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Risk preferences and other (ignored) behavioral factors in fertilizer management decisions: A systematic literature review

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ABSTRACT

Fertilizer management decisions entail significant economic and environmental implications at the farm and global levels. However, both underuse and overuse of fertilizers often occur, deviating from the economically optimal use. This raises the question of why non-optimal fertilizer behavior persists. One possible explanation is the influence of behavioral factors on farmers' decision-making processes. Therefore, we conducted a systematic review of behavioral factors in decision-making under risk and uncertainty, focusing on their association with fertilizer decisions in high-income countries. Fertilizer management decisions are inherently risky due to the presence of different sources of uncertainty, such as fertilizer prices, crop yields, and output prices. Our review of 64 peer-reviewed articles shows that most research focuses exclusively on farmers' risk preferences, often using expected utility theory. Few notable exceptions incorporate broader behavioral considerations. Our findings highlight the need for future research that extends beyond risk preferences and incorporates non-standard decision theories into fertilizer decision models. This could help explain some of the non-optimal fertilizer behaviors observed in practice. Finally, we emphasize the importance of combining primary data-driven behavioral research with secondary data to create a more comprehensive understanding of fertilizer decision-making. These insights may be applicable to other decision-making within and beyond agriculture.

1. Introduction

Risk and uncertainty pervade countless aspects of decision-making, including farmers' decisions regarding fertilizer management. When farmers decide on the timing, type, and amount of fertilizers to apply or on the number of fertilizer applications, they face uncertainty regarding future fertilizer prices, crop yields at the end of the growing season, and the market price buyers will pay for the produce (i.e., the output price). As a result, farmers' decisions about fertilizer management can be influenced by several behavioral factors related to decision-making under risk and uncertainty, such as risk and ambiguity preferences, probability weighting, loss aversion, subjective probabilities, and time preferences (Chai et al., 2023). The influence of these behavioral factors on decision-making under risk and uncertainty has been documented in several fields, including agricultural economics and farmers' behavior (e.g., Wuepper et al., 2023). Literature reviews have further explored the influence that such behavioral factors can have on farmers' adoption of sustainable practices (e.g., Dessart et al., 2019) and participation in agri-environmental schemes (e.g., Schaub et al., 2023). Research by Chai et al. (2023) emphasizes the need for a deeper understanding of these behavioral factors in farmers' nitrogen (N) decisions.

This paper contributes to this strand of literature by conducting a

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literature review on the specific influence of behavioral factors that can be formally integrated into economic (mathematical) models on farmers' usage of synthetic N-based fertilizers. This focus is driven by the growing interest of the agricultural economic community to integrate deviations from standard EUT models into farm-level bio-economic and agent-based models that rely on strong mathematical and economic structures (e.g., Appel & Balmann, 2019; Huber et al., 2022, 2023).[1] The literature review was conducted using the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) approach (Page et al., 2021). Understanding how and to what extent such behavioral factors explain farmers' fertilizer management decisions is critical for detecting potential deviations from standard economic theory, developing alternative models of fertilizer decisions, and designing agricultural policies that enhance both the economic resilience and environmental sustainability of farming systems. Focusing exclusively on research from high-income countries, our systematic literature review fills a gap in the current literature. To date, no literature reviews have specifically addressed this topic. The study closest in scope is an unsystematic literature review by Begho et al. (2022), which explores the relationship between risk aversion and fertilizer usage in South Asia. Fertilizers play a critical role in agriculture, serving as a cornerstone of increasing global food production and enhancing food security in many parts of the world over the past century (European Commission, 2022; Snapp et al., 2023; Stewart & Roberts, 2012). Among the primary plant nutrients, nitrogen (N) is used more extensively than phosphorus and potassium (FAO, 2025). However, there is evidence that synthetic N-based fertilizer application rates do not align with the optimal profit-maximizing levels in high-income countries (e.g., Chai et al., 2023).[2] Underapplication can have a negative impact on production, undermining the economic resilience of individual farms and entire farming systems in high-income countries, while overapplication raises concerns about the economic and environmental sustainability of farmers' fertilizer decisions (e.g., Mozumder & Berrens, 2007). Overapplication exposes farmers to income risks, particularly in light of the increasing price volatility of synthetic fertilizers due to fluctuating energy costs or Russia's invasion of Ukraine (e.g., Alexander et al., 2022; Schaub & Benni, 2024). At the same time, overapplication can generate negative environmental externalities, including air, water, and soil pollution (Menegat et al., 2022). In 2022, global N use efficiency (NUE) was only 56 %, meaning that 44 % of the applied N was not absorbed by plants (Mirzaee & Nafchi, 2025). Data-driven models suggest that global average NUE could be improved by up to 27 % through enhanced nutrient management alone (You et al., 2023). Particularly in high-income countries, there is some evidence suggesting that overapplication with respect to the profit maximization benchmark would be more prominent than underapplication (e.g., Chai et al., 2023). Findings from the United States indicate that farmers apply 19–36 % more N-based fertilizers than the agronomically optimal level (Wade et al., 2015). As the economic optimal application tends to be lower than the agronomic optimal application, it follows that overuse from an agronomic perspective implies overuse from an economic perspective (Chai et al., 2023). Another study from the US informs that 37 % of surveyed farmers apply N beyond the economic optimum (Houser, 2022). Several policies were developed and implemented in recent years to reach more adequate fertilizer applications. An example is the Global Partnership on Nutrient Management (GPNM) initiated by the United Nations Environment Program (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).

Further, there is substantial evidence that farmers' decisions deviate from profit maximization regardless of the direction of this misalignment (Howley, 2015; Lin et al., 1974; Zereyesus et al., 2021). This raises the question of whether alternative perspectives, other than mainly profit maximization, can better explain and predict farmers' fertilizer management decisions. An alternative approach that has been pursued in the literature is framing fertilizer decisions under a utility maximization perspective. This has the advantage of considering a broader range of individual-specific aspects, including behavioral factors, and implies that the optimal fertilizer amount is no longer a merely financial outcome, but is also relative to societal welfare (e.g., Chai et al., 2023; Lin et al., 1974; SriRamaratnam et al., 1987). The standard economic framework used under a utility maximization perspective is expected utility theory (EUT). Reviewing existing evidence on the role of behavioral factors related to decision-making under risk and uncertainty, we aim to synthesize existing knowledge regarding farmers' fertilizer management decisions from a behavioral perspective, investigate the extent to which potential deviations from standard EUT is contemplated, and identify gaps in the literature that can be addressed by further research.

This literature review builds on a conceptual framework that considers the main decisions that farmers generally make regarding fertilizer use, namely the application rate (amount) and the number as well as timing of fertilizer applications. These decisions are made under conditions of risk and uncertainty, and three main sources of uncertainty are contemplated: volatility of fertilizer prices, crop yields, and output prices. The conceptual framework considers several behavioral factors and related theories of decision-making under risk and uncertainty. Risk preferences and exponential time discounting relate to EUT, while the remaining behavioral factors signal deviations from EUT and relate to alternative theories of decision-making. More details are provided in the conceptual framework presented in the next section.

The literature review provides two main findings. First, except for two studies that investigate subjective probabilistic expectations and ambiguity preferences (SriRamaratnam et al., 1987; Tevenart & Brunette, 2021), all reviewed studies focus on the role of risk preferences in explaining fertilizer management decisions within an EUT framework. This highlights that 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, yields, and output prices. Second, our literature review reveals that two main branches of research exist that largely overlook each other. The richer branch (in terms of number of studies) relies on the use of mathematical methods to identify the level of fertilizer use that maximizes expected utility of profit under different levels of assumed farmers' risk aversion (e.g., Gandorfer et al., 2011). The other literature branch is narrower and aims to estimate or elicit risk preferences with the final goal of better understanding the potential correlation between risk preferences and observed 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 by collecting primary data (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 why farmers deviate from economically optimal levels of N fertilizer use.

Insights from this literature review can be relevant to other economic

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[1] This focus implies that behavioral factors like risk perception expressed in a probabilistic fashion (i.e., subjective probabilities), risk preferences measured as coefficients of risk and absolute risk aversion, or time preferences measured as discount rates, are relevant for our literature review. Meanwhile, other behavioral factors like perceived behavioral control, which cannot be fully and directly integrated into economic mathematical models of farmers' decision-making, are excluded.

[2] As defined by Chai et al. (2023), "[i]n the simplest model, the profit-maximizing fertilizer rate is that where the marginal benefit from increasing grain yield equals the marginal cost of applying additional fertilizer" (p. 3). The yield-maximizing rate equips the crop with the optimal amount of fertilizer to achieve maximum yield.

decisions, both within and beyond agriculture, particularly those involving the use of production inputs with high price volatility and significant environmental externalities. Herbicide and pesticide use can be fitting examples (e.g., Garcia, Möhring et al., 2024; Meunier et al., 2024). Similarly, the use of other resources (from a profit maximization perspective) like irrigation water can be explained by considering behavioral factors of decision-making under risk and uncertainty (e.g., Fitzsimmons et al., 2025; Rey et al., 2016). The same reasoning extends to other economic sectors where the use of highly energy-intensive production inputs generates substantial negative environmental externalities. Examples are the food processing industry, where synthetic preservatives and additives, as well as synthetic processing agents, are heavily used; the power and fuel industry, where fossil fuels are still primarily used as inputs; and many other production sectors like mining, metal, and textile.

The article is structured as follows. Section 2 provides the conceptual framework for farmers' fertilizer decisions under risk and uncertainty. Section 3 explains the approach used to conduct the literature review. Section 4 synthesizes evidence from the literature review, while Section 5 concludes.

2. Conceptual framework

Our conceptual framework, illustrated in Fig. 1 and Fig. 2, provides a foundation to investigate farmers' fertilizer management decisions from a behavioral perspective. It consists of three main components: (1) fertilizer management decisions under study, (2) sources of uncertainty that characterize such decisions, and (3) behavioral factors and underlying behavioral theories that can be used to model such decisions. Below, we examine these components in detail.

2.1. *Fertilizer management decisions*

Fertilizer decisions involve the management of synthetic and organic fertilizers, making it important to distinguish between them in this conceptual framework. While both types of fertilizer provide nutrients, primarily N, they differ in their composition and origin. Synthetic fertilizers are produced through energy-intensive manufacturing processes using natural raw materials,[3] whereas organic fertilizers are sourced directly from organic materials such as manure, compost, and crop residues. Organic fertilization can serve as an alternative to synthetic fertilization, reducing the reliance on synthetic N-based fertilizers (Krause et al., 2024). Just like synthetic fertilizers, the application of organic fertilizers requires good fertilizer management practices (e.g., FAO, 2025). In general, fertilizer decisions mainly relate to: i) the amount of fertilizer used per application, ii) the number of applications, and iii) the timing of applications. These decisions are interrelated in the sense that each one influences the others.

Fig. 1 displays that fertilizers are applied dynamically from (pre-) seeding to harvest, with management decisions for both synthetic and organic fertilizers across all production stages.[4] More specifically, as the season progresses after the crop choice stage, farmers begin implementing their fertilizer management plans. At the seeding stage, they decide on the fertilizer type (synthetic or organic) and apply it before or at planting (early application). The timing and application rate of fertilizer depend on the specific nutrient needs of the crop. Early nutrient availability is critical to support healthy crop growth. During the winter break, fertilizer is generally not applied and, in the growing stage, fertilizer applications resume. The timing of these applications is determined by the crop's nutritional requirements, its growth stage, and identified nutrient deficiencies. Nutrient availability during this phase is crucial for maintaining crop health and optimizing yield potential.

However, it is also important to note that fertilizer decisions are a key component of broader farm management. As shown in Fig. 1, other farm decisions directly influence the timing and amount of fertilizer application across production stages, including crop type selection, crop rotation, cover cropping, soil testing, tillage, irrigation practices, and the uptake of precision farming tools. Crop choice, made within the context of long-term planning, determines N demand before seeding. If farmers expect high fertilizer prices, they might switch to crops with lower fertilizer demands (e.g., legumes or less nutrient-intensive crops). Crop rotation and cover cropping can reduce fertilizer needs, improve soil health, and enhance nutrient use efficiency. Soil testing, conducted between crop choice and seeding, informs nutrient requirements for the upcoming crop. Tillage decisions, made before seeding, affect soil structure and nutrient retention, influencing fertilizer timing and type. Irrigation, typically set before or at seeding and maintained throughout the growing season, impacts nutrient mobility, uptake efficiency, and fertigation. Finally, decision support tools (DST), variable rate technology (VRT), and automatic steering (AS) allow for precise fertilizer applications. These interconnected farm management decisions shape the risks and uncertainties associated with fertilizer use and consequently influence how behavioral factors mediate fertilizer application across time. This underscores the importance of studying fertilizer decisions within a broader and dynamic behavioral and management context, rather than in isolation.

2.2. *Sources of uncertainty*

Farmers' fertilizer decisions involve managing both synthetic and organic fertilizers while navigating risks and uncertainties (see first two boxes in Fig. 2). According to Knight (1921), risks refer to situations where the probability distribution of the random variable is known, while uncertainties refer to situations where the probability distribution is not known or cannot be objectively determined. A further distinction can be made between uncertainty and ambiguity. Under uncertainty, decision makers are able to form a well-defined (subjective) probability distribution, while under ambiguity they do not (Harrison, 2011).[5] The middle box of Fig. 2 presents three main sources of uncertainty that characterize fertilizer management decisions: future fertilizer prices, crop yields (at harvest), and output prices (crop market prices at harvest). When farmers develop a fertilizer management plan, fertilizer prices are deterministic, whereas future fertilizer prices remain uncertain. Similarly, both output prices and crop yield at harvest are subject to considerable uncertainties at the time when farmers plan their fertilizer management decisions. This makes the ex-ante evaluation of fertilizer investment profitability highly uncertain. As displayed in the arrow in Fig. 2, we assume that the magnitude of uncertainty regarding future fertilizer prices, output prices, and yield diminishes over time, peaking during early fertilizer decisions around the seeding stage (see dark blue arrow section) and reaching its lowest magnitude with the final fertilizer decision before harvest time (see light blue arrow section).

