Do Modern Malt Barley Cultivars Reduce Producers' Economic Risk? Evidence from Southern Idaho

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Abstract

Although risk is inherent in the production of all agricultural crops, malt barley is relatively unique because the main buyers of malt barley (malt processors and beer brewers) have strict grain quality-related specifications, especially related to grain protein content, in their production contracts with producers. By nature, these production contracts that include specific quality parameters tightly link production risk with market or price risk to a stronger degree than is the case with other grains. Within the context of these multiple and interacting risks, malt barley producers make choices regarding the cultivars to plant and their associated nitrogen application rates during cultivation. Over the past several decades, there has been a substantial amount of research and development by public and private entities in the breeding, development, and testing of modern malt barley cultivars that have desired characteristics such as yield potential, disease resistance, and grain protein content. The objective of this paper was to determine whether modern malt barley cultivars reduce producers economic risk. We developed an economic model to represent the main decisions of malt barley producers. The model builds on the existing economic literature by accounting for both risk and ambiguity, which we argue pertains well to the situation of predicting pre-planting initial soil nitrogen values. The empirical analysis was implemented using field trial data on yield and grain protein response to nitrogen applications for four cultivars: two modern and two historical. The field trial data were supplemented by market data on nitrogen prices, other production costs, sales prices, and soil test cost. These data were incorporated into the profit estimation and utility simulation analyses associated with each cultivar under various nitrogen supply scenarios. The results indicate that modern cultivars do reduce economic risks compared to historical cultivars. The findings have several short and long-term implications for malt producer risk management and productivity and the performance of the malt processing and beer brewing industries.

Keywords: Risk, ambiguity, cultivars, malt barley, Idaho.

JEL Codes: D81, Q12, Q16

1 INTRODUCTION

Malt barley production, like production of other crops, has inherent risks. Each of the five types of agricultural risk, as defined by the US Department of Agriculture (USDA) Economic Research Service (ERS), including, production, price or market, financial, institutional, and human or personal (USDA ERS, 2025b), are relevant to some degree. Despite similarities with other crops, however, malt barley production is also relatively unique due to characteristics relating to the malt barley processing and beer brewing industry structures. Specifically, most barley that is grown in the study region of Idaho (ID), which is the top barley producing state in the US as of 2023 regarding cash receipts (USDA ERS, 2025a), is purchased by malt processors for use by beer brewers Idaho Farm Bureau Federation (2022). Such malt processors, which are commonly beer brewing companies, but some are also specialized in malt processing, engage directly with producers via production contracts with specific criteria such as grain quality parameters (Lewin et al., 2013). The strict quality parameters, especially those related to the grain protein content, are established by the American Malt Barley Association (AMBA, 2025). If the quality parameters are not met (e.g., protein content exceeds the threshold level), then malt processors can reject the grain. Producers whose grain is rejected do not receive the price agreed on in the contract but instead need to sell on the open market, often at a discount (Robertson and Wesenberg, 2003). While quality parameters are relevant for other grains such as wheat, the tight linkage between production and price or market risk for malt barley that is firmly bound by production contracts implies that malt barley is relatively unique to other grains regarding producers economic risk.

There is an extensive existing literature on risk preferences and mitigation within the agricultural economics literature, which was thoroughly reviewed by Komarek et al. (2020). In their examination of nearly 3,300 peer-reviewed studies between 1974 and 2019, Komarek et al. (2020) found, using the same five risk categories as USDA ERS (2025b), that 66% focus on only production risk, while 15% considered more than one type of risk. Thus, by nature of the market structure for malt barley production and processing, this study, which focuses on the economic risks among malt barley producers and encompasses aspects related to both production and price or market risk, fits in the rarer category of studies that account for multiple agricultural risk types.

The specific objective of this study is to analyze whether decades of breeding, development, and testing of modern malt barley cultivars has reduced barley producers' economic risks compared to production using historical cultivars. Such a question is important to answer because public and private entities have invested substantially in and collaborated via partnerships on the research and development (R&D) of

modern cultivars with the aim of enhancing productivity of malt barley producers.

We answered this research question by developing an economic model designed to capture the main decisions made by malt barley producers. The model builds on the extensive literature examining the importance of risk and risk preferences in producer decisions, such as in the relevant study by Babcock and Shogren (1995), by incorporating such aspects into a utility maximization framework. It also expands on the less extensive literature relating to ambiguity, or choices under true uncertainty, as described, for example, by Heath and Tversky (1991), by also accounting for ambiguity preferences. The pure uncertainty aspect of our study for which ambiguity is relevant pertains to knowledge of pre-planting initial soil nitrogen (N), for which a myriad of factors (e.g., weather, soil microbial activity, soil characteristics, prior planted crop, practices, other) are relevant and make it nearly impossible to predict with any reasonable accuracy (Kros et al., 1999; Nannipieri, 2020).

The empirical analysis encompasses data from field trial experiments implemented to quantify malt barley cultivar yield and protein response to N applications of different quantities in southern ID (Figure 1). We used field trial results for four adjunct cultivars, two modern (M69 and Voyager) and two historical (Harrington and Klages), in the analysis. Adjunct cultivars were analyzed since those are the cultivars used by the largest beer brewing companies in the US in their brewing practices (Weikert, 2024). These field trial data were supplemented with market data on N prices, other non-N production input costs, sales prices, and soil test costs. The empirical models, which are based in form on the economic model, were used to estimate profitability and simulate utility values for each cultivar under various N-supply scenarios. Our results provide strong supportive evidence that modern cultivars do reduce producers economic risk. Such results have short and long-term implications that are relevant for malt barley producer well-being and overall performance of the US malt processing and brewing industries.

2 BACKGROUND AND RELATED LITERATURE

ID has consistently ranked as the top state in the US for barley production since 2010. About 80% of the produced barley is processed as malt for use in brewing beer (Idaho Farm Bureau Federation, 2022). While there are many factors that have led to the ID barley industrys high productivity, the rich history in cultivated variety (cultivar) breeding, development, and testing via field trials has played a key role. University Extension publications show that scientists at the University of Idaho (UI) and the US Department of Agriculture (USDA) Agricultural Research Service (ARS) have cooperated on barley cultivar development and testing since the early 1970s (Roylance et al., 1974). The UI and USDA ARS have commonly partnered

with private sector entities, including large beer brewing companies (e.g., Anheuser-Busch InBev, Molson Coors), on both cultivar development and testing (IBC, 2008).

The main variables that researchers have focused on in developing new barley cultivars are yield, disease resistance, and protein content in the grain (IBC, 2008). The protein content is important because there are strict thresholds set by the American Malt Barley Association (AMBA) that are specific for each of the main brewing practices (adjunct, all-malt, and distillers). The AMBAs Ideal Commercial Malt Criteria include specific grain characteristic specifications required for adjunct and other types of brewing. We focus on adjunct brewing because it is the practice implemented by the largest US beer companies. It involves adding ingredients other than malted barley, hops, yeast, and water during brewing (Stewart, 2006; Weikert, 2024). A main AMBA criteria for adjunct brewing is that malt barley total grain protein levels cannot exceed 12.8% (AMBA, 2025). Barley grain with higher protein content than the 12.8% threshold level can be rejected by malt processors upon delivery. Such rejected barley is typically sold as animal feed at a highly discounted price (Robertson and Wesenberg, 2003). Thus, improved cultivars are those that can achieve higher yields while also keeping protein content below the industry accepted threshold level.

Given this background, the overarching goal of this study is to determine how historical and modern cultivars grown for adjunct brewing compare regarding the extent to which they mitigate economic risk. The main types of risk that influence barley producer choices that are relevant for this study that are production and price risks. Both types of risk are influenced by the amount of N applied (or N-supply, which is the sum of initial soil N and N applied) because grain yield and protein content have positive relationships with the amount of N in the soil (Stark and Brown, 2003). However, yield can decline at very high levels of N (Stark and Brown, 2003). The N application rate choice that producers make is challenging because it is commonly the case that the initial N (and other nutrient) content in soil before planting is unknown. So, barley producers are encouraged to do soil samples to determine nutrient content before application to determine appropriate rates (Stark and Brown, 2003).

Given this background of barley cultivar breeding, development, and testing, the remainder of this section discusses the relevant studies in the economics literature that relate to risk (production and price) and ambiguity (initial soil N). These studies are relevant for framing the typical production-related decision-making structure among ID farmers.

2.1 Risk and Ambiguity Literature

For purposes of this study, we define "risk" in a manner consistent with a robust strand of economic literature building on Knight (1921), as summarized in Komarek et al. (2020), which is a situation in which a specific future outcome is unknown, but the probability distribution of potential outcomes is known. This definition is expanded to account for the fact that the information set changes over time, and decision-makers commonly update their probability expectations per frameworks such as the "Bayes Rule" Wang (2003). This definition of risk applies for our case in the form of unknown yields and protein content of grown barley at the beginning of a growing season, for which data and/or experience provide a basis for forming expectations on yield and protein content. Similarly, we define "ambiguity" as the situation in which probability distribution is fully unknown (Ilut and Schneider, 2022). We propose in this article that, due to the multitude of factors, including prior crop grown, growing season conditions, soil microbial activity, weather, atmospheric conditions, among others, the probability distribution for initial N levels in the soil prior to planting is fully unknown (Kros et al., 1999; Nannipieri, 2020). Given these definitions, there are several relevant studies in the agricultural economics literature that pertain to risk and ambiguity preferences among agricultural producers.

Much of the theoretical literature on risk preferences among agricultural producers is based on the foundation that most agricultural producers are profit maximizers with varying degrees of risk aversion (Just, 1975). Such risk aversion is important for production decisions because reducing the probability of an undesirable outcome is costly (Babcock and Shogren, 1995). For the example of our case, reducing the probability of an outcome of lower than ideal yield or higher than threshold protein content requires taking costly actions such as changing fertilizer application plans or applying an additional pesticide.

There are fewer studies in the economics literature that account for ambiguity, likely due to underlying assumptions of many economic models relating to rationality and a formally defined information set (Stiglitz, 2002). Indeed, adding ambiguity increases the complexity of a decision-making framework by accounting for elements about which prior experience or data do not allow for the formation of a probability distribution. There are some examples of recent studies that have accounted for both risk and ambiguity within a utility maximization framework, including (Hayashi and Miao, 2011), Gneezy et al. (2015), and Hadera and Tadesse (2023). These models are instructive for our case because we propose that there is true uncertainty (ambiguity) regarding the initial soil N levels prior to planting due to the multi-factor complexity of the ecosystem that influences soil nutrient characteristics. Like the findings from Babcock and Shogren (1995) for risk aversion, findings from the study by Hadera and Tadesse (2023) suggest that reduc-

ing ambiguity is costly for producers. For the case of our study, the cost of reducing the uncertainty of soil N prior to planting is the cost of soil sampling and testing.

