2008	Spain
Koesling et al. (2004)	Risk preferences	Stated preference	-	RA	Organic adoption	RA increase ($RA_{organic} < RA_{convetional}$)	2002	Norway
Lambert (1990)	Risk preferences	Mathematical	n/a	ARAC (0-0.012)[b]	Optimal NF amount	RA decrease	1976 - 86	USA
Larson et al. (1998)	Risk preferences	Mathematical	-	Risk-neutral vs. risk-averse vs. risk-seeking	NF amount	RA decrease	1986 - 95	USA
Liontakis & Tzouramani (2016)	Risk preferences	Mathematical	n/a	ARAC (0-0.00024)[b]	Organic adoption	RA increase	n/a	Greece
Lu et al. (1999)	Risk preferences	Mathematical (Safety-First criterion)	-	Risk-neutral vs. risk-averse (own definition)	NF amount[+]	RA increase	1994 - 97	USA
Lu et al. (2003)	Risk preferences	Mathematical	n/a	ARAC (0-0.01)[b]	Organic adoption, NF amount[+]	RA decrease	1993 - 97	USA
Meyer-Aurich et al. (2009)	Risk preferences	Mathematical	Negative exponential	ARAC (0 - 0.01)[b]	Optimal NF amount[+]	RA decrease	1994 - 2006	Germany

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Meyer-Aurich & Karatay (2016)	Risk preferences	Mathematical	Negative exponential	ARAC (0 - 0.01)[b]	Optimal NF amount[+]	RA decrease	1995 - 2010	Germany
Meyer-Aurich & Karatay (2019)	Risk preferences	Mathematical	Negative exponential	ARAC (0 - 0.004)[b]	Optimal NF amount[+]	RA decrease	2001 - 05, 1996 - 99, 2002, 2012 - 16	Germany
Meyer-Aurich et al. (2020)	Risk preferences	Mathematical	Negative exponential	ARAC (0 - 0.004)[b]	Optimal NF amount	RA decrease	1996 - 2002	Germany
Monjardino et al. (2013)	Risk preferences	Mathematical	Negative exponential	ARAC (0 - 0.035)[b]	Optimal NF amount	RA decrease	2009 - 11	Australia
Monjardino et al. (2015)	Risk preferences	Mathematical	Negative exponential	ARAC (0 - 0.035)[b]	Optimal NF amount	RA decrease	1950 - 2010	Australia
Monjardino et al. (2019)	Risk preferences	Mathematical	(Follow Di Falco et al. (2007) to calculate risk premium and then max CE)	CRRA (0-4)[b]	Optimal NF amount	RA decrease	2001 - 2015	Australia
Parra-Lopez et al. (2007)	Risk preferences	Stated preference	-	Risk aversion	Organic adoption & adoption time	RA increase ($RA_{organic}$ < $RA_{convetional}$) [for both]	2000 - 01	Spain
Paudel et al. (2000)	Risk preferences	Mathematical	n/a	Risk aversion vs. regret minimization (own definition)	NF amount[+]	Regret minimizers apply more NF than risk minimizers	Only know: “simulated for a 30-year time horizon”	USA
Paulson & Babcock (2010)	Risk preferences	Mathematical	CARA UF	CARA (0 - 0.02)[b]	Optimal NF amount[+]	RA decrease	1985 - 90	USA
Pendell et al. (2007)	Risk preferences	Mathematical	Negative exponential	CARA (0 - 0.025)[b]	(Optimal) NF amount	RA decrease	1992 - 99	USA

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Rajsic et al. (2009)	Risk preferences	Mathematical	Negative exponential	CARA (0-0.01)[b]	NF overuse	RA decrease	1993 – 2001	Canada
Regev et al. (1997)	Risk preferences	Mathematical	(Use risk premium (Antle, 1987))	ARAC (0-3)[b]	Optimal NF amount	RA decrease	1984 -88 & 1991	Switzerland
Rössert et al. (2022)	Risk preferences	Mathematical	n/a	Risk neutral vs. moderate RA vs. strong RA (own definition)	Optimal NF amount	Mixed	2004 - 19	Germany
Roosen & Hennessy (2003)	Risk preferences	Mathematical (Stochastic dominance)	-	Risk-neutral vs. risk-averse	Optimal NF amount	RA decrease	1987 - 91	USA
Rosas et al. (2015)	Risk preferences	Mathematical	Negative exponential	Risk premium (0-50% of the standard deviation of profits)[b]	NF overuse	RA decrease	2010	USA
Schaub & Benni (2024)	Risk preferences	Mathematical (Stochastic dominance)	-	Risk-neutral vs. risk-averse	NF amount	RA decrease (for wheat)	1991 - 2022	Switzerland
Serra et al. (2008)	Risk preferences	Econometric	Flexible	Arrow-Pratt measure	Organic adoption	Zero	2001 - 03	Spain
Smith et al. (2012)	Risk preferences	Mathematical	Negative exponential	CARA (0 - 0.03)[b]	Optimal NF amount	RA decrease	2005 - 08	Canada
Smith et al. (2015)	Risk preferences	Mathematical	Negative exponential	CARA (0 - 0.025)[b]	Optimal NF amount[+]	RA decrease	1972 - 2013	USA
SriRamaratnam et al. (1987)	Risk preferences	Stated preference	-	Absolute risk aversion (low RA levels)	NF amount	RA increase	1977 - 84	USA

	Subjective probabilities	Stated preference	-	Subjective N yield response	NF amount	Subjective probabilities increase		
Tevenart & Brunette (2021)	Risk preferences	Stated preference	-	Holt & Laury (2002) values	NF amount + timing	RA decrease	2018 - 19	France
	Ambiguity preferences	Stated preference	-	Chakravarty & Roy (2009) values	NF amount (in first application)	Ambiguity aversion increase		
Tzouramani et al. (2011)	Risk preferences	Mathematical	n/a	ARAC (0.01 - 0.07) = hardly to very RA	Organic adoption	zero	1999 - 2003	Greece
Vollmer et al. (2017)	Risk preferences	Experimental	-	Holt & Laury (2002) values	Organic adoption	Zero	2013	Germany
Walburger et al. (2004)	Risk preferences	Mathematical	Negative exponential	CARA (0.000001- 0.0001) = low to very high RA	Organic adoption, optimal NF amount[+]	Mixed	1993 - 2000	Canada
Zentner et al. (1992)	Risk preferences	Mathematical	n/a	ARAC (0-0.05)[b]	Optimal NF amount & timing	RA decrease	1982 - 1990	Canada
Zentner et al. (2011)	Risk preferences	Mathematical (Stochastic dominance)	-	low, medium and high risk RA	Organic adoption, optimal NF amount[+]	RA decrease	1996 - 2007	Canada

Note: vNM = von Neumann-Morgenstern utility function; RA = risk aversion, CARA = constant absolute risk aversion, CRRA = constant relative risk aversion, DARA = decreasing absolute risk aversion, IRRA = increasing relative risk aversion, RRAC = relative risk aversion coefficient, “own definition” = have a context-dependent definition of risk preferences;

[a] neutral to general risk aversion, [b] neutral to (extremely) high risk aversion, [c] neutral to moderate risk aversion; [d] neutral to low risk aversion, [+] in crop rotation system

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