This uncertainty-reducing trend over time is certainly due to farmers progressively gaining information regarding future fertilizer prices, crop yields (at harvest), and output prices (crop market prices at harvest). At the crop choice stage, farmers have little knowledge about these three random variables. Generally, as the season progresses, some uncertainties regarding fertilizer management begin to resolve, due to observations of early production patterns, or information from extension services, exchanges with other farmers, and the publication of agronomic and marketing reports as well as articles in specialized magazines, for example. However, uncertainty about long-term weather conditions, final crop yields, and output prices is never fully resolved, continuing to

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[3] An example is using air (for N), natural gas (for ammonia) and mineral deposits (for phosphorus and potassium).

[4] This is also presented in the upper box in Fig. 2.

[5] We refer interested readers to Cerroni and Rippo (2023) for a further discussion on the interpretation of uncertainties and ambiguities.

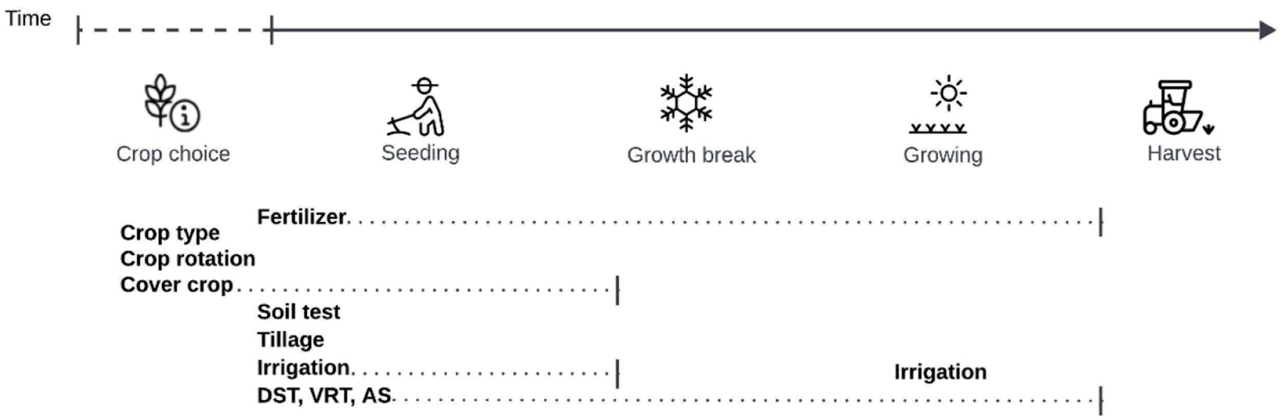

Fig. 1. Dynamic fertilizer and other related agricultural decisions. Note: DST = Decision system tools, VRT = Variable rate technology, AS = Automatic steering.

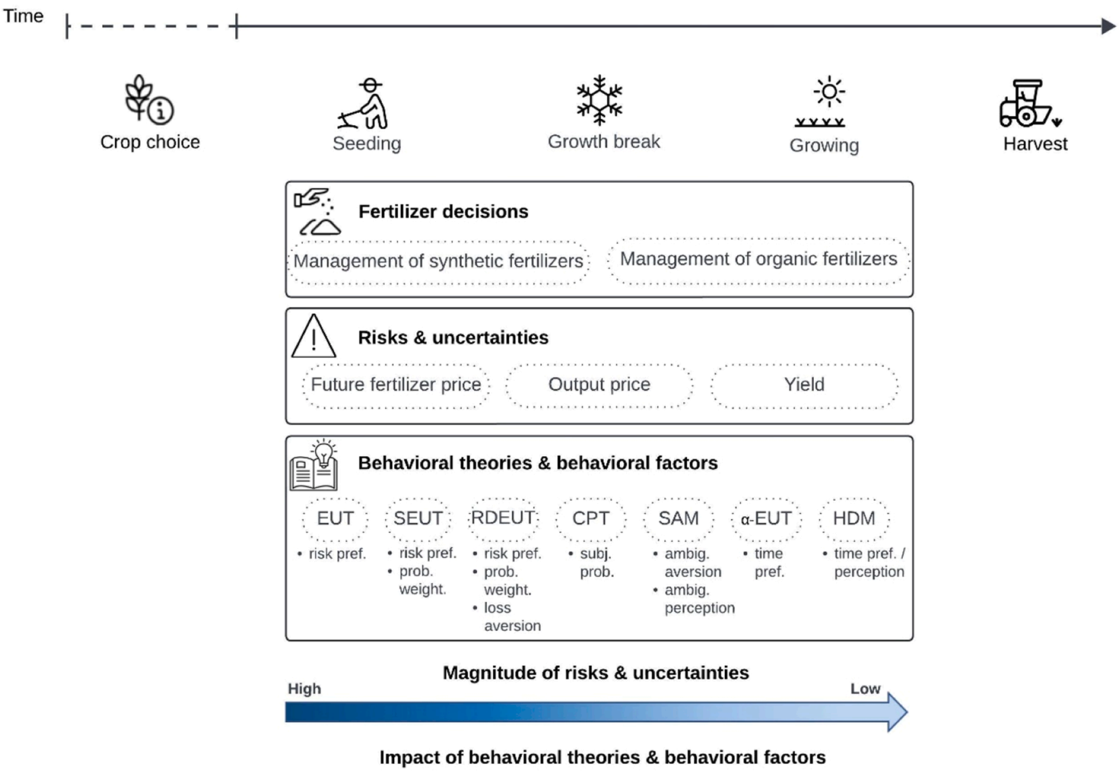

Fig. 2. Conceptual framework of dynamic fertilizer decisions under risks/uncertainties and behavioral influences. *Note*: EUT = expected utility theory, RDEUT = rank-dependent EUT, CPT = cumulative prospect theory, SEUT = subjective EUT, DUM = discounted utility model, HDM = hyperbolic discounting model.

shape farmers' fertilizer decision-making until the end of the production cycle. It is crucial to consider the dynamics across different production stages when analyzing how behavioral factors influence fertilizer decisions. Hence, behavioral factors that relate to intertemporal decision-making theories can contribute to explaining fertilizer management decisions, including deviations from a profit-maximizing fertilizer application strategy.

2.3. Behavioral factors and theories

Behavioral factors and underlying theories considered in this review are mapped in the lower box in Fig. 2. As risks and uncertainties decrease over time, from the crop stage to harvest, the influence that considered behavioral factors may have on farmers' decision-making follows the same pattern. Their impact is most pronounced in the early fertilizer decisions, from crop choice to the seeding stage (see dark blue arrow section), and gradually diminishes toward harvest where risks and uncertainties are progressively minimized (see light blue arrow section).

Fertilizer management decisions are usually modeled using expected utility theory (EUT), which is the standard model of economic decision-making under risk. EUT assumes that decision makers, based on their risk preferences, maximize their expected utility. Risk preferences indicate decision makers' willingness to take risks. Decision makers can be defined as risk averse, risk neutral, and risk seeking depending on whether they are unwilling, indifferent, or willing to take risks. Under EUT, the optimal level of fertilizer use is usually determined based on farmers' risk preferences to maximize their utility of profit in a simple "Bernoullian" fashion (e.g., Lin et al., 1974; Chai et al., 2023). The influence that risk preferences may have on fertilizer decisions depends on whether N-fertilizer is perceived as a risk-reducing or a risk increasing input (Chai et al., 2023). If farmers believe that fertilizers reduce production-related risks (i.e., a risk-reducing input), risk-averse farmers are inclined to fertilize more than risk-neutral farmers (Dequiedt et al., 2023; Rajsic et al., 2009). In contrast, if farmers believe that fertilizers increase production-related risks (i.e., a risk-increasing input), risk-averse farmers would be more likely to apply less N-fertilizer than their risk-neutral counterparts (Isik, 2002; Rajsic et al., 2009; Roosen & Hennessy, 2003). Examples of production-related risks include soil degradation (e.g., Geisseler & Scow, 2014), water pollution (e.g., Good & Beatty, 2011), and plant or pest diseases (e.g., Veromann et al., 2013). These risks can also expose farmers to financial burdens, such as the costs of compensating for production losses and restoring soil, water, and plant health (e.g., soil rehabilitation, water treatment technologies, increased pesticide use). Additionally, there may be regulatory costs to comply with environmental legislation (e.g., the EU Nitrates Directive). Thus, while fertilizer use generally protects farmers from risks, applying it beyond the ecological and economic optimum can introduce downside risk but cannot offer any upside risk. The role of risk perceptions in mediating the effect of risk preferences on fertilizer use highlights the importance of considering the potential interplay of different behavioral factors. It also suggests that drivers of decision making under uncertainty and ambiguity should be considered when studying fertilizer management decisions, as many farmers make fertilizer decisions under such conditions.

Therefore, we now turn our attention to decision-making theories and behavioral factors that are better suited to explain decision maker's decisions when probability distributions of random variables are not known. If decision makers 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 EUT with the only exception that objective probabilities are replaced by subjective probabilities. Subjective probabilities are decision makers' expectations about the occurrence of a random variable that are expressed in a numerical fashion (Manski, 2004). Farmers' expectations about future fertilizer prices, crop yields (at harvest), and output prices (crop market prices at harvest) can help explain fertilizer decisions that deviate from profit maximization. For example, optimistic farmers who overestimate the marginal yield gain from applying additional fertilizer, relative to empirical evidence, may tend to overapply, explaining fertilizer behavior deviations from profit maximization (SriRamaratnam et al., 1987).

If decision makers 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, Bleichrodt et al., 2018, 2018; Cerroni, 2020). Multiple theories of decision-making under ambiguity have been developed over time that consider different behavioral factors. Loss aversion and/or probability weighting characterize many reference-dependent theories, such as rank-dependent utility theory (RDEUT) (Quiggin, 1982), cumulative prospect theory (CPT) (Tversky & Kahneman, 1992), and reference-dependent utility theory (Kőszegi & Rabin, 2006, 2007). Loss aversion is present when decision makers' utility function is steeper for losses than for gains(Kahneman & Tversky, 1979). In the context of fertilizer use, this means that if farmers are loss averse and perceive fertilizer as a risk-increasing input, their application rate may deviate from profit maximization leaning towards underapplication to avoid expected income or yield losses (Chai et al., 2023). There is some evidence of this behavioral pattern in the pesticide-related literature. Hou et al. (2020) suggests that loss-averse farmers reduce their pesticide use intensity.

Probability weighting occurs when decision makers transform objectively measured cumulative probability distributions using a weighting function (Tversky & Kahneman, 1992). In other words, they inform on whether and to what extent decision makers underweight (or overweight) low- or high-probability outcomes. Consequently, if farmers overweigh the small probability of positive outcomes (high marginal yield gain from applying additional fertilizer), application rates may deviate from profit maximization, leaning towards overuse of fertilizers. This behavioral pattern echoes the discussion we proposed about the influence of subjective probabilities on fertilizer application.

Other ambiguity-related theories put more emphasis on ambiguity perception and aversion. A classic example is the smooth ambiguity model (SMA) by Klibanoff et al. (2005). Ambiguity perception measures the perceived level of ambiguity, in other words, it captures insensitivity toward likelihood changes. Ambiguity aversion is generally defined as decision makers' preference for options with known probabilities over those with unknown probabilities (Baillon, Bleichrodt et al., 2018; Baillon, Huang, et al., 2018). Similar to risk-averse farmers, those who are more ambiguity averse tend to overapply fertilizers (relative to the profit maximization benchmark) to avoid facing ambiguity about future yields, for example. This would be the most likely behavioral response of farmers who perceive fertilizer use an ambiguity-reducing strategy. A different behavioral pattern may arise if fertilizer is perceived as an ambiguity-increasing input. Studies on pesticide use confirm that farmers with a strong aversion to ambiguity are more inclined to apply pesticides than those who are neutral to it (Couture et al., 2024).

Regarding intertemporal decision-making, standard economic models (i.e., EUT) account for time preferences via exponential discounting that assumes decision makers discount future outcomes at a consistent rate through time (Andreoni & Sprenger, 2012). Again, observed behavior deviates from this assumption, showing that decision makers often make decisions according to present bias or hyperbolic discounting (Frederick et al., 2002). Hyperbolic discounting assumes that decision makers prefer immediate rewards over rewards that come later in the future. Different models of intertemporal decision-making have been proposed in the literature. Our focus is on the hyperbolic discounting and quasi-hyperbolic discounting models since they are the most investigated in the literature. For example, farmers exhibiting hyperbolic discounting may overuse fertilizers, thus deviating from profit maximization, as they prioritize immediate profits over long-term soil degradation or water pollution. This behavioral pattern will be more prevalent among farmers who perceive fertilizer as a risk- or ambiguity-reducing input compared to those who perceive it as risk- or ambiguity-increasing. Evidence from Burkina Faso confirms that greater patience tends to improve (increase) fertilizer use (Le Cotty et al., 2018).

Our conceptual framework highlights that different behavioral factors can be highly interrelated and their impact on fertilizer decisions is difficult to disentangle, both theoretically and empirically, as suggested by Just and Just (2016). For example, assumptions regarding farmers perceptions of fertilizers as a risk- or ambiguity-reducing or -increasing input are crucial to predict the effect that behavioral factors may have on farmers' decision making.