3 ECONOMIC MODEL OF MALT BARLEY GROWER DECISIONS

Our empirical analysis centers around the influence of risk and ambiguity aversions on malt barley growers decisions regarding fertilizer application rates and soil test choices that are made to maximize their respective utility. The relationships among yield, protein content, and N-supply for the respective cultivars of irrigated spring malt barley are known to producers in a general sense due to field trial implementation and result reporting such as that by (Stark and Brown, 2003). However, production and price risk remain ever present since factors such as growing season weather and soil characteristics interact with applied N to influence plant growth and grain formation. While relationships between yield, protein, and N-supply are established from prior research, the initial N content in the soil during the pre-planting period is essentially an unknown (Kros et al., 1999; Nannipieri, 2020). Hence, we argue that initial soil N content is a source of ambiguity. This is because N transformation from organic forms to inorganic forms (i.e., mineralization) is a highly complex process that involves too many factors (e.g., climate, weather, soil microbial activity, crop rotations, and other) than could reasonably be tracked by individual producers or other secondary sources given current methods.

3.1 Ambiguity of Initial Soil Nutrient Content

We developed the following proof to justify our assertion that initial pre-planting soil N content is ambiguous. First, we assume that there are two fields, A and B, and both are being cultivated. In field A, soil N content is measured periodically in the pre-planting periods, and the soil test results provide a known probability distribution of pre-planting soil N content (e.g., mean and variance from a historical calibration associated other bio-physical conditions). In contrast, in field B, N content is estimated using a model with unknown calibration quality and sparse data.

Let us define two actions taken within the context of:

First Condition: there is an assumption of equal N in field A and B.

Action I: Apply fertilizer in field A.

Action II: Apply fertilizer in field B.

Suppose the farmer takes an action that indicates they are indifferent between betting on a good yield and below threshold protein content from fields A and B. Thus, they are indifferent between actions I and II.

Next, the same farmer is offered the opportunity to select from two more options within the context of:

Second Condition: there is an assumption of low N in field A and B.

Action III: Apply fertilizer in field A.

Action IV: Apply fertilizer in field B.

If action III is preferred over IV such that they act on the known risk rather than the ambiguous estimate, then this violates the "Sure-Thing Principle" of preferences (Ellsberg, 1961). This is because if the farmer indicated indifference between field A and B under the first condition (equal N), then they should also remain indifferent under the second condition (low N). To remain consistent with the Sure-Thing Principle, they should also remain indifferent when the condition is unknown. If the farmer prefers A when uncertainty is introduced, this indicates ambiguity aversion. Thus, the determination of initial soil N content based on sparse or unreliable data constitutes ambiguity (unmeasurable uncertainty) rather than risk (measurable uncertainty).

To demonstrate that ambiguity regarding initial soil N is relevant empirically, we used field trial-based soil test data to simulate the distribution of initial soil N values. While this simulation does not represent all potential outcomes regarding initial soil N content since it is based on field trial data from the observation period of 2015 to 2019 and only a few experiment sites, it still provides insights regarding the heterogeneity of initial soil N across fields and years.

3.2 Simulation of Initial Soil Nitrogen Content

We used Monte Carlo simulation, following methods like those employed by Miller et al. (2006) and Bontems and Thomas (2000), to estimate distributions for the variables of initial (pre-planting) soil N content (N_{soil}), applied N fertilizer (N_{fert}), and total N supply (N_{supply}). The Monte Carlo simulations were parameterized using field trial-based soil test data (described in detail in section 5), and have the following form for each variable:

$$N_{soil} = min(max(\mathbb{N}(\mu_{soil}, \sigma_{soil}), min(N_{soil}), max(N_{soil})) \tag{1}$$

$$N_{fert} = min(max(\mathbb{N}(\mu_{fert}, \sigma_{fert}), min(N_{fert}), max(N_{fert})) \tag{2}$$

$$N_{supply} = N_{soil} + N_{fert} \tag{3}$$

where, $\mathbb{N}(.)$ is a normal random variable with mean μ and standard deviation σ. Also, $min(.)$ and $max(.)$ are the minimum and maximum soil N content or N applied as fertilizer as reflected in the field trial data.

The results for the simulation of initial N soil levels N_{soil} are displayed in a boxplot Figure 2. It is observed that the distribution as a positively skewed normal distribution with a mean of 83.9 kg N ha^{-1}. The ratio of the range of initial soil N values in the highest quartile to that of the lowest quartile is $\sim$2.7. While there is somewhat more concentration of observations towards the left tail than the right tail, the wide range of N contents and fairly even distribution of observations is indicative that it would be difficult to predict the initial soil N value with precision. We argue that this wide dispersion in the initial soil N data, combined with the assertion that the causal factors of determining the actual value are many and have complex interactions (Kros et al., 1999; Nannipieri, 2020), implies that ambiguity exists regarding predicting initial soil N values. For purposes of our case, an ambiguity averse farmer would pay to have a soil test implemented to determine initial soil N values and plan a N fertilization rate based on the soil test results.

3.3 Theoretical Model

The following theoretical economic model was developed to represent the decision-making process for ID malt barley producers. The model assumes that the producer has an objective to maximize utility and make production decisions to achieve this objective. The objective function builds on that of Gneezy et al. (2015) in that it accounts for both risk and ambiguity aversion, and its form is:

$$U = E(\pi) - \alpha A(N_{soil}) - \gamma R(\pi) \tag{4}$$

where, U is Utility, $E(\pi)$ is expected profit, α is the ambiguity aversion coefficient, where α=0 implies ambiguity loving and α>0 implies ambiguity aversion following Ghosh and Ray (1997) and Bajtelsmit et al. (2015), $A(N_{soil})$ is ambiguity premium to resolve soil N uncertainty, γ is the risk aversion coefficient, where γ=0 implies risk loving and γ>0 implies risk aversion following Babcock and Shogren (1995)), $R(\pi)$ is risk

premium to resolve protein content uncertainty. The expected profit function is decomposed as follows:

$$E(\pi) = (p(protein).y(N_{supply})) - c_{N_{fert}}N_{fert} - c_tT - c_{prod} \tag{5}$$

where, p(protein) is price of harvest dependent on protein content (i.e., if the protein content is less than 128 g kg^{-1} then the producers can sell it at higher price for malting otherwise it is sold as feed at a lower price), $y(N_{supply})$ is the yield function that is a function of the sum of initial soil N and N applied (N_{supply}), $c_{N_{fert}}$ is the cost of N fertilizer applied, c_t is the cost of soil testing, T is a binary variable pertaining to the choice to implement a soil test (0 for No; 1 for Yes), and c_{prod} are all non-fertilizer production costs. The ambiguity premium function has the form:

$$A(N_{soil}) = \phi(N_{soil}, \sigma^2_{N_{soil}}, T) = \begin{cases} \sigma^2_{N_{soil}}, \textit{ if } T = 1 \\ \sigma^2_{N_{soil}}N_{soil}, \textit{ if } T = 0 \end{cases} \tag{6}$$

where, ϕ is a parameter representing ambiguity preferences, N_{soil} is the observed (i.e., based on field trials) mean of soil N content, $\sigma^2_{N_{soil}}$ is observed variance of soil N. We assume that the producer beliefs about initial soil N values are based on the observed parameters N_{soil} and $\sigma^2_{N_{soil}}$. The risk premium function is specified such that it is determined by the variance of a multiplicative factor in the sales price and yield and has the form:

$$R(\pi) = \sigma^2[p(protein).y(N_{supply})] \tag{7}$$

The decision variables are N_{fert} and T. There are also two constraints pertaining to N_{supply} and protein content with the form:

$$N_{supply} = N_{soil} + N_{fert} \tag{8}$$

$$protein = f(N_{supply}) \tag{9}$$

3.4 Model Analysis

To achieve maximized utility, the malt barley producer chooses the optimizing level of N_{fert}. Such an optimization choice is represented by the First Order Conditions (FOC), obtained by differentiating both sides of equation (4) w.r.t. N_{fert}:

$$\begin{aligned} &\frac{dU}{dN_{fert}} = \frac{E(\pi)}{dN_{fert}} - \gamma \frac{dR(\pi)}{dN_{fert}} \\ \implies &\frac{dU}{dN_{fert}} = p'(N_{supply})y(N_{supply}) + p(N_{supply})y'(N_{supply}) - c_{N_{fert}} - \gamma \frac{d[\sigma^2(p \cdot y)]}{dN_{fert}} \end{aligned} \tag{10}$$

The Second Order Conditions are achieved by differentiating both sides of (10) w.r.t. N_{fert}:

$$\frac{d^2U}{dN_{fert}^2} = p''(N_{supply})y(N_{supply}) + 2p'(N_{supply})y'(N_{supply}) + p(N_{supply})y''(N_{supply}) - \gamma \frac{d^2[\sigma^2(p \cdot y)]}{dN_{fert}^2} \tag{11}$$

The sign of the second derivative in equation (11) depends on the variance of the revenue. If the sign is negative, as we would expect, the utility function is concave, which implies risk averse preferences (Fishburn and Kochenberger, 1979).

The second optimization choice pertains to whether to soil test or not, which relates to ambiguity preferences. The optimal soil test choice is determined through the FOC by differentiating both sides of equation (4) w.r.t. T:

$$\frac{dU}{dT} = -\alpha \frac{dA(N_{soil})}{dT} - c_t \tag{12}$$

where, $A(N_{soil})$ follows equation (6). Thus, equation (12) implies a discrete jump in the ambiguity premium depending on whether the soil test is performed or not. The difference in the utility between soil testing $(T = 1)$ and not $(T = 0)$ is presented as follows:

$$\Delta U_t = U(T = 1) - U(T = 0) = -\alpha\sigma^2(1 - N_{soil}) - c_t \tag{13}$$

such that if $\Delta U_t > 0$, which we would expect, soil testing improves utility.

4 DATA AND EMPIRICAL METHODS

The empirical methods demonstrate techniques used in calibrating the production and protein functions that were referenced in the economic model and that are encompassed into the empirical models used for estimating yield and protein. The estimates for yield and protein are key inputs for obtaining quantified estimates for profit and utility in a manner consistent with the economic model.

Our empirical analysis relies on field trial data collected at multiple site locations in Southern ID (Figure 1) for the soil and applied N, yield, and protein content variables, and market data for the parameters of N cost, sales prices, and soil sample test cost. The following subsections include details of each data type.