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 "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 strategy

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 A1 lists the final search strings that were utilized to retrieve all relevant literature in September 2024.

As shown in Fig. 3, this search strategy yielded 1407 references and 1114 after the removal of duplicates, excluded document types, and excluded languages. Two independent reviewers then screened the title and abstracts of these records against defined inclusion criteria (see Section 3.2) 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 were added afterward. Lastly, another study was added as a recommendation by an expert. Finally, we discovered 64 records relevant to our literature review.

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 (i) behavioral factors, (ii) methods used to incorporate these behavioral factors in fertilizer decision modeling, and (iii) 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. Fig. 4 presents the histogram of all quality scores that ranged between 2.5 and 4 (mean: 3.26, SD: 0.48), where “4″ indicates that all four criteria are met. We do not exclude any study from this review as the lowest score was 2.5.

3.2. Eligibility criteria

We only included studies that relate farmers’ behavioral factors and their N-based fertilizer use (including quantity, time, reduction, efficient use, optimal level, and 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 and that can be formally integrated into economic (mathematical) modeling: 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 management decisions are secondary data methods (econometric models, mathematical models) and primary data (stated preference surveys and economic experiments).[6] Moreover, we limit this literature review to highly developed agricultural systems[7] and only include research that was published as traditional peer-reviewed literature in the English language.

3.3. General data description

This systematic literature review identifies 64 peer-reviewed studies on farmers’ behavioral factors in fertilizer decision-making in high-income countries. As shown in Fig. 5, 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 seem to slightly decrease in relevance in the 2020s.

Most reviewed articles were published in the following top journal disciplines: agronomy (36), economy (22), 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), *American Journal of Agricultural Economics* (7), *Journal of Sustainable Agriculture* (4), and *Agronomy Journal* (4) (see Appendix Table A3). Thus, reviewed studies are mainly located outside of economic research. According to SCImago Journal Rank (SJR), reviewed articles were published in journals that ranked as the best quarter (41 %) or second quarter (25 %) in their discipline at the time of publication.[8]

Lastly, we observe some variation in the geographical distribution of reviewed studies (see Appendix Fig. A1): 52 % focus on Northern America, whereas the United States alone captures 42 %. Other studies address countries in Europe (42 %), Australia (6 %), or Israel (2 %).

A summary of all reviewed studies with relevant background information is presented in Appendix Table A2.

4. Results and discussion

All 64 reviewed studies explore the relationship between risk preferences and N-based fertilizer management decisions. Only two studies additionally consider other behavioral factors: ambiguity preferences (Tevenart & Brunette, 2021) and subjective probabilities (SriRamaratnam et al., 1987). Therefore, this section mainly focuses on risk preferences and divides into different subsections: (1) the mapping of all fertilizer management decisions considered in reviewed literature, (2) the mapping of methods used to investigate the relationship between risk preferences and fertilizer management decisions, (3) a summary of existing evidence on the relationship between risk preferences and fertilizer management decisions, and (4) evidence from the two studies exploring the role of ambiguity preferences and subjective probabilities. Appendix Table A2 provides a summary of all the details discussed for each reviewed study.

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

[7] Highly developed agricultural systems are located 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.

[8] Please note that the SJR ranking is missing for the year of publication in 25% of all reviewed studies.

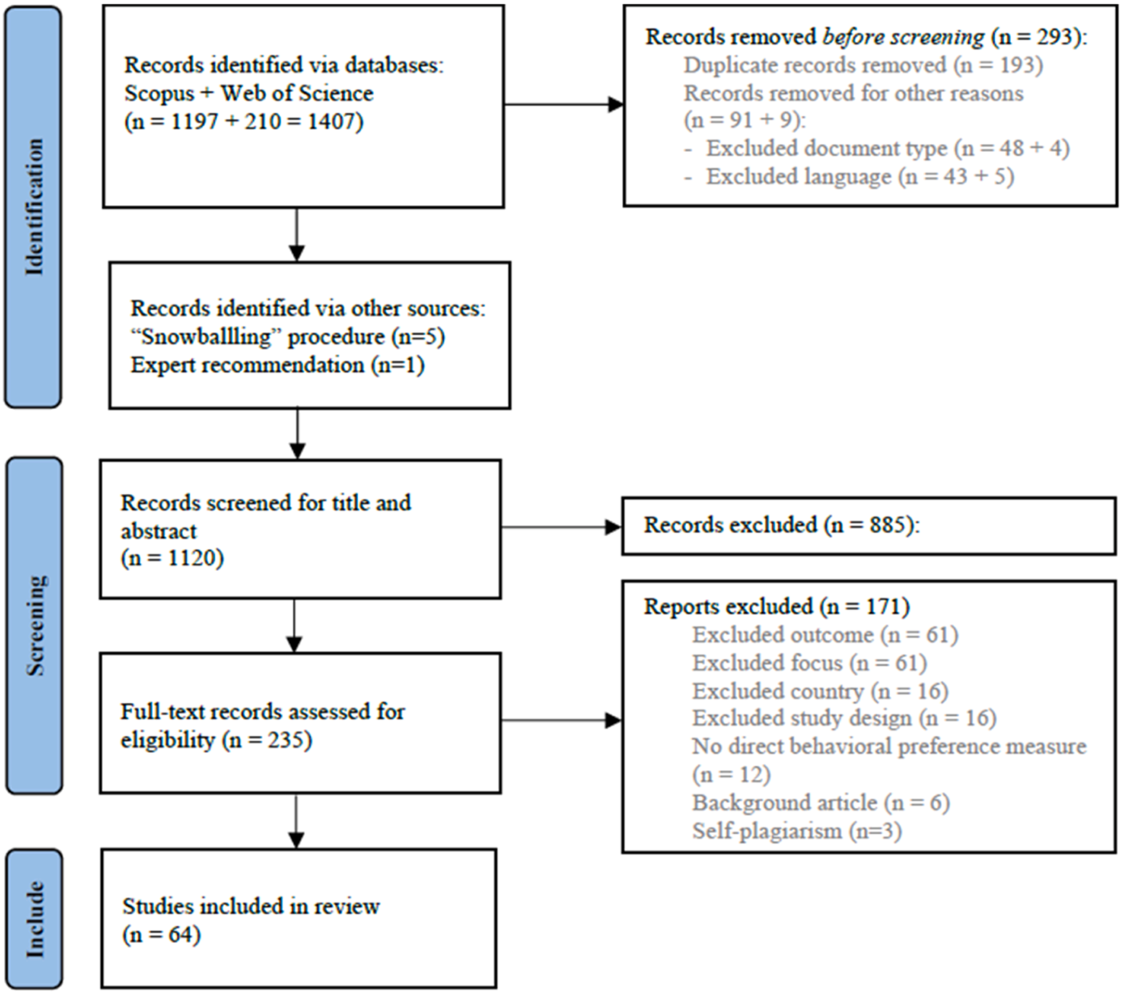

Fig. 3. PRISMA flow diagram: Study identification, screening, and inclusion process. Note: No automation tools were used in the identification or screening process.

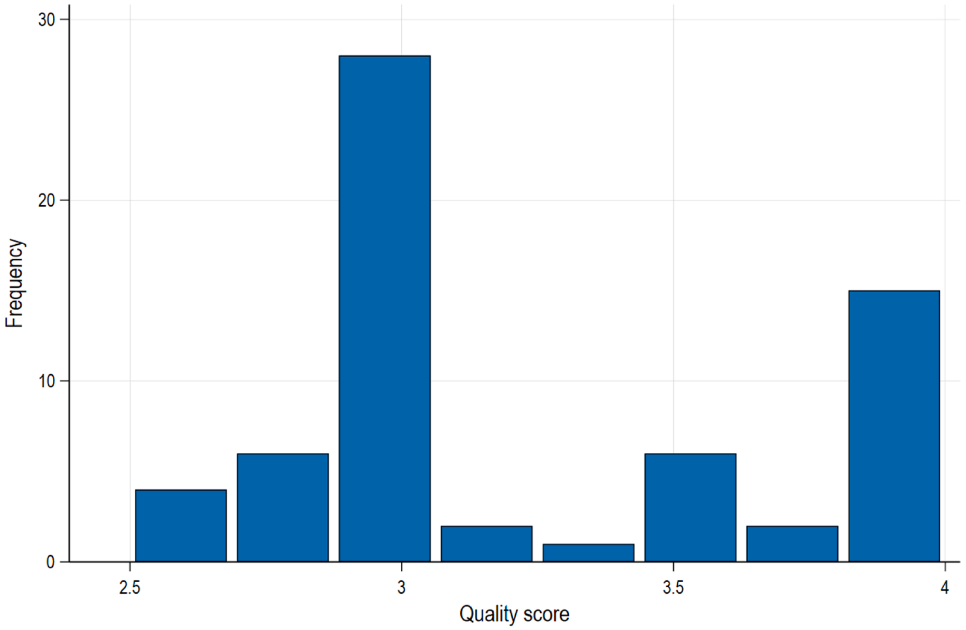

Fig. 4. Critical appraisal: Distribution of quality scores across all reviewed studies. Note: The quality score scale ranges from 0 (no quality criteria met) to 4 (all quality criteria met).

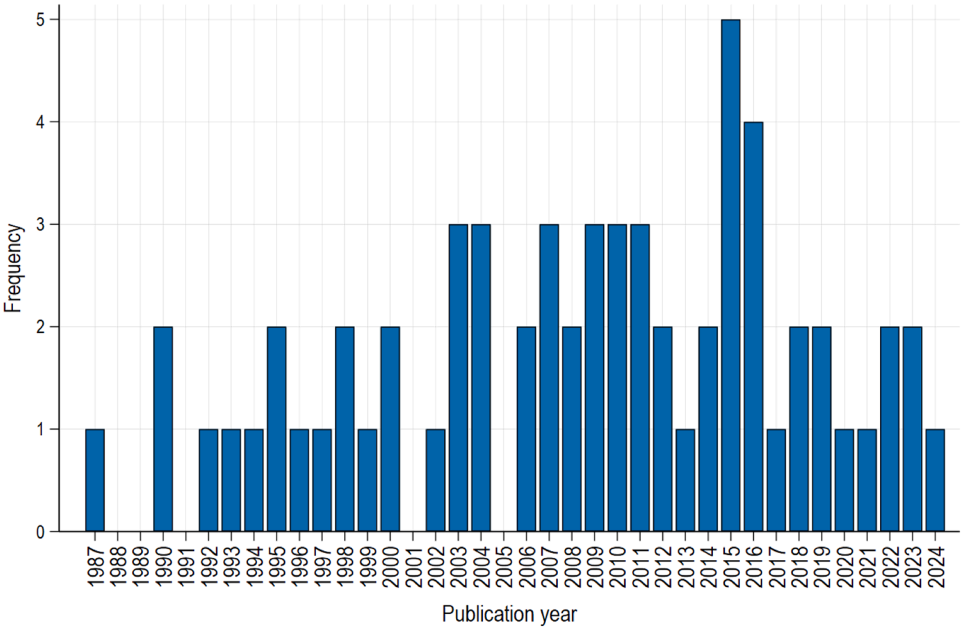

Fig. 5. Trends in publication frequency of reviewed studies by year.

4.1. *Mapping of studied fertilizer management decisions*

Fertilizer management decisions studied in this literature review are: i) the optimal amount of N-based fertilizer application as predicted by EUT, ii) the observed amount of N-based fertilizer application, iii) the overuse of N-based fertilizer application,[9] and iv) the application of organic fertilizers.

Fig. 6 indicates that 64 % (41 of 64) of reviewed studies aim to predict the optimal N-based fertilizer application amount that farmers should apply. 23 % (15 of 64) analyze organic fertilizer application decisions. Yet, only a limited number of studies examine observed fertilizer application and its overuse: 9 % (6 of 64 studies) and 3 % (2 of 64 studies), respectively.

Most of these studies do not distinguish between different fertilizer applications in one season (i.e., a static perspective). However, 12 studies (19 %) investigate the dynamic (i.e., intertemporal) nature of fertilizer management decisions. When modeling optimal N-based fertilizer decisions, eight studies separate the first from the total amount of N-based fertilizer application. Of these, five explore the optimal N-based fertilizer amount conditional on the probability of failing to apply fertilizer in the growing season. Only one study solely examines optimal N-based fertilization in the first application. When the research focuses on farmers' observed application amounts of N-based fertilizers, one study draws a distinction 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. Appendix Table A2 provides the full list of reviewed papers focusing on each of the listed fertilizer management decisions.

4.2. *Mapping of applied methods*

We provide a brief description of the methods used to consider risk preferences in farmers' fertilizer decision models. 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. Fig. 7 indicates the frequency of use for each method.

All secondary data methods rely on existing data. *Mathematical methods* study the relationship between farmers' risk preferences and the optimal N-based fertilizer application as predicted by EUT.[10] Two main approaches are applied in the literature: mathematical programming and stochastic dominance. Mathematical programming identifies the optimal amount of N-based fertilizer application by simulating (i.e., assuming) different degrees of farmers' risk preferences within defined constraints (e.g., Babcock & Hennessy, 1996; Finger, 2012; Finger et al., 2014). Stochastic dominance, instead, provides a decision rule to identify the optimal amount of N-based fertilizer application by comparing probability distributions related to uncertain outcomes (e.g., yields) under different levels of farmers' risk preferences (e.g., Roosen & Hennessy, 2003; Schaub & Benni, 2024).