4.1 Field trial data

The field trial-based data were obtained from research focusing on yield and protein response to varying N rates for different cultivars of two-row irrigated spring malt barley that were conducted from 2015 to 2019. The field trials utilized a randomized complete block design (RCBD) incorporating the four analyzed cultivars and six levels of N applications (0, 45, 90, 134, 179, and 224 kg N ha^{-1}) across four replicates per location. In total there were 17 locations and 62 site-years based on the cultivar and site combinations.

Four adjunct cultivars, two historical and modern cultivars, respectively, were chosen for analysis in this study. The first historical cultivar, "Klages," was a staple in the malting industry for much of the mid-20th century. Developed from a cross between "Betzes" and "Domen" in 1958, Klages was released by the USDA-ARS and the University of Idaho in 1973 (Wesenberg et al., 1974). The other historical cultivar is "Harrington," serves as a historical reference point, having been widely cultivated and still used by breeders and maltsters to verify malting quality. Harrington signifies the bridge between Klages and present-day cultivars (Harvey and Rossnagel, 1984). "Moravian 69" (M69) and "Voyager" are contemporary adjunct cultivars that typify the genetics developed through significant commercial breeding programs conducted by Molson Coors and Anheuser-Busch InBev, respectively. During the study period, M69 and Voyager accounted for nearly half of the barley production in Southern ID (AMBA, 2020).

In alignment with typical agricultural methods for the area, all sites underwent conventional spring tillage, utilizing disk plows and roller harrows to prepare the seedbed. Potassium levels were above the critical soil-test thresholds and so was not applied. However, where soil tests recommended, phosphorus was supplemented as triple superphosphate applied with a pull spreader (Stark and Brown, 2003). Nitrogen was manually distributed in the form of urea across individual plots at varying rates of 0, 45, 90,

134, 179, and 224 kg N ha^{-1}. The fertilizer was then incorporated to a depth of roughly 8 cm employing a spring tooth harrow to reduce ammonia loss (Dari and Rogers, 2021). Barley sowing typically advanced in order from the lowest to the highest elevations, and all trials were planted in April or early May. Barley was reaped using a small plot combine equipped with a grain weigh system, with yields recorded at 14.5% moisture content. A grain subsample (1000g) from each plot was collected, de-awned, and cleaned for quality assessment. Grain N content was measured through high-temperature combustion and converted to grain protein.

A detailed summary statistics of the cultivar-wise initial soil N, N-supply, yield, and protein content in the grains are presented in Table 1. Based on the average yield, the cultivars are ranked from lowest to highest as follows: Klages, Harrington, M69, and Voyager. However, the ranking sequence was reversed regarding average protein content. The modern cultivar Voyager had the lowest average protein content while the historical cultivar Klages ones had the highest.

4.2 Yield and protein functions

The empirical yield functions were estimated for each cultivar i using field trial data on yield and N-supply (N_{supply}). Site-year-specific linear plateau (LP; equation 14) and quadratic plateau (QP; equation 15) yield response models were estimated for each cultivar using methods like those employed by (Correndo et al., 2023) and have the following form:

$$y(N_{supply})_i = \begin{cases} \alpha_{ic} + \beta_{ic} N_{supply_{ic}} + \epsilon_{ic}, \ \textit{if } N_{supply_i} \geq N_{supply_{ic}} \\ \alpha_i + \beta_i N_{supply_i} + \epsilon_i, \ \textit{if } N_{supply_i} < N_{supply_{ic}} \end{cases} \tag{14}$$

$$y(N_{supply})_i = \begin{cases} \alpha_{ic} + \beta_{ic} N_{supply_{ic}} + \gamma_{ic} N^2_{supply_{ic}} + \epsilon_{ic}, \ \textit{if } N_{supply_i} \geq N_{supply_{ic}} \\ \alpha_i + \beta_i N_{supply_i} + \gamma_i N^2_{supply_i} + \epsilon_i, \ \textit{if } N_{supply_i} < N_{supply_{ic}} \end{cases} \tag{15}$$

where $y(N_{supply})_i$ is the grain yield, N_{supply_i} is the total N supply, and $N_{supply_{ic}}$ is the critical N supply (CNS) rate, particular for each cultivar, at which the yield started to plateau at 95% of maximum yield. The parameters for which estimated values were obtained from implementing regressions are α_i, β_i, and γ_i, and ϵ_i are the estimation residuals.

The grain protein content function was estimated for each cultivar i as a function of the N-supply using a simple linear regression model of the form:

$$protein_i = \alpha_i + \beta_i N_{supply_i} + \epsilon_i \tag{16}$$

where, $protein_i$ is the protein content, and α_i, β_i, and γ_i, and ϵ_i are as defined above.

The calibrated equations that encompass the regression results and associated parameter estimates are presented in Table 2 (yield and protein), Figure 3 (yield), and Figure 4 (protein). Results in Figure 3 and Figure 4 show that modern cultivars (M69 and Voyager) require a higher level of N-supply to attain yield plateaus and to reach the protein threshold of 128 kg ha^{-1}, compared to historical cultivars (Klages and Harrington). Thus, the risk of breaching the critical protein content threshold due to excess N is lower for modern cultivars than it is for historical cultivars. For the remainder of the paper, we focus on the results from the QP models, since, as observed in Figure 3, those are representative of more of an upper bound of CNS values relative to the LP models. The results from the LP models are included in the Appendix for reference.

4.3 Market data

In the empirical economic analysis, the field trial data were supplemented by market data on fertilizer cost, sales prices, and soil test cost. From 2015 to 2019, the average price for fertilizer-N was \$0.90 kg^{-1} according to historical N prices included in the University of Idaho enterprise budgets (University of Idaho, 2019). The cost of production of spring malt barley other than the N cost is estimated to be \$869 ha^{-1} (University of Idaho, 2019). During the same time frame (2015-2019), the average prices for malt barley and feed barley were \$0.20 kg^{-1} and \$0.13 kg^{-1}, respectively (IBC, 2019). These data show that barley does not meet barley processor specifications and so is sold as livestock feed receives a substantially discounted sales price. The market-related parameters are listed in Table 3.

Soil sampling is common in the study region but not conducted by every farm during every season. The intensity of such sampling is dependent on the homogeneity of the field area being sampled, with higher frequency improving testing accuracy regarding existing nutrient content. Specific factors influencing the needed intensity include variation in soil types, field topography, and previous crop, and climate, among many other field-specific factors. Irrigated production in southern ID largely occurs along the Snake River Plain on fields with small elevation gradients and where soils are reasonably similar, being predominantly Aridisols and loamy in texture (Rogers et al., 2019). However, crop rotations commonly extend up to 4 or more years, and include cereals (barley, corn, wheat), broadleaf (alfalfa, edible dry beans, potato, sugar,

beet), and other specialty crops in small areas (Spangler et al., 2022). Sampling recommendations vary with lower-intensity recommendation maximums being as little as 1 composite sample per 16-20 ha^{-1}, with others targeting 8 ha^{-1} as the maximum (Walsh et al., 2023; USDA NRCS, 2007, 2023). We estimated the soil test cost for this study based on a maximum reasonable area of 15 ha per composite sample, based on recommendations and characteristics of the region. The resulting estimated cost of a soil sample is \$30 (Western Laboratories, Inc., 2024; Stukenholtz Laboratory, Inc., 2025), which implies a cost of \$2 ha^{-1} per our area-based sampling intensity estimate.

4.4 Profit and utility functions for empirical estimation

We adapted the utility and profit functions from the theoretical model subsection 3.3, equations (4) and (5), respectively, for empirical estimation by implementing the following steps.

4.4.1 Profit estimation

The profit functions for each cultivar (i) are estimated following equation (17) :

$$\widehat{E(\pi)}_i = p(protein)_i.y(\widehat{N_{supply}})_i - c_{N_{fert_i}} N_{fert_i} - c_{t_i} T_i - c_{prod} \tag{17}$$

where, $\widehat{E(\pi)}_i$ is the estimated profit for each cultivar (i), price of the harvest depends on protein content represented as:

$$p(protein)_i = \begin{cases} \$0.20\ kg^{-1} & \text{if } \widehat{protein}_i \leq 128\ g\ kg^{-1}, \\ \$0.13\ kg^{-1} & \text{otherwise,} \end{cases}$$

$y(\widehat{N_{supply}})_i$ is the calibrated yields based on cultivars, and definition of the other variables remains same as that of the equation (5), and $\widehat{protein}_i$ is the calibrated protein content based on cultivars following equation (9) and results of calibrated protein equations are in Table 2.

4.4.2 Utility simulation

The simulated utility estimates for each cultivar (i) are based on the equation (18), which depends on the estimated profit in equation (17) along with risk and ambiguity premium and coefficients and has the form:

$$\widehat{U_i} = \widehat{E(\pi)}_i - \alpha_i A(N_{soil})_i - \gamma_i R(\pi)_i \tag{18}$$

The specific values for the ambiguity aversion coefficient α we considered in the analysis ranged from 0 to 0.5, following methods like those of Ghosh and Ray (1997) and Bajtelsmit et al. (2015). The values for the risk aversion coefficient γ we used in the analysis ranged from 0 to 1, based on methods in Babcock and Shogren (1995)).

We further estimate the average probability of the positive utility for each cultivar based on risk (γ) and ambiguity (α) coefficients and N_{supply} bins, following equation (19):

$$\overline{P_i^{jk}(\widehat{U_i > 0})} = \frac{1}{MN} \sum_{j=1}^{M} \sum_{k=1}^{N} P_i^{jk}(\widehat{U_i > 0}), \tag{19}$$

where, $(\widehat{U_i > 0})$ is the estimated utility for cultivar (i), $P_i^{jk}(\widehat{U_i > 0})$ is the probability of positive utility for cultivar i, considering risk coefficient level j and ambiguity coefficient level k. $\overline{P_i^{jk}(\widehat{U_i > 0})}$ represent average probability of achieving positive utility for these coefficient levels in each N-supply bin. The simulated values vary following yield estimates and choices related soil test (farmers did soil test or not).

4.4.3 Simulated variables

For both the profitability estimation and utility simulations, a dataset for each of the key variables (N_{soil}, N_{fert}, N_{supply}, $yield$, and $protein$) was generated through Monte Carlo simulation and calibrated using the field trial data. Generating these datasets was conducted to better represent the total population of potential outcomes for barley producers in Southern Idaho than is represented in just the field trial data. The summary statistics of these simulated variables are presented in Table 4. The main purpose of Table 4 is to demonstrate that the simulated values that were used in the analysis align well with the underlying field trial data (Table 1) on which they were based.

5 RESULTS

We present the results for the empirical analysis sequentially in alignment with the outline of the data and empirical methods description in the previous section. The results and associated discussion pertaining to the profitability calculations are first and they are followed by the utility simulation results.

5.1 Profit estimation results

Per the description of the profit analysis in the empirical method section, the profitability estimates are like the the utility simulations but do not account for risk or ambiguity preferences. Detailed analyses of the profit estimates based on several N-supply bins ranging from 0 to 350 kg ha^{-1} in 50 kg ha^{-1} intervals and cultivars are presented in Figure 5 and Table 5.

Figure 5 is a plot of individual profit estimates for each N-supply bin. The plot shows that all cultivars have similar profitability estimates for the lowest N-supply bins of 0-50 and 50-100 kg ha^{-1}, but they start to diverge from each other by the 100-150 kg ha^{-1} bin. Regarding the lowest N-supply bin of 0-50 kg ha^{-1}, the profitability estimates for the historical cultivars (Klages and Harrington) were negative, while those for the modern cultivars (M69 and Voyager) were positive. All cultivars were estimated to achieve maximum profitability in the N-supply bin 150-200 kg ha^{-1}. The maximum profit estimates ranged from \$580 to \$870 ha^{-1}. This range is closely aligned with the range of profit estimates of \$460 to \$850 ha^{-1} for the maximum offered price (\$5.25 bu^{-1} or \$0.24 kg^{-1}) of malt barley in University of Idaho enterprise budgets developed during the study period (University of Idaho, 2019). The modern cultivars (M69 and Voyager) had higher profit estimates than the historical cultivars (Klages and Harrington) for all N-supply bins. A notable result is that profitability started to decline for all cultivars for N-supply bins greater than 200-250 kg ha^{-1}. However, the decrease in profitability in the higher N-supply bins was most pronounced for the historical cultivars, especially Klages. Lastly, Klages was the only cultivar to have negative estimated profitability for N-supply bins of 250-300 and 300-350 kg ha^{-1}.

Table 5 has a more detailed description of the profit estimates and includes standard errors and a 95% confidence interval (CI) for each estimate. While the results in Table 5 largely correspond with those in Figure 5, we mention a couple additional findings. First, it is easier to recognize that negative profit estimates were more common for the historical cultivars (Klages and Harrington) than the modern cultivars (M69 and Voyager), and that these were negative for the full 95% CI, which cannot be observed in Figure 5. Second, the standard errors associated with the profit estimates for the lowest N-supply bin of 0-50 kg ha^{-1} are higher for the historical cultivars (Klages and Harrington) than the modern cultivars (M69 and Voyager).

To summarize the profitability estimates, the rankings regarding the highest to lowest average profitability estimates across all N-supply bins are as follows: Voyager (modern), M69 (modern), Harrington (historical), and Klages (historical). Only the historical cultivars had profit estimates that were negative, and these were associated with the lowest and highest N-supply bins. This indicates that there is risk of

negative profit due to both under and overapplying N, but that the risk of such outcomes is much greater for historical than modern.

5.2 Utility simulation results

Consistent with the description in the empirical methods section, the utility simulation analysis expands on the profitability analysis by accounting for producer preferences regarding risk and ambiguity. To reiterate, the risk and ambiguity averse farmers have risk and ambiguity parameter values that are greater than zero, while risk and ambiguity loving farmers have associated parameter values that are equal to zero. The results for the utility simulation are presented in the form of estimates of the probability of achieving positive utility based on the choice of each cultivar and N-supply bin combination. This can be interpreted as the likelihood that a malt barley producer would be satisfied with their choice of a cultivar and N-supply combination.

One technical note is that the results were estimated separately for the scenario of with a soil test and without a soil test, and the presented results are the average of these results. The complete results for the separate estimation of each of these are included in the Appendix (Figure A.3 to Figure A.6). The average of the respective probability of positive utility for the scenario with a soil test and without a soil test when analyzed together are presented in the main section in Figure 6 and Table 6.

We start the utility simulation results discussion with those presented as a heat map plot in Figure 6, which provides a broader view of the simulated utility outcomes. Regarding interpretation, each square represents a combination of risk aversion preference, ambiguity preference, and N-supply bin. If the square is darker blue, then there is a higher probability of achieving a positive utility outcome, while the lighter blue squares indicate a lower probability of achieving positive utility. A blank square indicates that there is a zero probability of achieving a positive utility.

We emphasize several key results in Figure 6. First, in a broad sense, there are more blue (both dark and light) squares present for the combinations that include modern cultivars than there are historical cultivars. Second, and focusing on results for combinations associated with the mid-range of the ambiguity parameter with a value of 0.25, the probability patterns across bins generally follow those observed with the profitability analysis. Specifically, for all cultivars, there is a lower probability of positive utility for the lowest N-supply bins, and, to a lesser degree, the highest N-supply bins than the middle level N-supply bins. Lastly, for all cultivars, there is a lower probability of a positive utility under higher levels of risk and ambiguity aversions (γ>0 and α>0) than no risk and ambiguity aversions (γ=0 and α=0). This result aligns

with the point made in (Friedman and Savage, 1948) and (Babcock and Shogren, 1995) that risk mitigation is costly for risk averse producers. Our findings also imply that ambiguity mitigation is costly for ambiguity averse producers.

A bit more detailed results for the utility simulation analysis are displayed in Table 6. The benefit of displaying the results in tabular format in addition to the heat map diagram is that one can better observe how much the magnitudes of the estimates change across risk aversion, ambiguity aversion, and N-supply bin combinations. Additionally, the column all N-supply bins represents an average value of the probability of achieving a positive probability across all N-supply bins for each risk aversion and ambiguity aversion coefficient combination. The results across all N-supply bins align with those in Figure 6 in that the lowest probability of achieving a positive utility outcome were associated with the historical cultivars (Klages and Harrington) while the modern cultivars (M69 and Voyager) had the highest probabilities. Another way to interpret these results is that the historical cultivars had a higher probability of achieving zero or negative utility than the modern cultivars. Lastly, the estimates of probability of having positive utility were higher for the N supply bin of 150-200 kg ha^{-1} than those of 0-50 kg ha^{-1} and 300-350 kg ha^{-1}. This reflects that the increased risk of achieving an undesirable outcome by both under-applying and over-applying N applies for all cultivars.

The main takeaway message from the utility simulation is that across malt barley producers with different levels of risk and ambiguity aversion, the likelihood of achieving a positive utility outcome is higher with the modern cultivars than it is with historical cultivars, regardless of their N-supply choice. Likewise, the probability of achieving a zero or negative utility outcome is higher under production using the historical cultivar than it is using a modern cultivar. These results demonstrate that planting modern malt barley cultivars has lower economic risk than does planting historical cultivars.

6 CONCLUSIONS AND IMPLICATIONS

We implemented this study to answer the question of whether modern malt barley cultivars reduce economic risk for producers compared to historical cultivars. The results from the profitability estimation and utility simulations provide empirical evidence to support the assertion that modern cultivars do substantially reduce economic risk relative to historical cultivars. Notably, the analysis was implemented for adjunct types of malt barley, which are those used by the largest beer brewing companies in the U.S. (e.g., Anheuser-Busch InBev, Molson Coors) in their brewing practices (Weikert, 2024). Thus, thousands of U.S. barley producers have benefited from the decades of breeding, development, and testing of modern cul-

tivars conducted through partnerships between public (universities and USDA ARS) and private entities (beer brewing companies).

The employed empirical methods and findings in this study provide several contributions to the literature. First, the inclusion of risk aversion preferences in the empirical model and findings that mitigating risk is costly for producers builds on findings in a long strand of research in the agricultural economics literature, including the relevant study by Babcock and Shogren (1995). Additionally, our study contributes to the more emergent literature addressing the issue of ambiguity preferences among agricultural producers. In our case, ambiguity pertained to the high degree of uncertainty regarding initial pre-planting N, by encompassing such preferences into the economic and empirical models in manner that builds on studies such as that by Hadera and Tadesse (2023).

There are short and long-term implications of the findings this study. Regarding the short-run, stakeholders in the U.S. brewing industry have indicated that historical cultivars are still currently being planted by malt barley producers because of preferences (e.g., taste) of some brewing companies regarding their produced brewing ingredients. Since our results show that historical cultivars have higher economic risk, this implies that producers of such cultivars should expect a price premium for producing them instead of modern cultivars.

The long-term implications pertain to the issue of research and development (R&D) to create new malt barley cultivars by public and private entities, and the partnerships among them, which are essential for advancing productivity and reducing economic risk of agricultural producers. The results from this study imply that decades long investments in seed genetics, human capital, and best production practice research and development have been critical for reducing economic risk among US malt barley producers. While this study focused on malt barley in ID, we expect that such investments in technology and human capital to facilitate activities pertaining to developing new cultivars applies for other crops and other regions. This finding lends support to arguments such as those by Fuglie (2018) that continued increases in agricultural productivity globally will require sustained investments in R&D. Our study emphasizes particular importance in sustained R&D to support modern cultivar breeding, development, and testing to ensure that genetic improvements continue to yield benefits as market structures and growing conditions evolve over time.