Econometric models in reviewed studies estimate farmers' risk preferences within an EUT framework using data on observed application amounts. Structural or non-structural approaches are applied to obtain risk preference parameters. 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 imply changes in expected utility (e.g., Antle, 1987, 1989).

Primary data methods generally elicit risk preferences using *stated preference methods* and *economic experimental methods*. In many studies, the final goal is to measure the correlation between elicited risk preferences and farmers' intended or real decisions regarding fertilizer application amounts. In this review, the distinction between *stated preference methods* and *economic experimental methods* relies on the notion of incentive compatibility. Incentive compatibility is achieved when a proper monetary incentive scheme is included that induces participants to provide truthful responses (Cummings et al., 1997; V. L. Smith, 1986). *Stated preference methods* elicit risk preferences using two main approaches. The first approach asks farmers to directly state their attitudes towards risk or risky scenarios using Likert Scales (e.g., Dohmen et al., 2011; Finger et al., 2023). The second approach infers risk

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[9] Our results section does not discuss underfertilization because none of the reviewed studies address this topic.

[10] Reviewed studies using mathematical methods apply EUT to explore the utility of profit or similar economic measures, such as wealth.

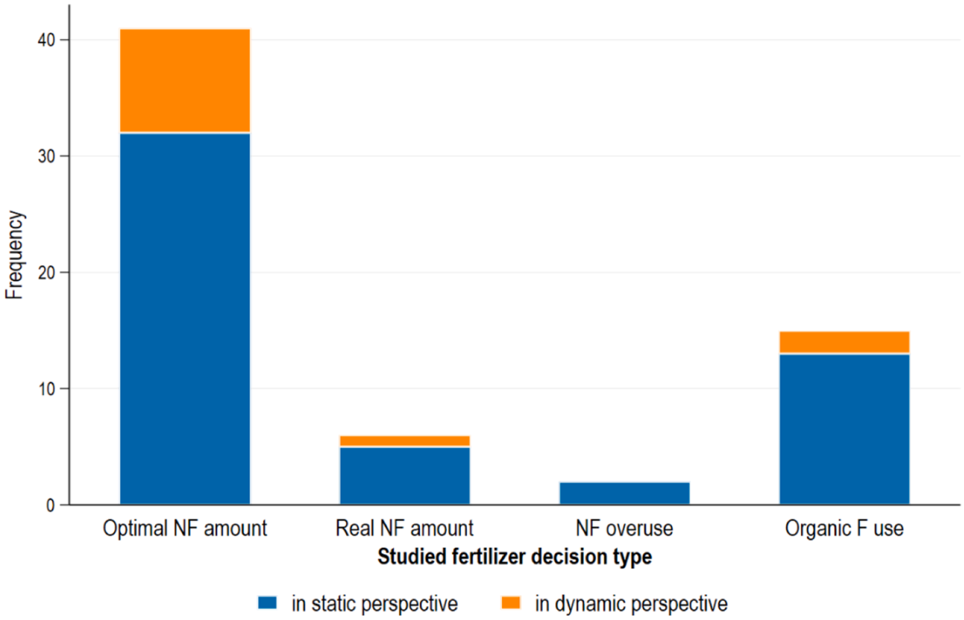

Fig. 6. Distribution of studied fertilizer decision types in a static versus dynamic perspective. Note: "F" refers to nitrogen and "F" to fertilizer. The static perspective shows the total N fertilizer applied; the dynamic perspective also includes application timing.

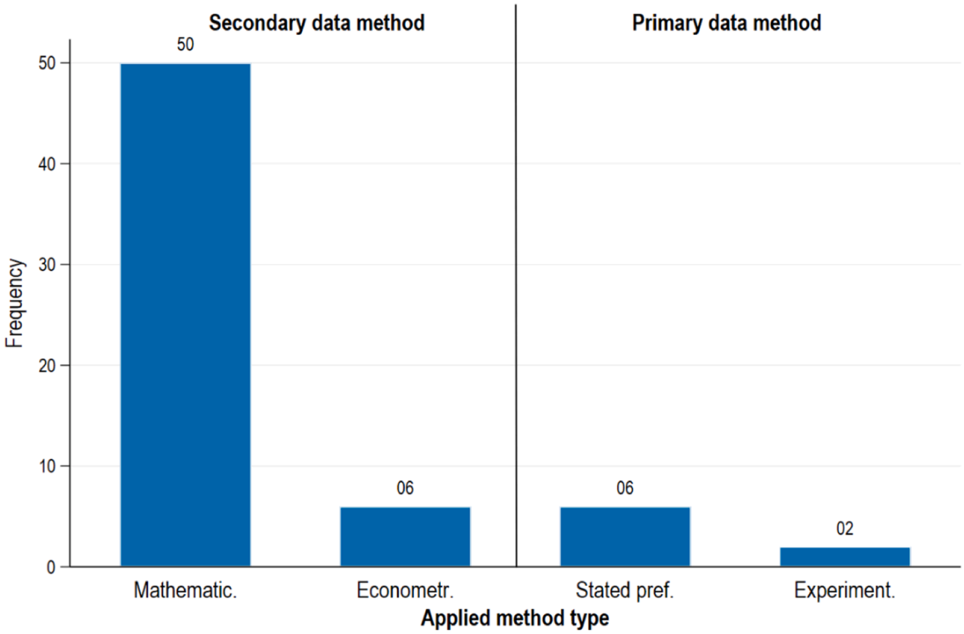

Fig. 7. Frequency of applied method types for incorporating behavioral factors in fertilizer decision models. *Note*: Applied method types are mathematical, econometric, stated preference, and economic experimental approaches.

preferences by asking farmers to make choices between risky prospects (i.e., lotteries) without providing any monetary incentives or using improper monetary incentive schemes that alter the incentive compatibility of the elicitation mechanism (e.g. flat payment) (e.g., Menapace et al., 2013). Neither approach is incentive compatible. *Economic experimental methods* use incentive-compatible lottery tasks to elicit farmers' risk preferences (e.g., Rommel et al., 2023; Tanaka et al., 2010).[11] 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

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[11] It follows that when, in a study, farmers are exposed to a lottery task (e.g., Holt and Laury's MPL format) that is properly incentivized, the study is categorized as an *economic experiment*. If another study uses the same lottery task (e.g., Holt and Laury' MPL format) but this task is not incentivized or improperly incentivized (e.g., flat payment), then the study is categorized as a *stated preference study*.

discussion of the pros and cons of economic experiments, we refer to Cerroni et al. (2023), Danz et al. (2022, 2024), and Harrison et al. (2004).

Fig. 7 indicates that 88 % of the studies (56 of 64) in this literature review investigate risk preferences in fertilizer decision modelling using secondary data. Of these, 78 % (50 studies) apply mathematical methods and 9 % (6 studies) econometric methods. Seminal work using secondary data methods in our literature review includes Babcock and Hennessy (1996), Bontems and Thomas (2006), Gardebroek (2006), Isik and Khanna (2003), Serra et al. (2008). Primary data methods are applied less frequently, accounting only for 13 % (8 of 64) of reviewed studies. Of these, 75 % (6 of 8 studies) use stated-preference methods and 25 % (2 of 8 studies) use economic experiments. We consider Kallas et al. (2010), SriRamaratnam et al. (1987), and Vollmer et al. (2017) as seminal work for primary data methods. Appendix Table A2 provides the full list of reviewed papers using mathematical, econometric, stated preference and economic experimental methods.

Next, Fig. 8 shows the relationship between fertilizer management decisions and applied methods to incorporate risk preferences in fertilizer decision modeling. Different methods may be better suited to study specific fertilizer decision problems than others. Studies that focus on optimal application amounts of N-based fertilizers mainly apply mathematical methods (93 % = 38 of 41 studies), while only three studies employ econometric methods.[12] The dominance of mathematical methods is not surprising in optimal fertilizer decisions as these methods are commonly employed to predict optimal behavior, as suggested by EUT.

Most studies that focus on observed amounts of N-based fertilizer applications apply mathematical methods (67 % – 4 of 6 studies), while only two use stated preference methods.[13] Research on N-based fertilizer overuse is scant (2 studies). Of these, one study implements a mathematical method,[14] while the remaining one employs an econometric approach.

We observe more heterogeneity in research on organic fertilization: 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.

4.3. The relationship between risk preferences and fertilizer management decisions

We now present findings on the relationship between risk preferences and N-based fertilizer management decisions, while also considering the underlying methodological approach used to investigate this relationship. We categorize the correlation findings for each fertilizer management decision separately as presented in Fig. 9.

4.3.1. Optimal N-based fertilizer application amount (41 studies)

Most studies (63 % – 26 of 41 studies) apply mathematical methods and observe that the optimal N-based fertilizer application amount generally decreases as farmers' risk aversion increases. In particular, several reviewed studies find that farmers with very high-risk aversion tend to have a lower optimal N-based application amount compared to risk-neutral farmers (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). Other studies indicate that this correlation also holds for more moderate levels of risk aversion (Chen et al., 2024; Finger, 2012; Finger et al., 2014; Isik, 2002; Roosen & Hennessy, 2003), and also when various contextual conditions vary: soil nitrate level (Paulson & Babcock, 2010), the introduction of crop or revenue insurance coverage (Babcock & Hennessy, 1996), and the implementation of N taxes (Finger, 2012).

20 % (8 of 41) of reviewed studies report opposite results, indicating that risk-averse farmers may have a higher optimal N-based fertilizer application amount than risk-neutral farmers. This relationship holds when using mathematical methods (e.g., Anderson & Kyveryga, 2016) as well as an econometric approach (Dequiedt et al., 2023). Another 7 % (3 of 41 studies) present mixed results (e.g., Bontems & Thomas, 2006) and two studies show null effects (e.g., He et al., 2022). All studies except Dequiedt et al. (2023) employ mathematical methods. Overall, these results appear to align with the idea that farmers consider N-based fertilizers as a risk-increasing production input.

We next focus only on studies that incorporate a dynamic perspective, specifically fertilizer applications over time during a season (see Fig. 10). Standard economic theory predicts that risk-averse farmers apply higher fertilizer amounts early in the season than risk-neutral farmers (Huang et al., 1993, 1994; Huang & Uri, 1995). Considering studies that use mathematical methods to investigate the optimal N-based fertilizer application amount, 67 % (6 of 9 studies) show a positive correlation between risk aversion and N-based fertilizer amount. 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 studies (3 of 9 studies), all employing dynamic mathematical methods, report either mixed results (Bontems & Thomas, 2006; Huang & Uri, 1995) or a negative correlation between risk aversion and the optimal N fertilizer amount (Zentner et al., 1992).

4.3.2. Real amount of N fertilization (six studies)

When using mathematical methods, 50 % (2 of 4 studies) indicate that the actual N fertilizer application is lower among more risk-averse farmers, suggesting a negative correlation between risk aversion and the amount of N fertilizer applied (Larson et al., 1998; Schaub & Benni, 2024). Lu et al. (1999) observe the opposite association, whereas Paudel et al. (2000) take a different approach and compare fertilizer amounts of risk-minimizing and regret-minimizing farmers.[15] The authors conclude that regret-minimizers appear to apply more N fertilizers than risk-minimizers.

The two studies based on stated preference surveys provide inconsistent evidence. SriRamaratnam et al. (1987) find that farmers are risk neutral or moderately risk averse, and risk aversion (slightly) increases the N-based fertilizer application amount. However, Tevenart and Brunette (2021) discern that the majority of farmers are risk averse and find that risk-averse farmers tend to use lower total amounts of N-based fertilizers (compared to the others), which is consistent with evidence from mathematical method studies.

In the context of investigating the real N fertilizer amount, only

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[12] Dequiedt et al. (2023) adopt an approach that minimizes the gap between individually observed fertilizer levels and those estimated from a yield-response function. The authors state that this "approach is more common in agronomic research than in economics" (p. 741). Groom et al. (2008) and Regev et al. (1997) use Antle's moment-based approach (Antle, 1987) to elicit risk preferences and then run scenario simulations to predict fertilizer elasticities with respect to water, assuming that farmers maximize (their utility) of profit.

[13] Studies applying mathematical methods to examine observed N fertilizer application apply various approaches: stochastic dominance frameworks (Larson et al., 1998; Schaub et al., 2023), the "safety-first'' criterion (Lu et al., 1999), or a linear programming model to relate desired income levels to observed fertilizer use (Paudel et al., 2000). The stated-preference studies use observed N-based fertilization application amounts to study correlation between elicited risk preferences and fertilizer decisions at farm level (SriRamaratnam et al., 1987; Tevenart & Brunette, 2021).

[14] Rajsic et al. (2009) calibrate the optimal nitrogen rate and assess overuse as the difference between actual and recommended (optimal) N rates across different simulated levels of risk aversion.

[15] According to Paudel et al. (2000), regret-minimizing behavior refers to farmers aiming to achieve an income level as close as possible to the maximum attainable, thereby reducing feelings of regret.