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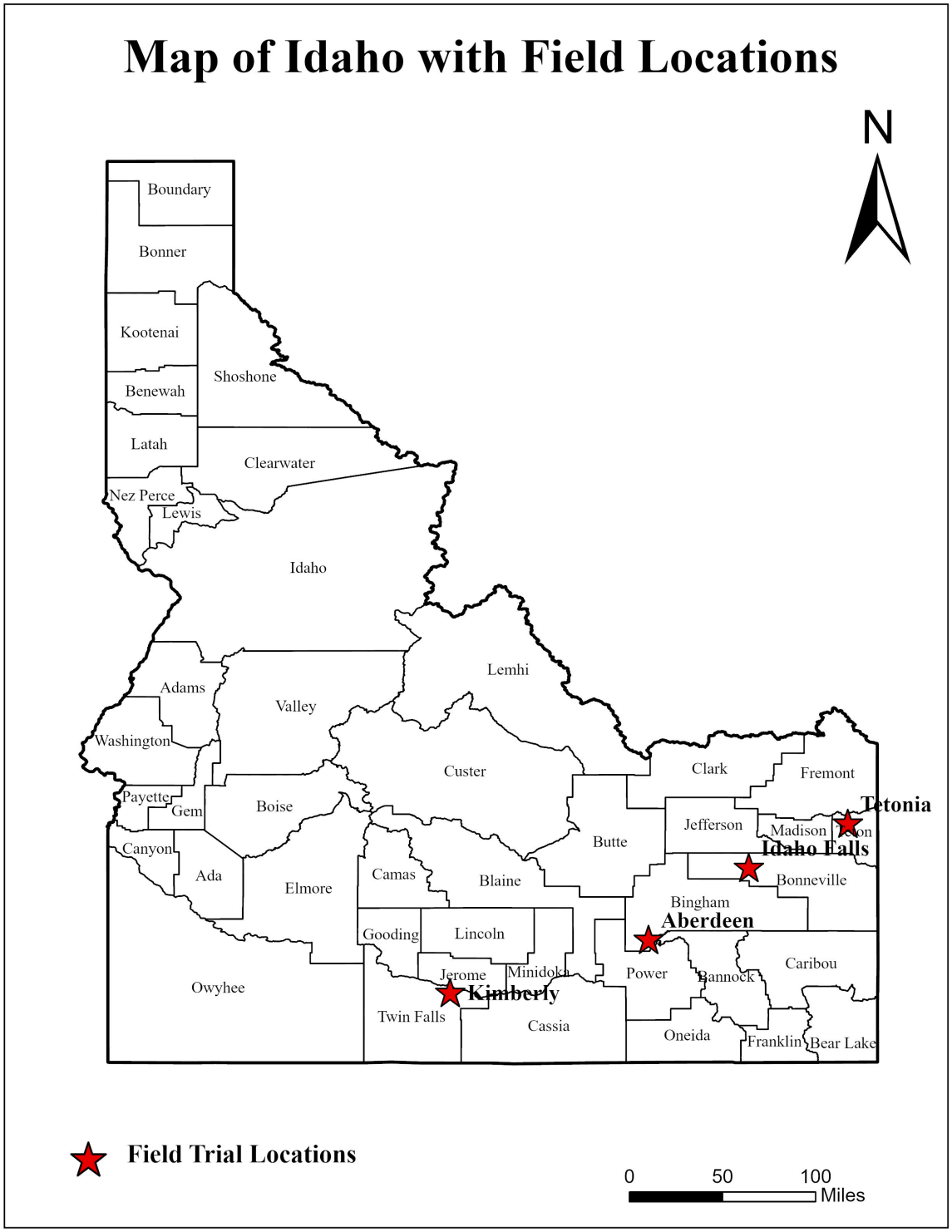
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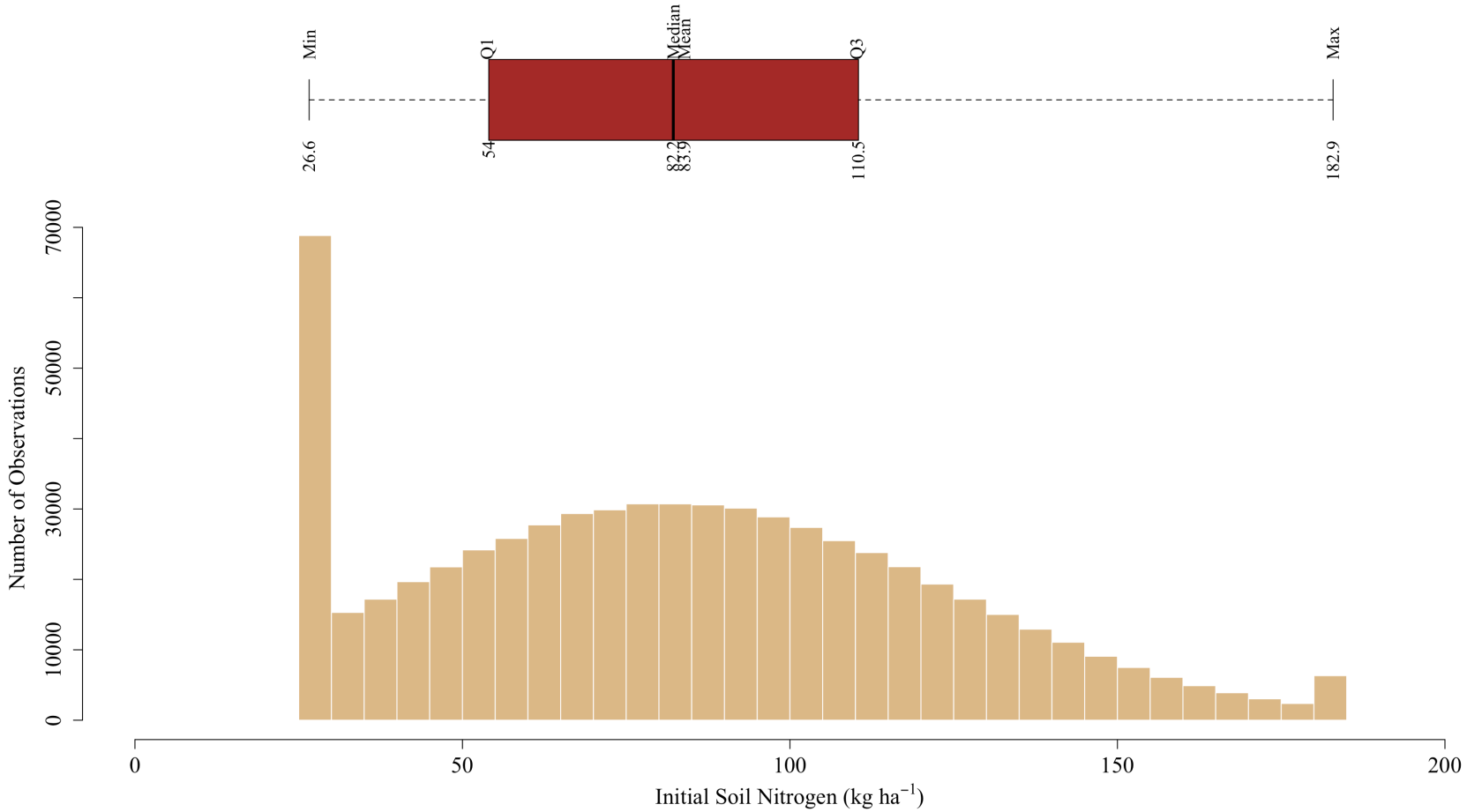
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Figures and Tables



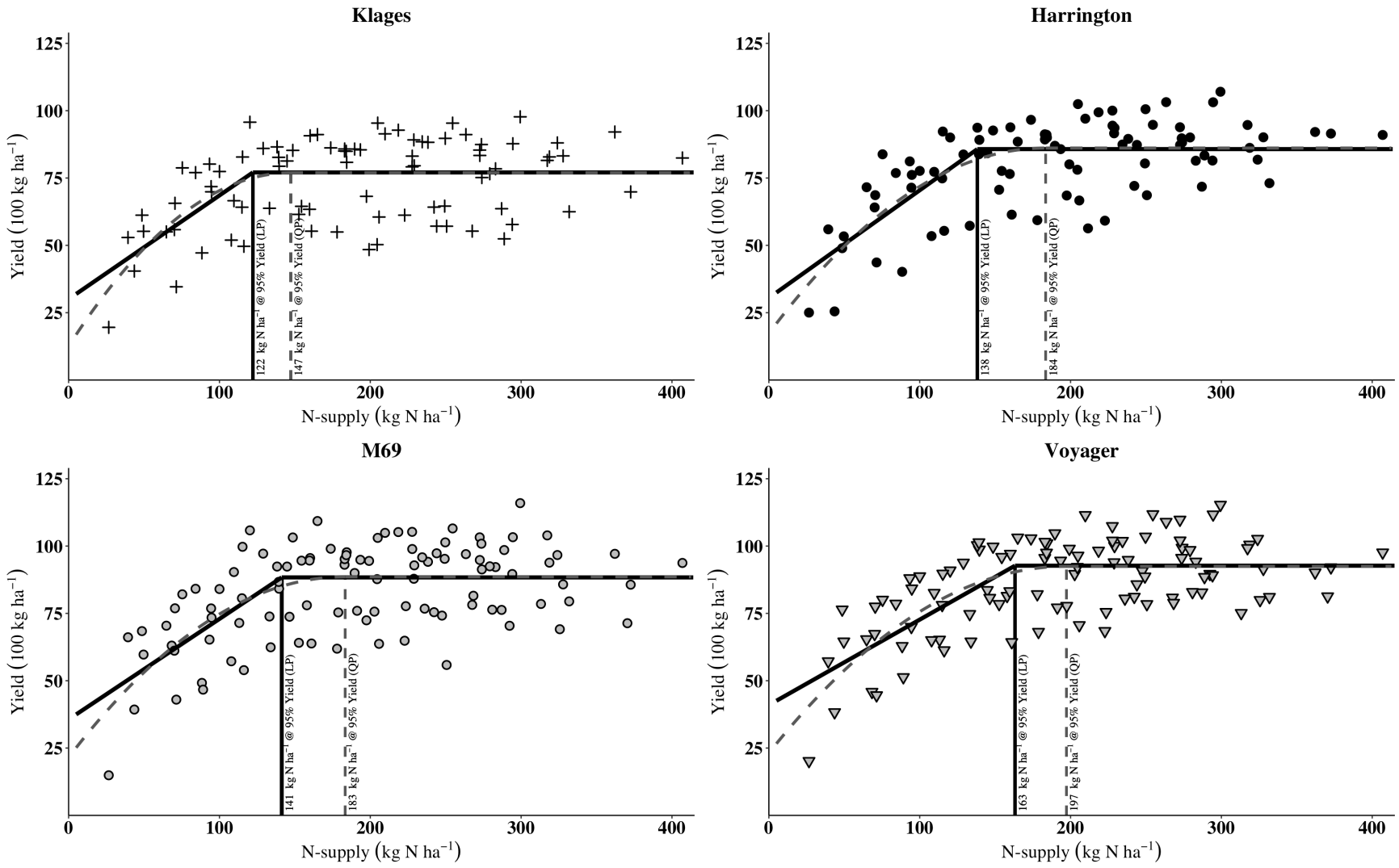
Source: Idaho Geospatial Office GIS data clearing house.