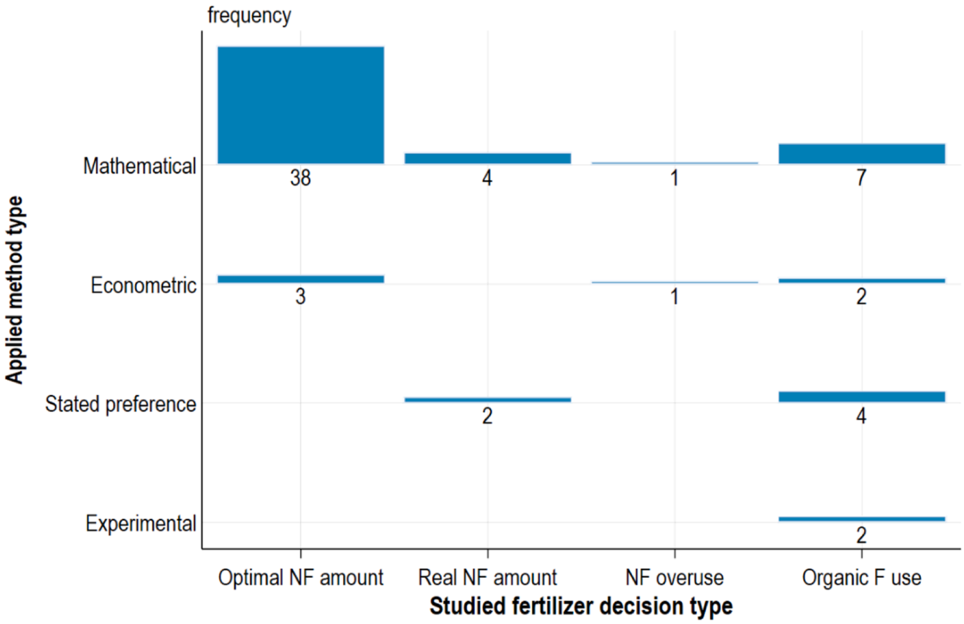

Fig. 8. Frequencies of interactions between applied method type for incorporating behavioral factors and studied fertilizer decision type. *Note*: "N" refers to nitrogen and "F" to fertilizer.

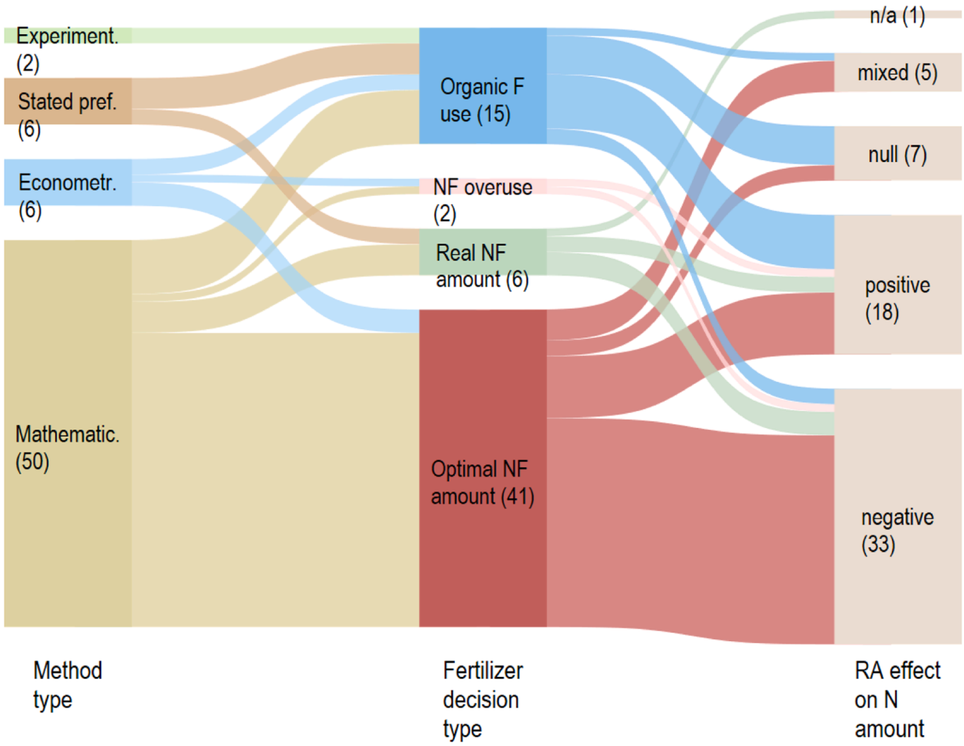

Fig. 9. Correlation between applied method type, studied fertilizer decision type, and relationship of risk aversion with applied N-based fertilizer amount. *Note*: Applied method types are mathematical, econometric, stated preference, and economic experimental methods. "N" refers to nitrogen, "F" to fertilizer, "n/a" to a study not distinguishing between different levels of risk preferences, and "RA" to risk aversion.

Tevenart and Brunette (2021) consider a dynamic perspective. According to the authors, more risk-averse farmers seem to have a statistically significantly lower amount of N fertilizer application throughout all production stages ($p < 0.01$), but no statistically significant link on the first application ($p > 0.1$).

4.3.3. *Overuse of N-based fertilizers (two studies)*

Only two studies investigate the overuse of N-based fertilizers, which represents a deviation from profit maximization. In this category, Rajsic et al. (2009) converge on the result that more risk-averse farmers are associated with a reduction in the overuse of N fertilizer using a mathematical method. Employing an econometric method, Isik and Khanna (2003) observe that risk-averse farmers tend to fertilize more under

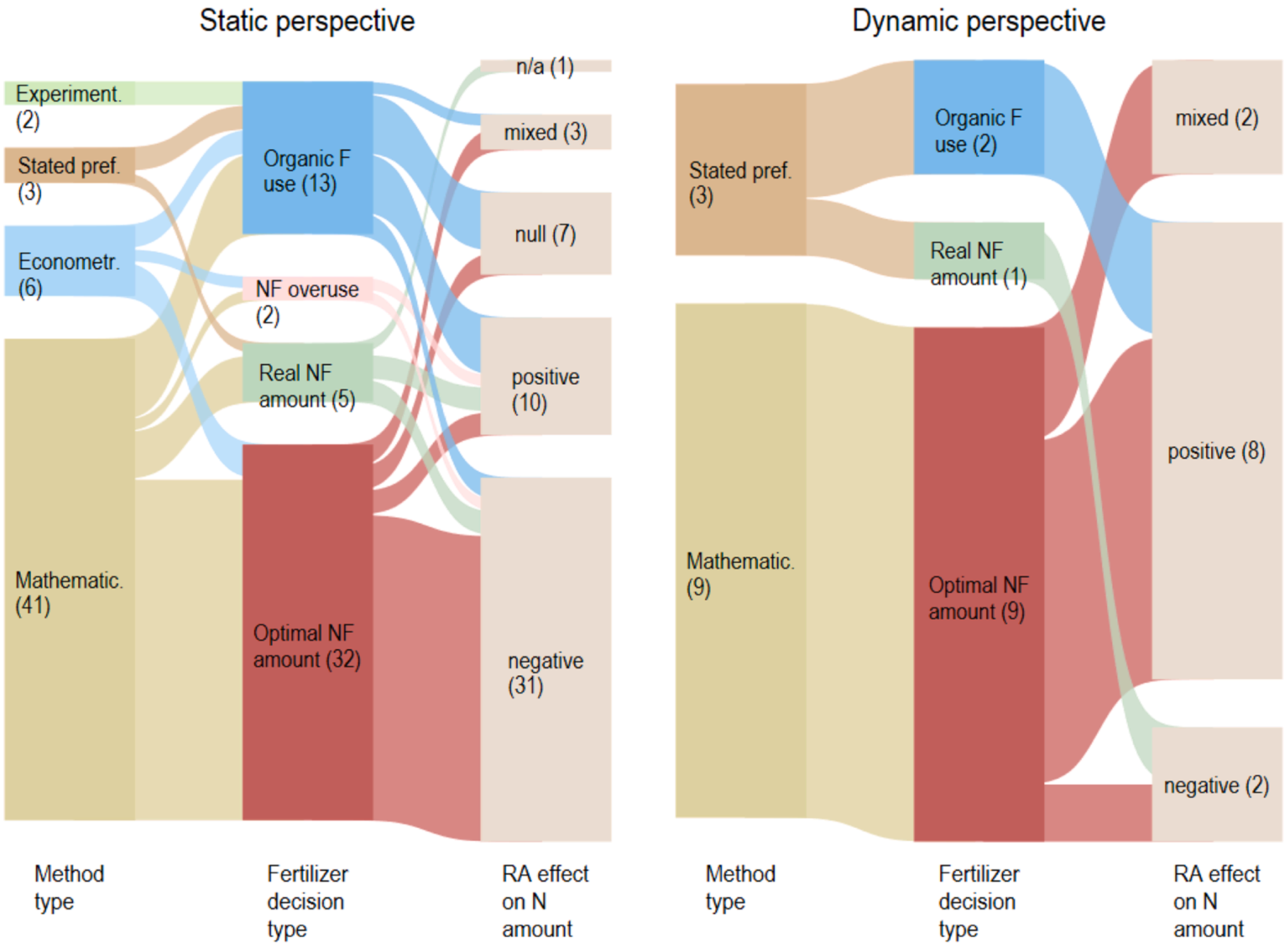

Fig. 10. Correlation between applied method type, studied fertilizer decision type, and relationship of risk aversion with applied N-based fertilizer amount in the static versus dynamic perspective. *Note*: Applied method types are mathematical, econometric, stated preference, and economic experimental methods. "N" refers to nitrogen, "F" to fertilizer, "n/a" to a study not distinguishing between different levels of risk preferences, and "RA" to risk aversion. The static perspective shows the total N fertilizer applied; the dynamic perspective also includes timing.

uncertainty and that risk-averse farmers are less likely to adopt site-specific technologies (SST) to apply adequate fertilizer rates. None of these two studies on overfertilization considers a dynamic perspective.

4.3.4. *Organic fertilization (15 studies)*

In the context of organic farming, 13 % (2 of 15 studies) observe that risk-averse farmers tend to use more organic fertilizers and reduce N fertilizer amounts (Lu et al., 2003; Zentner et al., 2011). Both studies employ mathematical approaches. The majority of the studies (47 % – 7 of 15 studies) report a positive correlation between risk aversion and conventional farming associated with higher N fertilizer use. This evidence appears consistent across methods: mathematical methods (Acs et al., 2009; Liontakis & Tzouramani, 2016), econometric methods (Gardebroek, 2006), and stated preference methods (Flaten et al., 2005; Kallas et al., 2010; Koesling et al., 2004; Parra-Lopez et al., 2007). Another 33 % (5 of 15 studies) report null effects between risk preferences and organic fertilization using various methodological approaches: mathematical methods (Flaten & Lien, 2007; Tzouramani et al., 2011), econometric methods (Serra et al., 2008), and economic experimental methods (Hermann et al., 2016; Vollmer et al., 2017). Lastly, one study presents mixed results (Walburger et al., 2004).

Two organic studies apply stated preference methods and consider a dynamic perspective. This branch of research consistently finds that more risk-averse farmers require more time to convert from conventional to organic farming, compared to risk-loving farmers (Flaten et al., 2005; Kallas et al., 2010), which may be associated with an increase in applied N-based fertilizer amounts.

4.3.5. *Incorporating product-specific N demand (all studies)*

Agricultural products have different N requirements, which should be considered to better understand the relationship of risk aversion with applied N amounts. One of the reviewed studies does not specify the type of agricultural production and is therefore excluded from this part of the analysis. It should also be noted that not all studies provided detailed information on the share of cultivated crops. Therefore, the N demand in these studies is based on the highest N requirement among the reported crops. While this approach does not allow for a precise analysis, it serves as a sufficient indicator for general N demand patterns.

To begin the analysis, we primarily follow recommendations on agricultural product-specific N requirements in high-income countries, as outlined in sources such as the FAO report and Teagasc guidelines (Roy et al., 2006; Wall & Plunkett, 2020). Based on the crops analyzed in reviewed studies, we classify crop-specific N demand into three

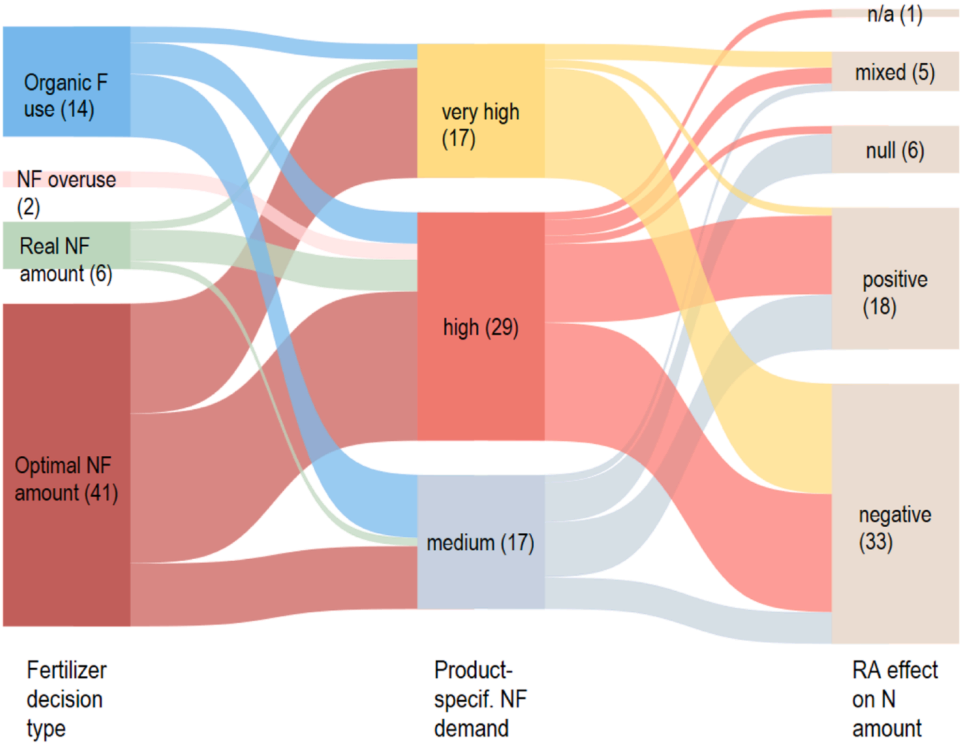

Fig. 11. Correlation between studied fertilizer decision type, product-specific N demand, and relationship of risk aversion with applied N-based fertilizer amount. *Note*: "N" refers to nitrogen, "F" to fertilizer, "n/a" to a study not distinguishing between different levels of risk preferences, and "RA" to risk aversion. Product-specific N demand is defined as: very high (≥200 kg N/ha), high (150–200 kg N/ha), medium (80–150 kg N/ha).

categories: medium, high, and very high.[16]

Fig. 11 shows the association between the type of fertilizer decision studied, the product-specific N fertilizer demand, and the correlation between risk aversion and the amount of N-based fertilizer used. We observe all three levels of product-specific N demand in all fertilizer decision types. However, organic fertilizer decisions are more commonly associated with medium N demand agricultural products, whereas other fertilizer decisions tend to focus on products with high or very high N requirements. Moreover, the relationship between risk aversion and N fertilizer application appears to vary according to the N demand of the cultivated agricultural product. When N requirements are very high, 82 % of the studies (14 of 17) report that risk aversion typically leads to a reduction in applied N. This relation tends to gradually weaken as product-specific N requirements decrease. Only 52 % (15 of 29 studies) and 24 % (4 of 17) of the studies focusing on crops requiring high and medium N still find a negative association, respectively. These findings suggest that the correlation between risk aversion and N use is shaped by how farmers perceive the consequences of fertilization. Risk-averse farmers who grow high N-requirement crops may perceive fertilizer as a risk-increasing input, and they tend to reduce fertilizer use to avoid the potential financial, agronomic, or regulatory risks associated with overuse. This behavioral pattern appears to reverse when risk-averse farmers produce medium-N requirements products. Those farmers seem less exposed to risks related to high fertilization, and therefore may be more prone to perceive fertilizer as a risk-reducing input that protects them from yield losses. This behavioral shift and result heterogeneity reflect the complexity of farmers' fertilizer decisions and the need to study and interpret these decisions in relation to other farm management decisions.

4.3.6. *Incorporating relevant production system practices (all studies)*

As outlined in the conceptual framework, the amount and timing of fertilizer applications are affected by other agricultural decisions at the farm level. Here, we focus on the decision to adopt two key production system practices: crop rotation and tillage.[17] Fig. 12 examines whether the correlation between risk aversion and N application varies with the presence of a crop rotation system. Although 42 studies (66 %) lack clear information about crop rotation practices, an interesting pattern emerges. Among studies explicitly implementing a crop rotation system, 60 % (12 of 20) show an association between risk aversion and reduced N application, whereas only 20 % (4 of 20) report the opposite association. This finding remains unchanged when controlling for the implementation of either a crop rotation or cover cropping system (see Appendix Fig. A2). Fig. 13 indicates the role of tillage practices in how risk aversion relates to N application decisions. Among studies examining no-till or minimum-till systems, 89 % (8 of 9) show that risk-averse farmers seem to have lower N use. In contrast, only 50 % (3 out of 6) of studies involving conventional tillage observe the same pattern. This association may be determined by the fact that tillage- and fertilizer-related decisions are made concurrently.

These behavioral patterns suggest that the adoption of crop rotation systems and/or reduced tillage are associated with risk-mitigating strategies that could allow risk-averse farmers to apply less fertilizer. Crop rotation and no-tillage improve soil fertility and reduce production risk, making lower N application a more viable strategy. In addition, farmers who adopt crop rotation and/or reduced tillage appear more likely to perceive fertilizer as a risk-increasing input, so a reduced use of

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[16] Product-specific N demand is defined as: very high (≥200 kg N/ha), high (150-200 kg N/ha), medium (80-150 kg N/ha). Carrot, grape, olive, cotton, sorghum, and livestock are classified as medium N demand; malting barley, aloe vera, maize, and potato as high N demand; and wheat and barley as very high N demand.

[17] These agricultural decisions are the most frequently investigated in the reviewed studies.

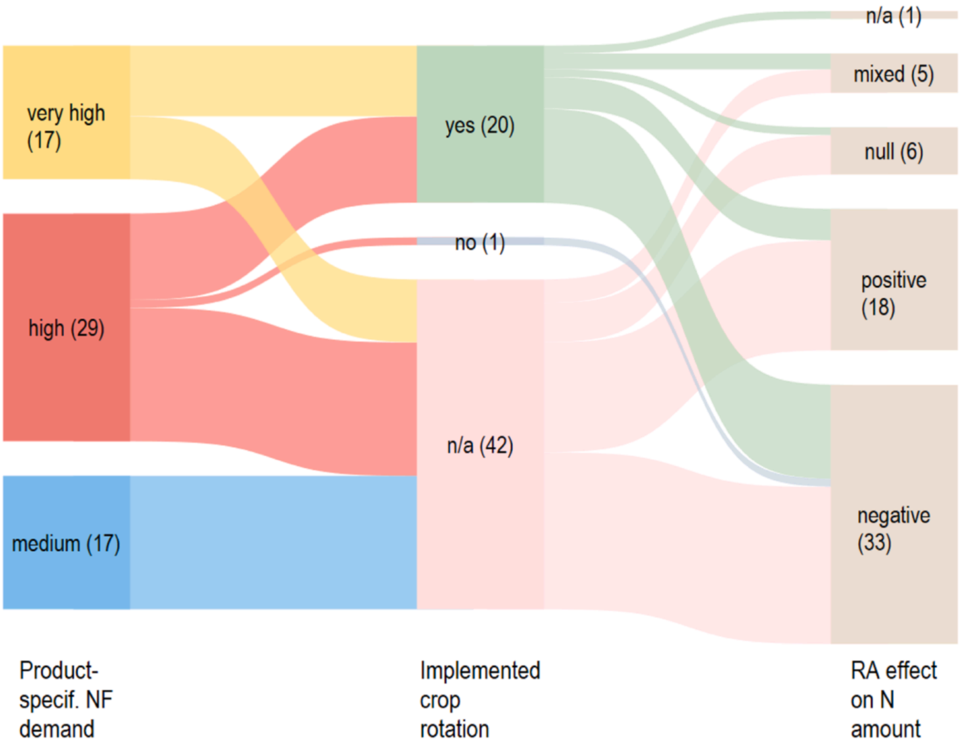

Fig. 12. Correlation between product-specific N demand, implemented crop rotation, and relationship of risk aversion with applied N-based fertilizer amount. *Note*: "N" refers to nitrogen, "n/a" (last column) to a study not distinguishing between different levels of risk preferences, and "RA" to risk aversion.

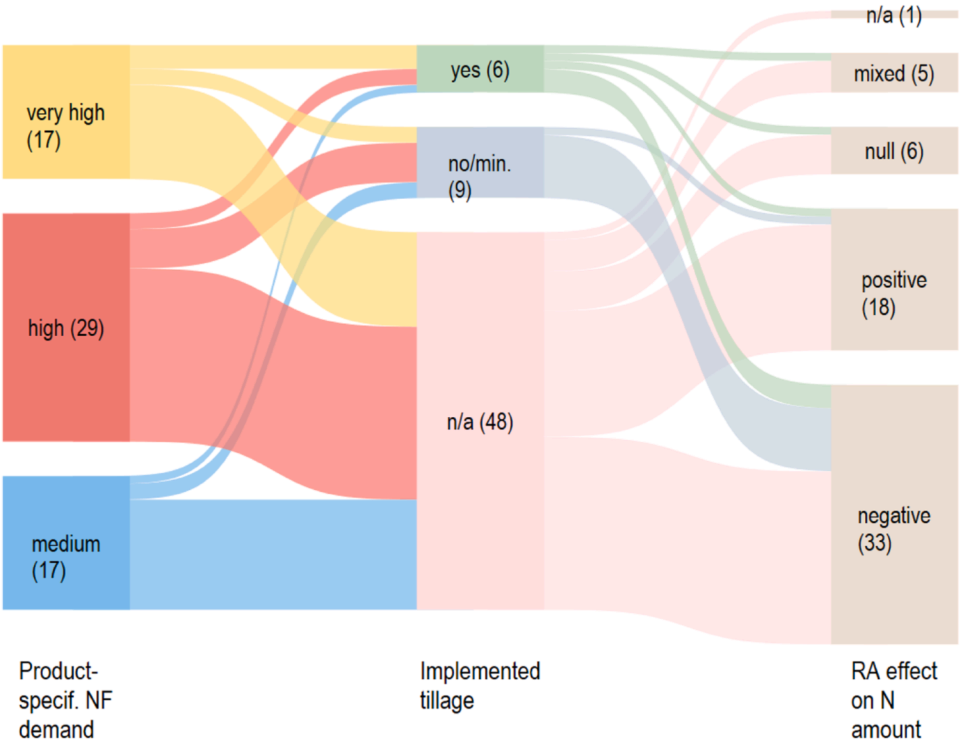

Fig. 13. Correlation between product-specific N fertilizer demand, an implemented tillage system, and relationship of risk aversion with applied N-based fertilizer amount. *Note*: "N" refers to nitrogen, "n/a" (last column) to a study not distinguishing between different levels of risk preferences, and "RA" to risk aversion.

fertilizer seems to align with the adoption of these farming practices.

4.3.7. Summary on risk preferences

This section outlines a synthesis of the evidence regarding how risk preferences relate to fertilizer decision types across various methodological approaches (see Table 1).

First, most empirical evidence from studies using mathematical methods mainly suggests that risk aversion is associated with lower N-

Table 1
Synthesis of the evidence of risk preferences on fertilizer decision type across different method type.

Method Fertilizer decision	Mathematical methods (50 studies)	Econometric methods (6 studies)	Stated preference methods (6 studies)	Economic experiments (2 studies)	Overall assessment
Optimal N fertilizer (41 studies)	*38 studies*: mostly: risk aversion ↓ optimal N rate. 9 studies con-sider dynamic fertilizer use.	*3 studies*: risk aversion ↑ optimal N rate, or mixed results.	/	/	Quite good general evidence, little knowledge on method sensitivity, correlation effect seems method-dependent. Little evidence on dynamic fertilization decisions.
Actual quantity N fertilizer (6 studies)	*4 studies*: mostly: risk aversion ↓ N rate.	/	*2 studies:* mixed results, 1 study considers dynamic fertilizer use.	/	Little general evidence, little knowledge on method sensitivity, correlation effect seems method-dependent. Little evidence on dynamic fertilization decisions.
Overuse (2 studies)	*1 study:* risk aversion ↓ overuse	*1 study*: risk aversion ↑ N overuse.	/	/	Overall, very limited knowledge on everything!
Organic fertilizer (15 studies)	*7 studies*: rather mixed correlation results.	*2 studies*: risk aversion ↓ organic fertilizer adoption.	*4 studies:* risk aversion ↓ organic fertilizer adoption. 2 studies con-sider dynamic adoption be-havior.	*2 studies*: no significant associations.	Good general evidence, good knowledge on method sensitivity, correlation effect seems method-dependent. Little evidence on dynamic organic fertilization decisions.

based fertilizer use, meaning that more risk-averse farmers tend to apply less N-based fertilizers than others. This aligns with the assumption that N is regarded as a risk-increasing production input.

Second, evidence on the relationship between risk preferences and actual fertilizer use or overuse is scarce (only 8 studies overall) and mixed. This inconsistency may arise from very different methodological approaches employed in these studies and different geographical contexts. For example, econometric approaches often overlook the link between risk perceptions and risk preferences. As a result, estimated risk preferences may in fact reflect underlying risk perceptions, thereby contributing to the observed heterogeneity in farmers' behavior (Just & Just, 2016).

Third, for organic farming, we find divergent evidence on how risk preferences relate to the amount of organic fertilizer application, which 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 also has important consequences on other farming aspects, such as crop management practices, soil health improvements, pest control methods, and compliance with certification standards.

Fourth, research that accounts for dynamic fertilizer applications is scant. It generally reveals contrasting correlation effects between behavioral factors in early and later (or total) fertilizer amounts. We suggest that modeling the fertilizer amount in different time periods is essential.

Lastly, we observe that farmers' fertilizer behavior is often analyzed in isolation, ignoring the association with other farm management decisions that may alter the correlation between risk preferences and fertilizer decisions. Our analysis shows that crop selection relates to this association. Likewise, a few studies indicate that certain farm management practices, such as crop rotation or reduced tillage, may shape how risk preferences link to fertilizer use decisions.

4.4. The relationship between other behavioral factors and fertilizer management decisions

Two studies exploring the amount of observed N-based fertilizer application shed light on other behavioral factors. SriRamaratnam et al. (1987) elicit subjective probabilities about yield expectation under different levels of N-based fertilizer use. Interestingly, the authors 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 use seem over-optimistic about the N-response in yield and tend to revise their probabilistic beliefs. Farmers with historical experience only seem to slightly revise their prior beliefs, which, in general, are already quite accurate. Research by Tevenart and Brunette's (2021) presents the only attempt to elicit ambiguity preferences and to relate these to farmers' N-based fertilizer use. This study indicates that farmers are predominantly ambiguity-neutral, but ambiguity preferences show a slight association with N fertilizer decisions (only in the first splitting – not on the total annual fertilizer application).