Figure 1: Map of the experimental sites across Southern Idaho



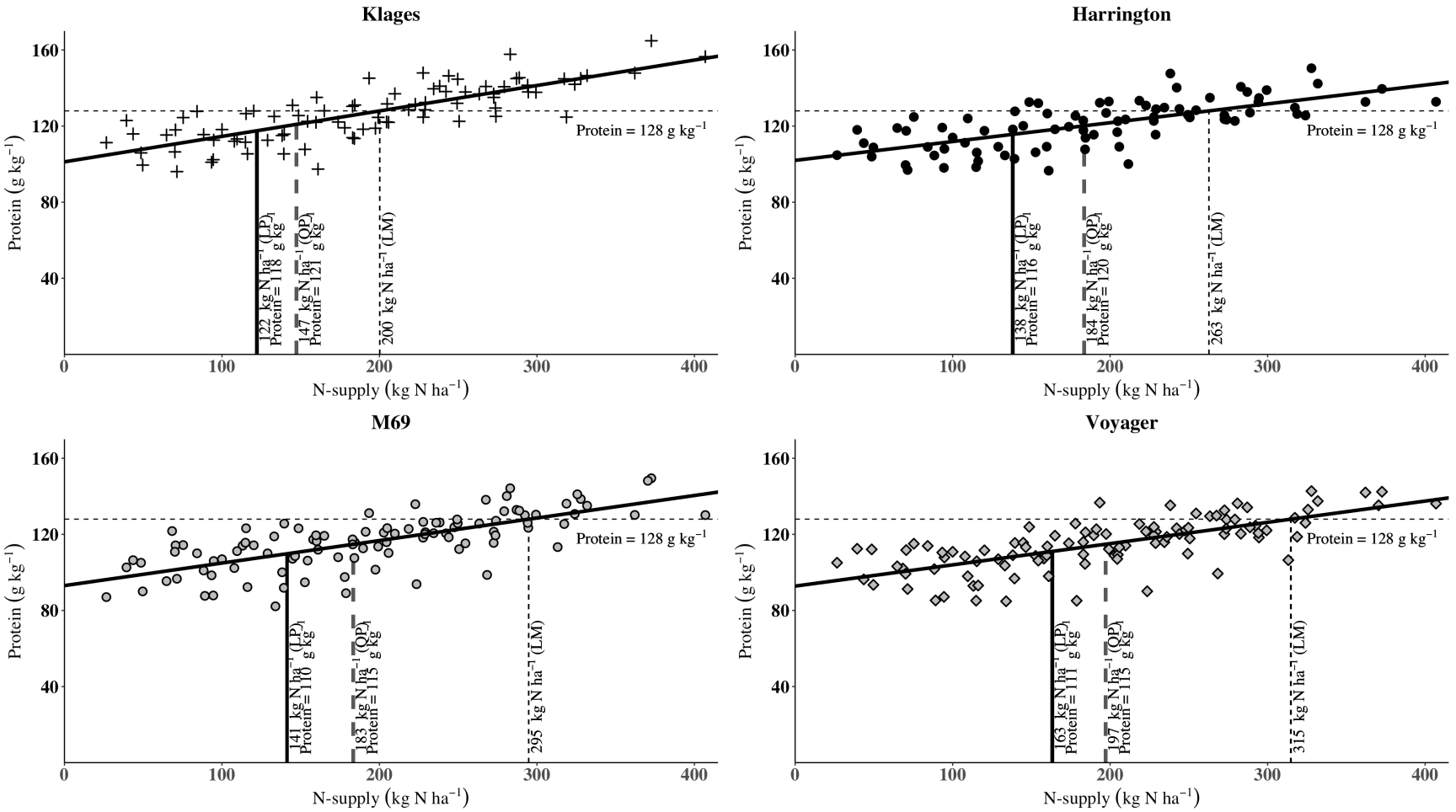
Source: Authors data from field trials implemented in Southern ID from 2015 to 2019.

Figure 2: Boxplot and histogram of initial soil nitrogen content based on simulated values



Source: Authors data from field trials implemented in Southern ID from 2015 to 2019.

Figure 3: Yield response (100 kg ha^{-1}) to N-supply (fertilizer-N + soil total inorganic-N) based on linear- and quadratic-plateau regression yield models (solid line, dashed line) and critical N-supply (CNS) at 95% Yield (vertical lines) by cultivar for malt barley N-supply studies conducted in the Snake River Plain of southern Idaho from 2015 to 2019



Source: Authors data from field trials implemented in Southern ID from 2015 to 2019.

Figure 4: Protein response (g kg^{-1}) to N-supply (fertilizer-N + soil total inorganic-N) based on linear, quadratic-plateau regression yield models (solid line, dashed line) and linear protein models (dotted line) and critical N-supply (CNS) at 95% Yield (vertical lines) by cultivar for malt barley N-supply studies conducted in the Snake River Plain of southern Idaho from 2015 to 2019

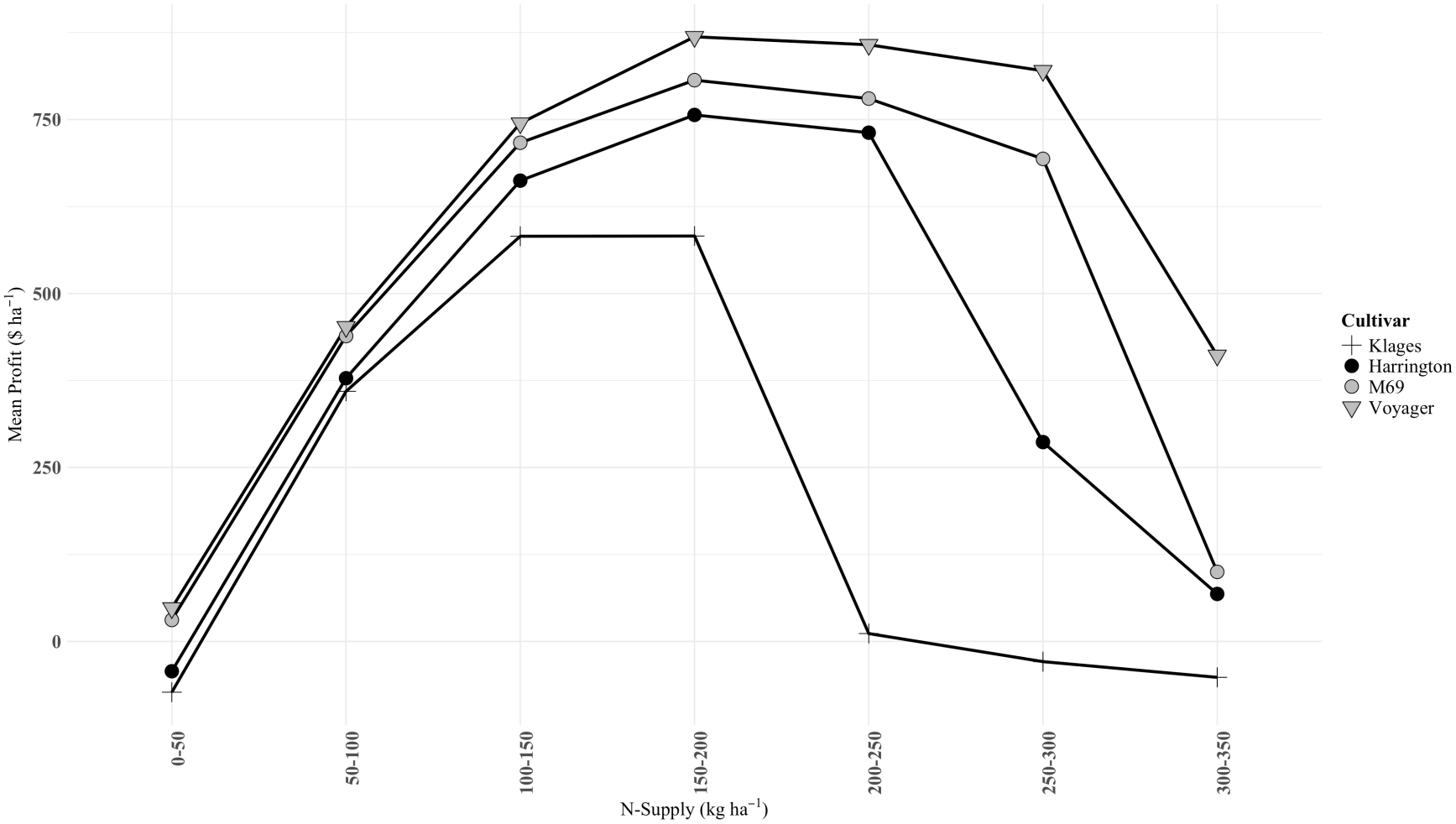
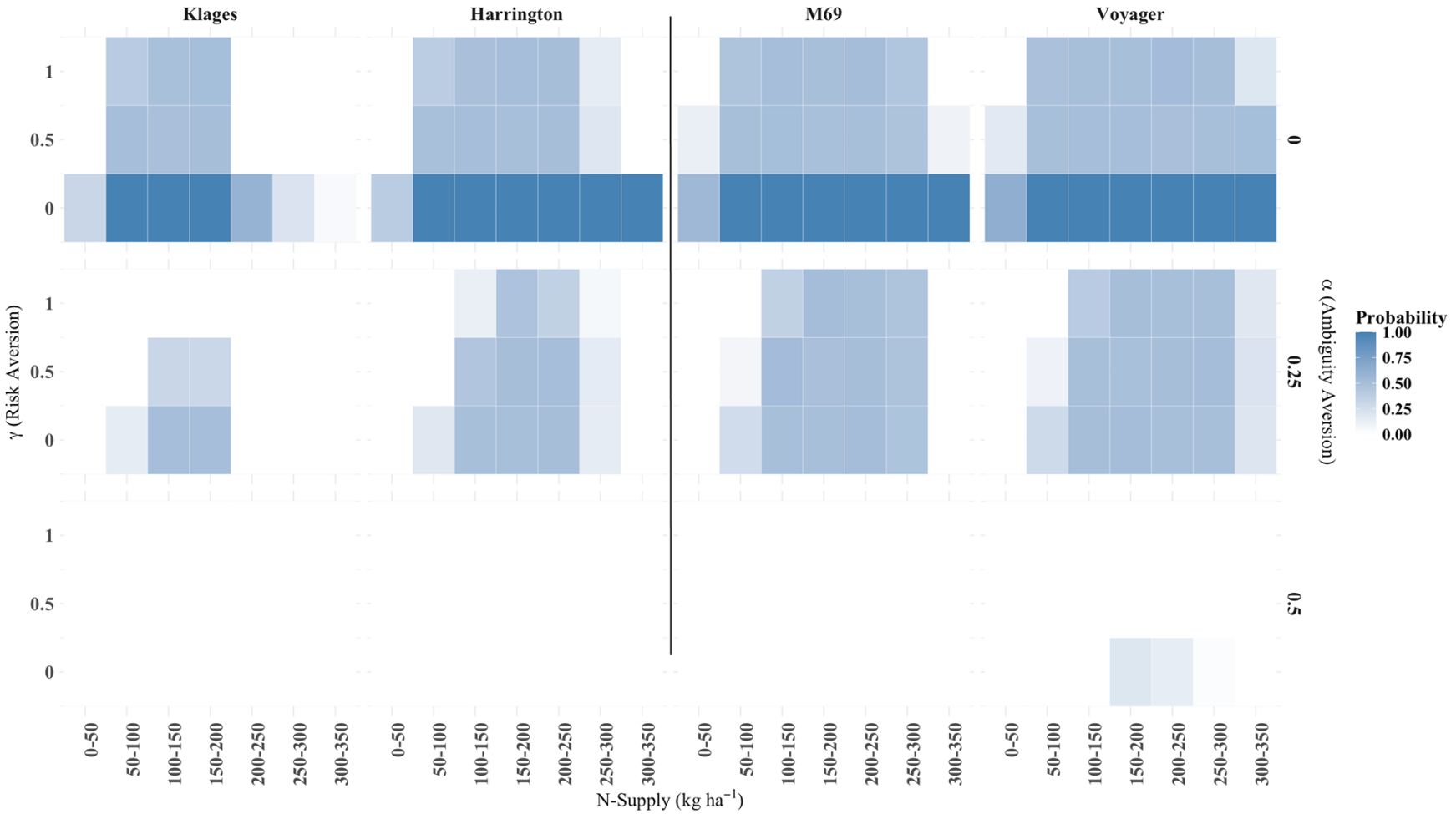


Figure 5: Cultivar-wise profit of the N-supply bins for the production function as a quadratic plateau model (Sample group with and without soil test)



Note: The farmers with a risk aversion coefficient value of 0 are risk-loving, and those with a value of 1 are risk-averse. Similar interpretation for the ambiguity aversion coefficient.