5. Key insights and directions for future research

Four main insights that could stimulate interesting considerations for further research emerge from our literature review. First, most studies examine the association of risk preferences on fertilizer applications within an expected utility framework that assumes profit maximization. This highlights that, although farmers' fertilizer decisions often deviate from profit maximization at the farm level, the scientific community seems to mostly ignore this phenomenon and its causes. In addition, while most of fertilizer management decisions involve some level of uncertainty about future fertilizer prices, crop yields, and output prices, current research tends to overlook theories of decision-making under uncertainty and ambiguity. This probably leads to mainly disregarding 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-adequate fertilizer applications are reference-dependent theories, rank-dependent utility theory (Quiggin, 1982), cumulative prospect theory (Tversky & Kahneman, 1992), reference-dependent utility theory (Kőszegi & 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). As also suggested by Chai et al. (2023), future research shall recognize that farmers' fertilizer behavior actually requires a utility maximization perspective that accounts for a broad range of behavioral factors and potential deviations from standard EUT. Including additional behavioral factors might raise challenges, as both our conceptual framework and the broader behavioral literature suggests that behavioral factors are closely interrelated. Future research shall aim to disentangle the effect of this wide variety of behavioral factors on fertilizer decision using empirical approaches that allow for such analysis (Just & Just, 2016).

Second, and related to the first finding, our literature review emphasizes that most research tends to ignore the specific direction of deviation from profit maximization. Most reviewed studies use mathematical approaches to understand how EUT-predicted (optimal) fertilizer rates vary over different assumed degrees of risk aversion. No studies explore the association between risk preferences and underuse, while only a scarce number of studies address the relationship between risk preferences and actual N fertilizer use or overuse, and results from these studies are inconsistent. Moreover, evidence is limited when considering dynamic fertilization decisions (early vs. later applications). As shown in the conceptual framework, uncertainties reduce over time, and thus, it is surprising that only scant literature incorporates time aspects into fertilizer decision modeling. This suggests that future research is needed to shed light on intertemporal correlations between actual fertilization and risk preferences, as well as other behavioral factors that relax EUT assumptions of pure utility maximization (often profit maximization).

Third, and related to the previous point, our literature review shows that most studies explore the relationship between risk preferences and fertilizer application in isolation without considering other farm management decisions. Focusing solely on isolated fertilizer decisions may not entirely reflect the relationship between risk aversion and fertilizer use, potentially due to selection biases from other farm management choices. Two lines of further research emerge as promising in this regard. One line relies on the investigation of fertilizer decision using a broader perspective, considering its interrelation with other farm management decisions. Highly risk-averse farmers who perceive fertilizer as a risk-increasing input may decide to reduce their reliance on N-based fertilizers and may address associated risks and uncertainties by growing crops with low N demand, implementing crop rotation or cover cropping systems, and avoiding tillage practices. We cannot discount the possibility that this could lead to the inclusion of a sample of less risk-averse farmers in our empirical analyses. Additionally, whether farmers internalize or outsource their fertilizer decision-making could influence the correlation between risk aversion and fertilizer application. Evidence from pesticide decisions suggests that risk-averse farmers seem less likely to outsource pesticide practices (Van Deynze & Malone, 2025). Whether a similar pattern exists for fertilizer decisions remains unexplored in the literature. If it does, a key question is whether farmers or fertilizer application services apply fertilizer that is closer to the economic optimum for the farm. Outsourcing can also reflect proactive behavior, such as seeking tailored advice through agricultural extension services, digital advisory platforms, or precision agricultural tools. This raises important questions about the role and value of customized information. Couture et al. (2024) demonstrate that ambiguity-averse farmers tend to place the highest value on information about pest outbreaks, particularly when pesticide costs are high. It seems plausible that these findings replicate in the fertilizer context, though further research is needed to confirm this. Another emerging area of research could examine how neglecting a broader farm risk management perspective influences the measured association between risk preferences and N fertilizer use.

Fourth, our review suggests a gap between research using different methodological approaches. Studies that rely on mathematical models tend to be disconnected from those that estimate risk preferences through econometric methods, stated preference surveys, or economic experiments. An important step to take for further research would be the use of quantitative risk preference coefficients that are estimated via econometric approaches or elicited through economic experiments in mathematical methods based on optimization procedures. This seemingly small step already presents some fundamental challenges. An example is the endogeneity that may arise from measurement errors when eliciting quantitative risk preference coefficients using stated preference and economic experiments (see Cerroni, 2020; Cerroni et al., 2023 for a discussion). Further, there is a large amount of empirical evidence that elicited risk preferences, using hypothetical and incentivized lottery tasks, are unstable across methods and time (e.g., Finger et al., 2023; Reynaud & Couture, 2012).

Relaxing EUT assumptions by incorporating elements of non-standard economic theories would be even more challenging. This approach would introduce additional complexities and raise the computational burden of mathematical optimization procedures. The most realistic step would be to integrate behavioral factors from cumulative prospect theory, such as loss aversion and probability weighting, into agent-based models. This could 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, McCallum et al., 2024; Rommel et al., 2023). In addition, there exist attempts to incorporate behavioral insights in agent-based models 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 rather challenging in the near future. One barrier is the lack of empirical evidence about farmers’ ambiguity preferences. Only a few studies have attempted to elicit farmers' uncertainty and ambiguity preferences, and research is not yet consolidated in this area (e.g., Bougherara et al., 2017; Cerroni, 2020).

Additional research is needed to more accurately understand how behavioral factors relate to farmers' fertilizer decisions.

6. Conclusion

Fertilizer use in agricultural production is key for the economic resilience of farming systems and global food security. Suboptimal N-based fertilizer applications (related to the profit maximization benchmark) can have important consequences: excessive use raises environmental and economic concerns, while under-fertilization can threaten food security. To develop a comprehensive understanding of the observed deviations from applying profit-maximizing N levels, this review presents a conceptual framework that outlines the key decisions farmers typically make about fertilizer use, specifically application amount and timing. These decisions are made under conditions of risk and uncertainty regarding three main random variables: future fertilizer prices, yields, and output prices. The conceptual framework accommodates deviations from profit maximization by acknowledging the dynamic influence of behavioral factors that underly standard and non-standard expected utility theories. Examples of such behavioral factors are: loss aversion, ambiguity preferences, hyperbolic discounting, probabilistic expectations, and probability distortions.

To gain deeper insights into the literature on the role of behavioral factors in fertilizer decision-making in high-income countries, we conducted a literature review following the PRISMA approach. Main findings indicate that literature on economic behavior in fertilizer applications appear to predominantly focus on risk preferences within an expected utility framework that implies profit maximization. Second, our review shows most research tends to ignore the direction of deviation from profit maximization (i.e., overuse, underuse, actual use) and there seems limited evidence on the timing of fertilization (early vs. late applications). Third, most studies examine the correlation between risk preferences and fertilizer application in isolation. However, our analysis shows that risk preferences are associated with differences in fertilizer application decisions, depending on crop-specific N requirements or the adoption of farm management practices such as crop rotation or reduced tillage. Fourth, our literature review suggests that strands of research with different methodological approaches tend to ignore each other. Research employing mathematical models seems largely detached from research that estimates risk preferences through econometric approaches, stated preference surveys, and economic experiments.

We recognize that incorporating behavioral insights into complex and realistic fertilizer decision models poses a challenge. However, we believe that a more coordinated and coherent integration of behavioral research, mainly conducted using primary data methods, with secondary data methods, is key to gaining a better understanding of farmers’ fertilization behaviors. This is a prerequisite for designing policies that can improve the sustainability and resilience of farming and food systems. These insights could also be easily extended to other agricultural decisions and broader economic choices that require the use of energy-intensive production inputs, which create negative environmental externalities. Examples include herbicides and pesticides in agriculture, synthetic preservatives and additives in the food processing, and fossil fuels in various production sectors.

One caveat of our review is that it does not include behavioral, social, or cognitive factors that cannot be formally incorporated into mathematical modelling. This omission is due to the scope of the literature review, rather than a lack of significance of these factors. As demonstrated by Weersink and Fulton (2020) in technology adoption and by Dessart et al. (2019) regarding the adoption of sustainable practices, these factors are highly relevant and complement economic factors – particularly in the early stages of decision-making, characterized by recognition and evaluation (Weersink & Fulton, 2020). For example, in the fertilizer context, social norms seem to significantly influence the uptake of sustainable digital fertilization methods, while behavioral and control factors appear not to be influential (Hüttel et al., 2022). Future research should build upon our systematic review by incorporating behavioral, social, and cognitive factors to gain deeper insights into observed fertilizer decisions as suggested by DeDecker et al. (2022).

We aim for our literature review to contribute to understanding the gaps in the current literature regarding how farmers' behavioral factors relate to fertilizer application decisions, thereby informing the development of more targeted research strategies.

CRediT authorship contribution statement

Laura Moritz: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Riccardo Spada:** Writing – review & editing, Software, Data curation, Conceptualization. **Jens Rommel:** Writing – review & editing, Funding acquisition, Conceptualization. **Tobias Dalhaus:** Writing – review & editing, Funding acquisition, Conceptualization. **Simone Cerroni:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization.

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Appendix

Table A1
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

Table A2
Study overview.

Study	Behavioral factor (BF)	Method to incorporate BF	Assumed utility function	Assumed/ measured/ estimated BF preference	Fertilizer (F) decision	Static/ Dynamic F decision	Finding of BF on N use	Crop/ Livestock	Production practices	Year of analysis	Country
Acs et al. (2009)	Risk preferences	Mathematical	Negative exponential	CARA (0 - 0.0000048)[b]	Organic adoption	Static	RA increase	Winter & spring wheat, spring barley, ware & seed potato, sugar beet, onion, carrot, kidney bean, green pea, alfalfa, celeriac	Crop rotation	n/a	Netherlands
Anderson and Kyveryga (2016)	Risk preferences	Mathematical	n/a	Risk-tolerant, risk-neutral, risk-averse (*own definition*)	Optimal N F amount[+]	Static	RA increase	Corn, soybean	Crop rotation	2006 - 2014	USA
Asci et al. (2015)	Risk preferences	Mathematical	n/a	RRAC (0 vs. 2)[b]	Optimal N F amount	Static	RA decrease	Potato	n/a	1952 - 2010	USA

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Table A2 (*continued*)

Study	Behavioral factor (BF)	Method to incorporate BF	Assumed utility function	Assumed/ measured/ estimated BF preference	Fertilizer (F) decision	Static/ Dynamic F decision	Finding of BF on N use	Crop/ Livestock	Production practices	Year of analysis	Country
Babcock and Hennessy (1996)	Risk preferences	Mathematical	Negative exponential	CARA (0- 0.01)[b]	Optimal N F amount	Static	RA decrease	Corn	n/a	1986 - 1991	USA
Bontems and Thomas (2006)	Risk preferences	Mathematical	vNM	CRRA (0–5)[b]	Optimal N F amount & timing	Dynamic	Mixed	Corn	n/a	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	Static	RA decrease	Corn, cotton, soybean	Crop rotation	2006 - 2012	USA
Boyer et al. (2018)	Risk preferences	Mathematical	Negative exponential	ARAC (0–0.03)[b]	Optimal N F amount	Static	RA decrease	Cotton	W/o winter cover crops (winter wheat, hairy vetch); w/o tillage	1984 −2012	USA
Capitanio et al. (2014)	Risk preferences	Mathematical	Negative exponential	DARA (1 vs. 3, low vs. high RA)	Optimal N F amount	Static	RA decrease	Wheat, tomato	n/a	2003 - 2008	Italy
Chen et al. (2024)	Risk preferences	Mathematical	Negative exponential	CARA (0–0.008)[d]	Optimal N F amount	Static	RA decrease	Winter wheat	Crop rotation	2018 - 2022	USA
Choi and Feinerman (1995)	Risk preferences	Mathematical	CRRA UF: $U = -\pi^{1-R}$	CRRA (0 vs. 123)[b]	Optimal N F amount in early application	Dynamic	RA increase	Wheat	n/a	1969 - 1970	Israel
Cox et al. (2010)	Risk preferences	Mathematical	Negative exponential	CARA (0–0.02)[b]	Optimal N F amount	Static	RA decrease	Wheat, sorghum, mungbean, chickpea	Crop rotation	1995 - 1998	Australia
Dequiedt et al. (2023)	Risk preferences	Econometric	Negative exponential	CARA (%risk-loving > %risk-averse > % risk-neutral)	Optimal N F amount	Static	RA increase	(Durum) wheat, oat, rapeseed, fodder & grain corn, spring & winter barley, sunflower, triticale^{+}	Crop rotation	2010 - 2013	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	Dynamic	RA increase	Corn	n/a	1955 - 1987	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	Static	RA decrease	Corn	n/a	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	Static	RA decrease	Livestock	n/a	1993 - 2002, simulate 2071 - 2100	Switzerland
Flaten et al. (2005)	Risk preferences	Stated preference	-	Risk aversion	Organic adoption	Static	RA increase $(\mathrm{RA}_{\mathrm{organic}} < \mathrm{RA}_{\mathrm{convetional}})$	Livestock	n/a	2002 - 2003	Norway
Flaten and Lien (2007)	Risk preferences	Mathematical	Negative exponential	CARA (0- 0.000003)[b]	Organic adoption	Static	Zero	Livestock	n/a	2003 - 2004	Norway
Gandorfer et al. (2011)	Risk preferences	Mathematical	CRRA UF: $U = c + dW_t^{1-R}$	RRAC (0–4)[b]	Optimal N F amount^{+}	Static	Zero	Potato, wheat, corn	Crop rotation; different tillage systems	1994 - 2006	Germany
Gardebroek (2006)	Risk preferences	Econometric	“is not explicitly defined”	Elicit CARA	Organic adoption	Static	RA increase $(\mathrm{RA}_{\mathrm{organic}} < \mathrm{RA}_{\mathrm{convetional}})$	Mainly wheat, potato, sugar	n/a	1990 - 1999	Netherlands

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Table A2 (*continued*)

Study	Behavioral factor (BF)	Method to incorporate BF	Assumed utility function	Assumed/ measured/ estimated BF preference	Fertilizer (F) decision	Static/ Dynamic F decision	Finding of BF on N use	Crop/ Livestock	Production practices	Year of analysis	Country
								beet, vegetables			
Groom et al. (2008)	Risk preferences	Econometric	Flexible	Elicit ARAC, Down-side risk aversion	Optimal N F amount	Static	Mixed	Coriander, broad bean, barley, wheat	n/a	1998	Cyprus
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	Static	RA decrease	Cotton	W/o winter cover crop (winter wheat, hairy vetch, crimson clover); w/o tillage	1981 - 2012	USA
He et al. (2022)	Risk preferences	Mathematical	Negative exponential	ARAC (0- 0.0017)[b]	Optimal N F amount	Static	Zero	Carrot	n/a	2016 – 2018	USA
Hermann et al. (2016)	Risk preferences	Experimental	-	Holt & Laury (2002) values	Organic adoption	Static	Zero	Livestock	n/a	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	Dynamic	RA increase	Cotton	n/a	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	Dynamic	RA increase	Cotton	n/a	1989	USA
Huang and Uri (1995)	Risk preferences	Mathematical	Power UF: $U = \frac{\pi^{1-R}}{1-R}$	CRRA (0 vs. 1.5)[c]	Optimal N F amount & timing	Dynamic	Mixed	Cotton	n/a	1989	USA
Huang et al. (1998)	Risk preferences	Mathematical	n/a	ARAC (0–0.02)[b]	Optimal N F amount & timing	Dynamic	RA increase	Corn	n/a	1991	
Huang et al. (2000)	Risk preferences	Mathematical	n/a	ARAC (0–0.02)[b]	Optimal N F amount & timing	Dynamic	RA increase	Corn	n/a	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	Static	RA decrease	Corn	n/a	1975 - 1999	USA
Isik and Khanna (2003)	Risk preferences	Econometric	Flexible	Elicit DARA & IRRA	NF overuse	Static	RA increase	Corn	n/a	1993 - 1994	USA
Kallas et al. (2010)	Risk preferences	Stated preference	-	Risk aversion	Organic adoption & adoption time	Dynamic	RA increase ($RA_{organic} < RA_{convetional}$) [for both]	Grapes	n/a	2008	Spain
Koesling et al. (2004)	Risk preferences	Stated preference	-	Risk aversion	Organic adoption	Static	RA increase ($RA_{organic} < RA_{convetional}$)	Livestock	n/a	2002	Norway
Lambert (1990)	Risk preferences	Mathematical	n/a	ARAC (0–0.012)[b]	Optimal NF amount	Static	RA decrease	Cotton	n/a	1976 - 1986	USA
Larson et al. (1998)	Risk preferences	Mathematical	-	Risk-neutral vs. risk-averse vs. risk-seeking	NF amount	Static	RA decrease	Corn	Cover crops (no, winter wheat, hairy vetch, crimson clover); no tillage	1986 - 1995	USA
Liontakis and Tzouramani (2016)	Risk preferences	Mathematical	n/a	ARAC (0- 0.00024)[b]	Organic adoption	Static	RA increase	Aloe vera	n/a	n/a	Greece
Lu et al. (1999)	Risk preferences	Mathematical (Safety-First criterion)	-	Risk-neutral vs. risk-averse (*own definition*)	NF amount	Static	RA increase	Corn, winter wheat, soybean	Crop rotation; no tillage	1994 - 1997	USA
Lu et al. (2003)	Risk preferences	Mathematical	n/a	ARAC (0- 0.01)[b]	Organic adoption, NF amount	Static	RA decrease	Corn, soybean, wheat	Crop rotation or winter cover crop (hairy vetch, wheat); no/reduced tillage	1993 - 1997	USA
Meyer-Aurich et al. (2009)	Risk preferences	Mathematical	Negative exponential	ARAC (0 - 0.01)[b]	Optimal NF amount	Static	RA decrease	Corn, wheat, potato, wheat	Crop rotation; different tillage systems	1994 - 2006	Germany

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Table A2 (*continued*)

Study	Behavioral factor (BF)	Method to incorporate BF	Assumed utility function	Assumed/ measured/ estimated BF preference	Fertilizer (F) decision	Static/ Dynamic F decision	Finding of BF on N use	Crop/ Livestock	Production practices	Year of analysis	Country
Meyer-Aurich et al. (2016)	Risk preferences	Mathematical	Negative exponential	ARAC (0 - 0.01)[b]	Optimal NF amount	Static	RA decrease	Winter rye, winter barley	Crop rotation	1995 - 2010	Germany
Meyer-Aurich and Karatay (2019)	Risk preferences	Mathematical	Negative exponential	ARAC (0 - 0.004)[b]	Optimal NF amount	Static	RA decrease	Winter wheat	Crop rotation	2001 - 2005, 1996 - 1999, 2002, 2012 – 2016	Germany
Meyer-Aurich et al. (2020)	Risk preferences	Mathematical	Negative exponential	ARAC (0 - 0.004)[b]	Optimal NF amount	Static	RA decrease	Winter wheat, winter rye, winter barley, canola	Crop rotation	1996 - 2002	Germany
Monjardino et al. (2013)	Risk preferences	Mathematical	Negative exponential	ARAC (0 - 0.035)[b]	Optimal NF amount	Static	RA decrease	Wheat	n/a	2009 - 2011	Australia
Monjardino et al. (2015)	Risk preferences	Mathematical	Negative exponential	ARAC (0 - 0.035)[b]	Optimal NF amount	Static	RA decrease	Wheat	n/a	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	Static	RA decrease	Wheat	Conventional tillage	2001 - 2015	Australia
Parra-Lopez et al. (2007)	Risk preferences	Stated preference	-	Risk aversion	Organic adoption & adoption time	Dynamic	RA increase ($RA_{organic} < RA_{convetional}$) [for both]	Olive	n/a	2000 - 2001	Spain
Paudel et al. (2000)	Risk preferences	Mathematical	n/a	Risk aversion vs. regret minimization (*own definition*)	NF amount	Static	Regret minimizers apply more NF than risk minimizers	Peanut, corn	Crop rotation	Only know: “simulated for a 30-year time horizon”	USA
Paulson and Babcock (2010)	Risk preferences	Mathematical	CARA UF	CARA (0 - 0.02)[b]	Optimal NF amount	Static	RA decrease	Corn, soybean	Crop rotation	1985 - 1990	USA
Pendell et al. (2007)	Risk preferences	Mathematical	Negative exponential	CARA (0 - 0.025)[b]	(Optimal) NF amount	Static	RA decrease	Corn	W/o tillage	1992 - 1999	USA
Rajsic et al. (2009)	Risk preferences	Mathematical	Negative exponential	CARA (0–0.01)[b]	NF overuse	Static	RA decrease	Corn	n/a	1993 –2001	Canada
Regev et al. (1997)	Risk preferences	Econometric	Flexible	ARAC (0–3)[b]	Optimal NF amount	Static	RA decrease	Wheat	n/a	1984 –1988, 1991	Switzerland
Rössert et al. (2022)	Risk preferences	Mathematical	n/a	Risk neutral vs. moderate RA vs. strong RA (own definition)	Optimal NF amount	Static	Mixed	Winter wheat, winter barley, grain, silage corn, winter rapeseed, sugar beet, potato	Crop rotation	2004 – 2019	Germany
Roosen and Hennessy (2003)	Risk preferences	Mathematical (Stochastic dominance)	-	Risk-neutral vs. risk-averse	Optimal NF amount	Static	RA decrease	Corn	n/a	1987 - 1991	USA
Rosas et al. (2015)	Risk preferences	Mathematical	Negative exponential	Risk premium (0- 50 % of the standard deviation of profits)[b]	Optimal NF amount	Static	RA decrease	Corn	No crop rotation; tillage (not further specified)	2010	USA
Schaub and Benni (2024)	Risk preferences	Mathematical (Stochastic dominance)	-	Risk-neutral vs. risk-averse	NF amount	Static	RA decrease (for wheat)	Wheat, grassland for milk production	Crop rotation	1991 - 2022	Switzerland
Serra et al. (2008)	Risk preferences	Econometric	Flexible	Arrow-Pratt measure	Organic adoption	Static	Zero	n/a	n/a	2001 - 2003	Spain
Smith et al. (2012)	Risk preferences	Mathematical	Negative exponential	CARA (0 - 0.03)[b]	Optimal NF amount	Static	RA decrease	Malting barley	n/a	2005 - 2008	Canada
Smith et al. (2015)	Risk preferences	Mathematical	Negative exponential	CARA (0 - 0.025)[b]	Optimal NF amount	Static	RA decrease	Wheat	Crop rotation	1972 - 2013	USA
SriRamaratnam et al. (1987)	Risk preferences	Stated preference	-	Absolute risk aversion (low RA levels)	NF amount	Static	RA increase	Grain sorghum	Conventional tillage	1977 - 1984	USA
	Subjective probabilities	Stated preference	-	Subjective N yield response	NF amount	Static	Subjective probabilities increase				

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Table A2 (*continued*)

Study	Behavioral factor (BF)	Method to incorporate BF	Assumed utility function	Assumed/ measured/ estimated BF preference	Fertilizer (F) decision	Static/ Dynamic F decision	Finding of BF on N use	Crop/ Livestock	Production practices	Year of analysis	Country
Tevenart and Brunette (2021)	Risk preferences	Stated preference	-	Holt & Laury (2002) values	NF amount + timing	Dynamic	RA decrease	Mostly cereals (wheat, corn)	n/a	2018 - 2019	France
	Ambiguity preferences	Stated preference	-	Chakravarty & Roy (2009) values	NF amount (in first application)	Dynamic	Ambiguity aversion increase				
Tzouramani et al. (2011)	Risk preferences	Mathematical	n/a	ARAC (0.01 - 0.07) = hardly to very RA	Organic adoption	Static	zero	Livestock	n/a	1999 - 2003	Greece
Vollmer et al. (2017)	Risk preferences	Experimental	-	Holt & Laury (2002) values	Organic adoption	Static	Zero	Livestock	n/a	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	Static	Mixed	Wheat, legume	Crop rotation; different tillage systems	1993 - 2000	Canada
Zentner et al. (1992)	Risk preferences	Mathematical	n/a	ARAC (0–0.05)[b]	Optimal NF amount & timing	Static	RA decrease	Spring wheat	No tillage	1982 - 1990	Canada
Zentner et al. (2011)	Risk preferences	Mathematical (Stochastic dominance)	-	low, medium and high RA	Organic adoption, optimal NF amount	Dynamic	RA decrease	Wheat, canola, lentil, rye, pea, barley, oat, alfalfa	Crop rotation; different tillage systems	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, [+]typical local varieties (secondary data).

Table A3

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

Note: Journals only publishing one reviewed study are not listed here.

Fig. A1. Geographical distribution and frequency of countries analyzed in reviewed studies.

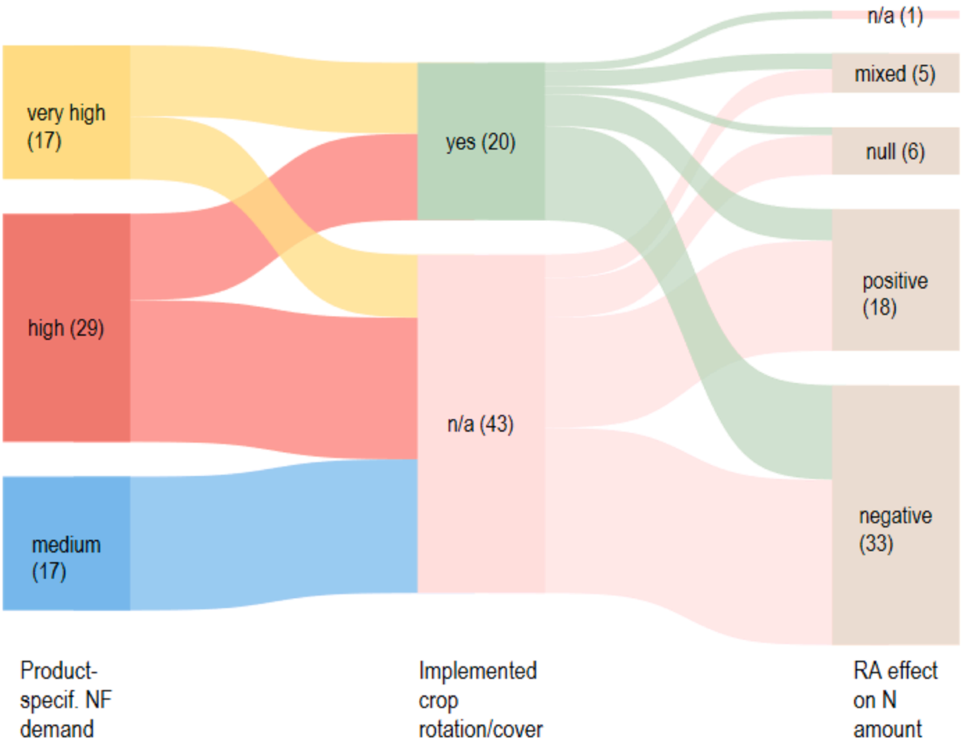

Fig. A2. Correlation between product-specific N fertilizer demand, an implemented crop rotation or cover crop system, and relationship of risk aversion with applied N-based fertilizer amount. Note: "N" refers to nitrogen, "n/a" (last column) to a study not distinguishing between different levels of risk preferences, and "RA" to risk aversion.

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