Figure 6: Cultivar-wise probability of the positive utility for different groups of γ(0, 0.5, 1) and α(0, 0.25, 0.50) malt barley producers including scenarios with and without soil tests based on the N-supply bins for the production function as a quadratic plateau model

Table 1: Summary Statistics of the variables under study

Cultivar Groups	Cultivar	Site-years	# Observations	Mean (SD)			
				N-soil	N-supply	Yield	Protein
				kg ha^{-1}	kg ha^{-1}	100 kg ha^{-1}	g kg^{-1}
Historical	Klages	14	84	80.20	192.00	73.00	114.23
				(42.40)	(87.88)	(16.15)	(13.24)
	Harrington	14	84	80.20	192.00	79.76	108.86
				(42.40)	(87.51)	(16.97)	(11.20)
Modern	M69	17	102	80.20	195.92	82.88	104.66
				(41.68)	(87.46)	(17.55)	(12.94)
	Voyager	17	102	80.20	195.92	85.69	103.24
				(41.68)	(87.46)	(16.96)	(12.32)

Source: Authors data from field trials implemented in Southern ID from 2015 to 2019.
Note: N-supply = (0 to 60-cm inorganic soil N + applied fertilizer-N). Applied fertilizer rates were (0, 45, 90, 134, 179 and 224 kg N ha^{-1}). The standard deviation (SD) values are in the parenthesis.

Table 2: Calibrated yield and protein model equations

Cultivars	Equations	
	QP model for Yield	Linear model for Protein
Klages	$\hat{y}_i = \begin{cases} 1255.67 + 87.44N_{\text{supply}} - 0.30N^2_{\text{supply}} & \text{if } N_{\text{supply}} \leq 147.27 \\ 7694.25 & \text{otherwise} \end{cases}$	$\hat{protein}_i = 101.22 + 0.13N_{\text{supply}}$
Harrington	$\hat{y}_i = \begin{cases} 1728.57 + 75.04N_{\text{supply}} - 0.20N^2_{\text{supply}} & \text{if } N_{\text{supply}} \leq 183.51 \\ 8613.59 & \text{otherwise} \end{cases}$	$\hat{protein}_i = 101.98 + 0.10N_{\text{supply}}$
M69	$\hat{y}_i = \begin{cases} 2152.43 + 73.18N_{\text{supply}} - 0.20N^2_{\text{supply}} & \text{if } N_{\text{supply}} \leq 183.34 \\ 8860.56 & \text{otherwise} \end{cases}$	$\hat{protein}_i = 93.07 + 0.12N_{\text{supply}}$
Voyager	$\hat{y}_i = \begin{cases} 2316.08 + 70.29N_{\text{supply}} - 0.18N^2_{\text{supply}} & \text{if } N_{\text{supply}} \leq 197.19 \\ 9246.55 & \text{otherwise} \end{cases}$	$\hat{protein}_i = 92.80 + 0.11N_{\text{supply}}$

Source: Authors data from field trials implemented in Southern ID from 2015 to 2019.
Note: The quadratic plateau models estimate the critical nitrogen supply (CNS) at which yield plateaus (i.e., becomes constant). The equations for N_{supply} below CNS are quadratic, and for values above, the yield is constant. For example, the yield of Klages plateaus for N_{supply} above 147.27 kg ha^{-1}, at a yield of 7694.25 kg ha^{-1}.

Table 3: Values of Parameters included in the Profit Estimations and Utility Simulations

Parameter	Value	Source
Cost of nitrogen ($ kg^{-1})	0.90	University of Idaho (2019)
Total cost of cultivation for all inputs except nitrogen ($ ha^{-1})	869	University of Idaho (2019)
Price of malt barley ($ kg^{-1})	0.20	Idaho Barley Commission (2019)
Price of feed barley ($ kg^{-1})	0.13	University of Idaho (2019)
Soil sample test ($ ha^{-1})	2	Stukenholtz Laboratory, Inc., (2025)

Table 4: Summary statistics of the simulated variables under study (QP model estimates)

Cultivar Groups	Cultivar	Mean (SD)				
		N-soil	N-fertilizer	N-supply	Yield	Protein
		kg ha^{-1}	kg ha^{-1}	kg ha^{-1}	100 kg ha^{-1}	g kg^{-1}
Historical	Klages	83.91	112.08	195.99	74.37	127.43)
		(38.20)	(66.84)	(76.97)	(7.10)	(10.29)
	Harrington	83.92	112.24	196.16	81.63	121.43
		(38.29)	(66.80)	(77.04)	(9.41)	(7.63)
Modern	M69	83.88	112.04	195.92	84.18	116.28
		(38.24)	(66.82)	(77.09)	(9.23)	(9.13)
	Voyager	83.98	111.82	195.81	87.03	114.70
		(38.40)	(66.88)	(77.17)	(10.22)	(8.63)

Note: The number of simulated observations for each cultivar was 162000. The standard deviation (SD) values are in parentheses.

Table 5: Profit Estimates for Each Cultivar by N-supply Bins (Quadratic plateau model estimates and considering scenarios with and without soil tests)

Cultivars	N-supply bin	Avg. Profit	Std. Error	95% CI	
	kg ha^{-1}	\$ ha^{-1}			
		Historical cultivars			
	0-50	-72.22	1.71	-75.71	-68.74
	50-100	359.11	0.90	357.27	360.94
	100-150	581.72	0.24	581.22	582.21
Klages	**150-200**	**582.26**	**0.18**	**581.90**	**582.62**
	200-250	11.27	0.28	10.70	11.84
	250-300	-29.08	0.20	-29.49	-28.66
	300-350	-51.20	0.21	-51.62	-50.77
	0-50	-39.47	1.58	-42.69	-36.26
	50-100	376.45	0.95	374.50	378.40
	100-150	662.14	0.38	661.35	662.92
Harrington	**150-200**	**756.69**	**0.17**	**756.35**	**757.04**
	200-250	731.13	0.18	730.77	731.50
	250-300	285.27	1.75	281.70	288.83
	300-350	68.07	0.21	67.65	68.49
		Modern cultivars			
	0-50	30.05	1.52	26.96	33.15
	50-100	438.12	0.92	436.24	439.99
	100-150	716.65	0.37	715.90	717.40
M69	**150-200**	**806.53**	**0.17**	**806.18**	**806.88**
	200-250	780.56	0.18	780.19	780.93
	250-300	694.36	1.05	692.21	696.50
	300-350	100.30	0.21	99.88	100.73
	0-50	48.68	1.47	45.68	51.67
	50-100	452.10	0.92	450.22	453.99
	100-150	744.86	0.41	744.03	745.69
Voyager	**150-200**	**868.85**	**0.18**	**868.48**	**869.22**
	200-250	857.71	0.18	857.34	858.08
	250-300	820.26	0.20	819.84	820.67
	300-350	414.20	2.91	408.27	420.12

Table 6: Cultivar wise distribution positive utility probabilities (average) based on ambiguity and risk aversion and N-supply bins (Quadratic plateau model estimates and considering scenarios with and without soil tests)

Cultivars	α	β	All N-supply bins	Selected N-supply bins		
				0-50	150-200	300-350
Historical cultivars						
Klages	0	0	0.59	0.30	1.00	0.04
	0	0.50	0.21	0	0.50	0
	0	1.00	0.20	0	0.49	0
	0.25	0	0.17	0	0.50	0
	0.25	0.50	0.09	0	0.31	0
	0.25	1.00	0	0	0	0
	0.50	0	0	0	0	0
	0.50	0.50	0	0	0	0
	0.50	1.00	0	0	0	0
Harrington	0	0	0.91	0.38	1.00	1
	0	0.50	0.32	0	0.49	0
	0	1.00	0.30	0	0.50	0
	0.25	0	0.27	0	0.50	0
	0.25	0.50	0.23	0	0.50	0
	0.25	1.00	0.14	0	0.47	0
	0.50	0	0	0	0	0
	0.50	0.50	0	0	0	0
	0.50	1.00	0	0	0	0
Modern cultivars						
M69	0	0	0.94	0.56	1.00	1.00
	0	0.50	0.38	0.12	0.51	0.10
	0	1.00	0.35	0	0.50	0
	0.25	0	0.32	0	0.50	0
	0.25	0.50	0.29	0	0.50	0
	0.25	1.00	0.26	0	0.50	0
	0.50	0	0	0	0.01	0
	0.50	0.50	0	0	0	0
	0.50	1.00	0	0	0	0
Voyager	0	0	0.94	0.60	1.00	1.00
	0	0.50	0.45	0.12	0.50	0.51
	0	1.00	0.38	0	0.50	0.21
	0.25	0	0.35	0	0.49	0.19
	0.25	0.50	0.33	0	0.50	0.19
	0.25	1.00	0.30	0	0.51	0.20
	0.50	0	0.05	0	0.20	0
	0.50	0.50	0	0	0	0
	0.50	1.00	0	0	0	0

Appendix

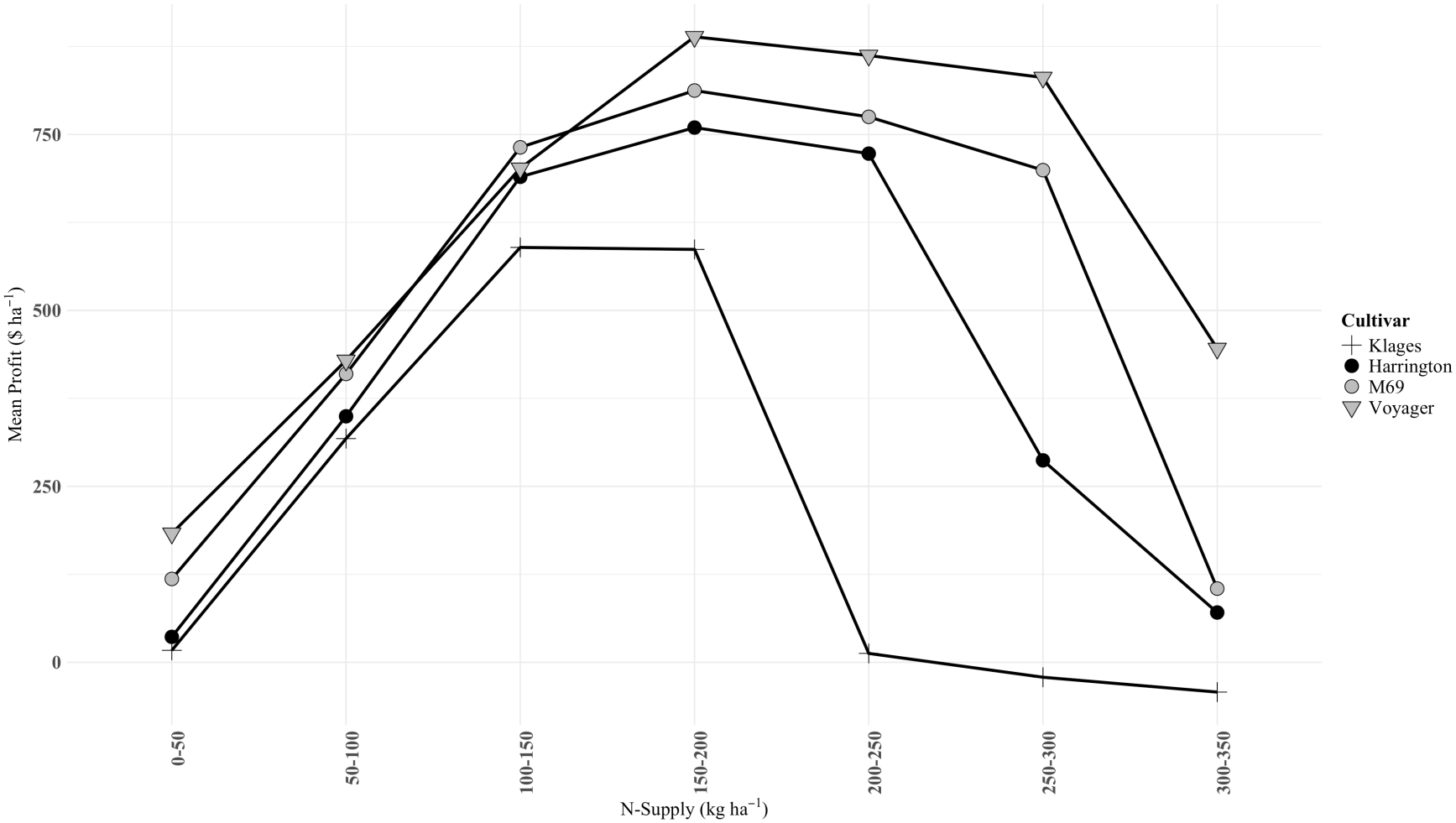
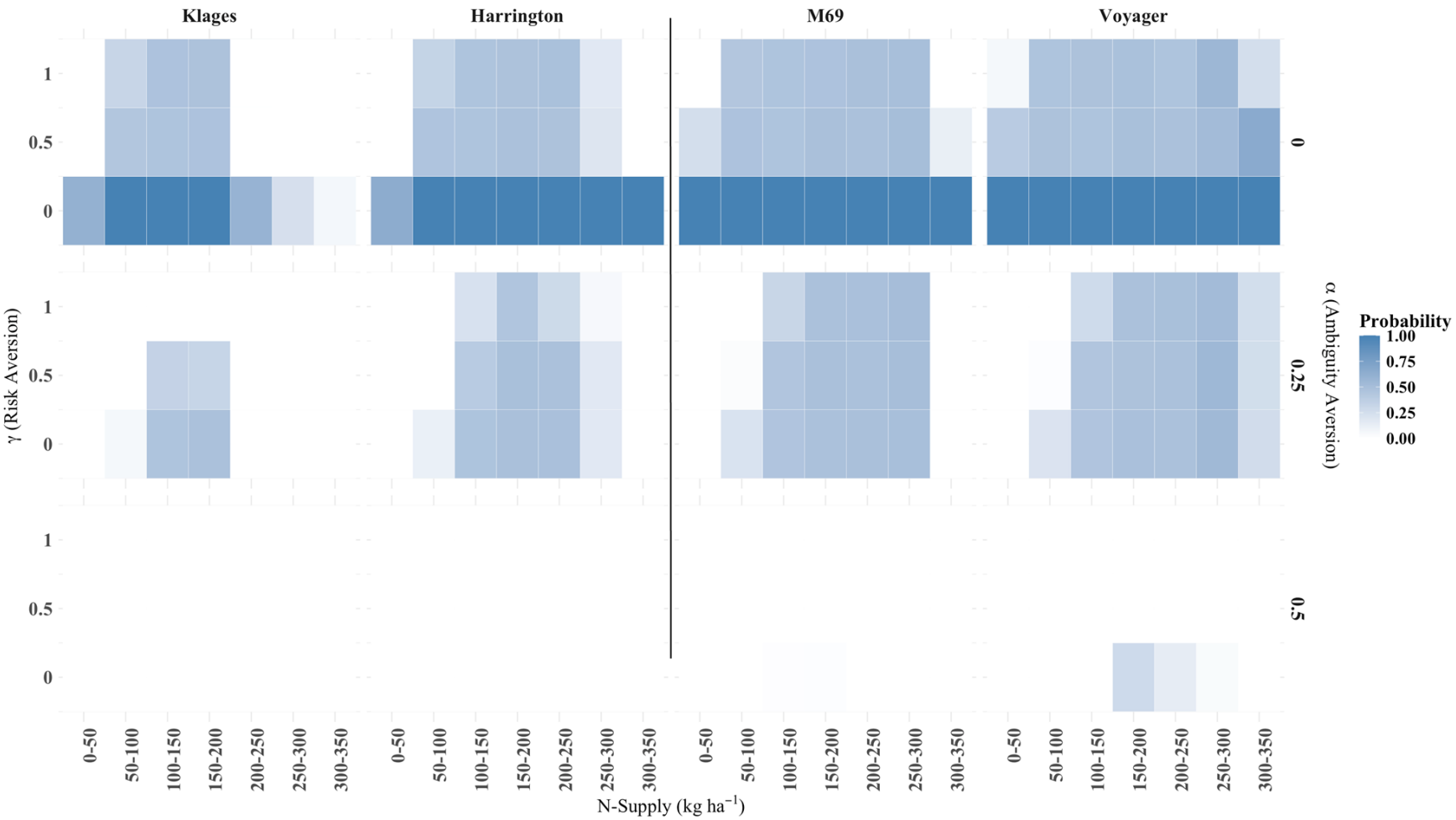
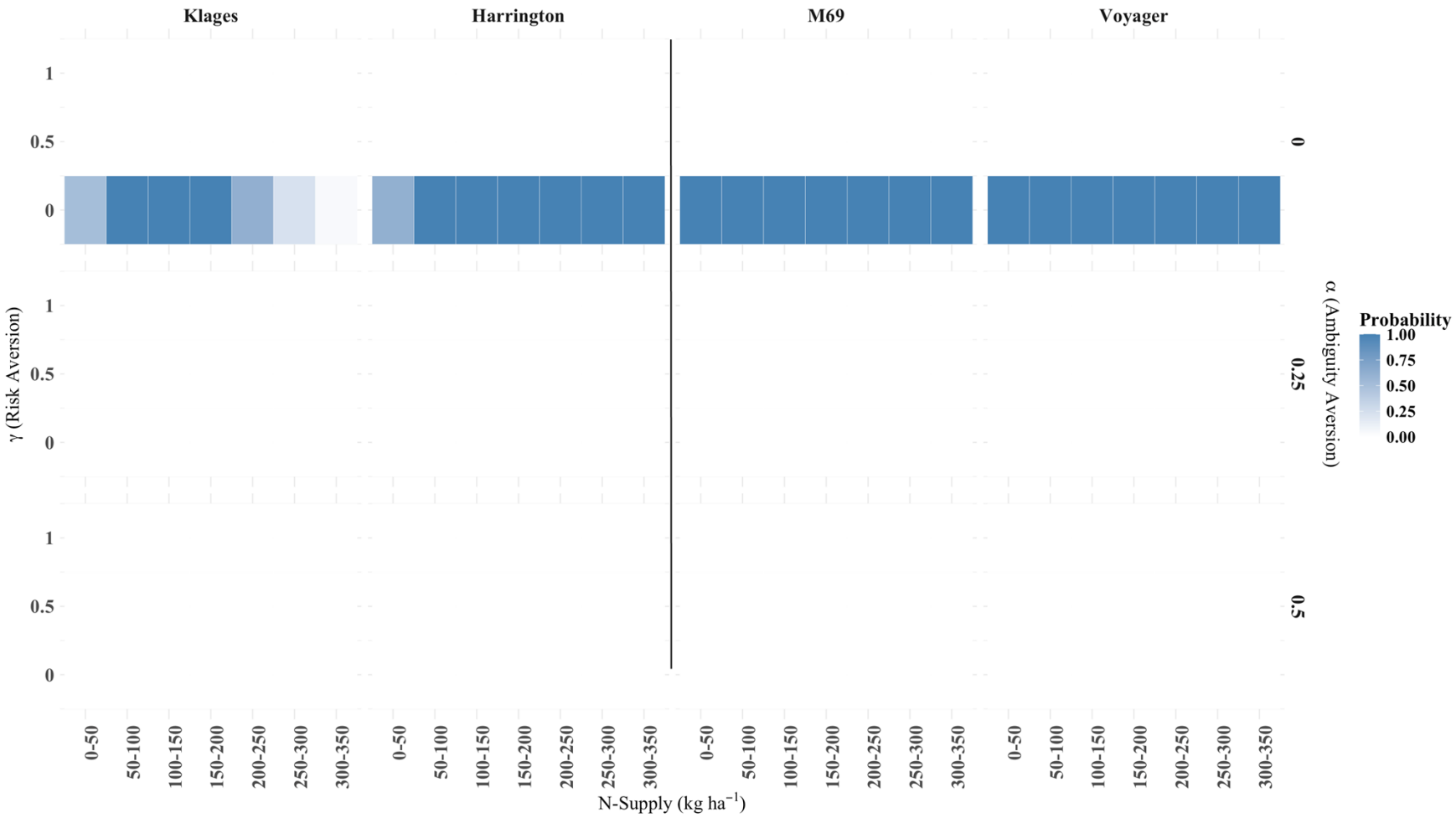


Figure A.1: Cultivar-wise profit of the N-supply bins for the production function as a linear plateau model (Sample group with and without soil test)



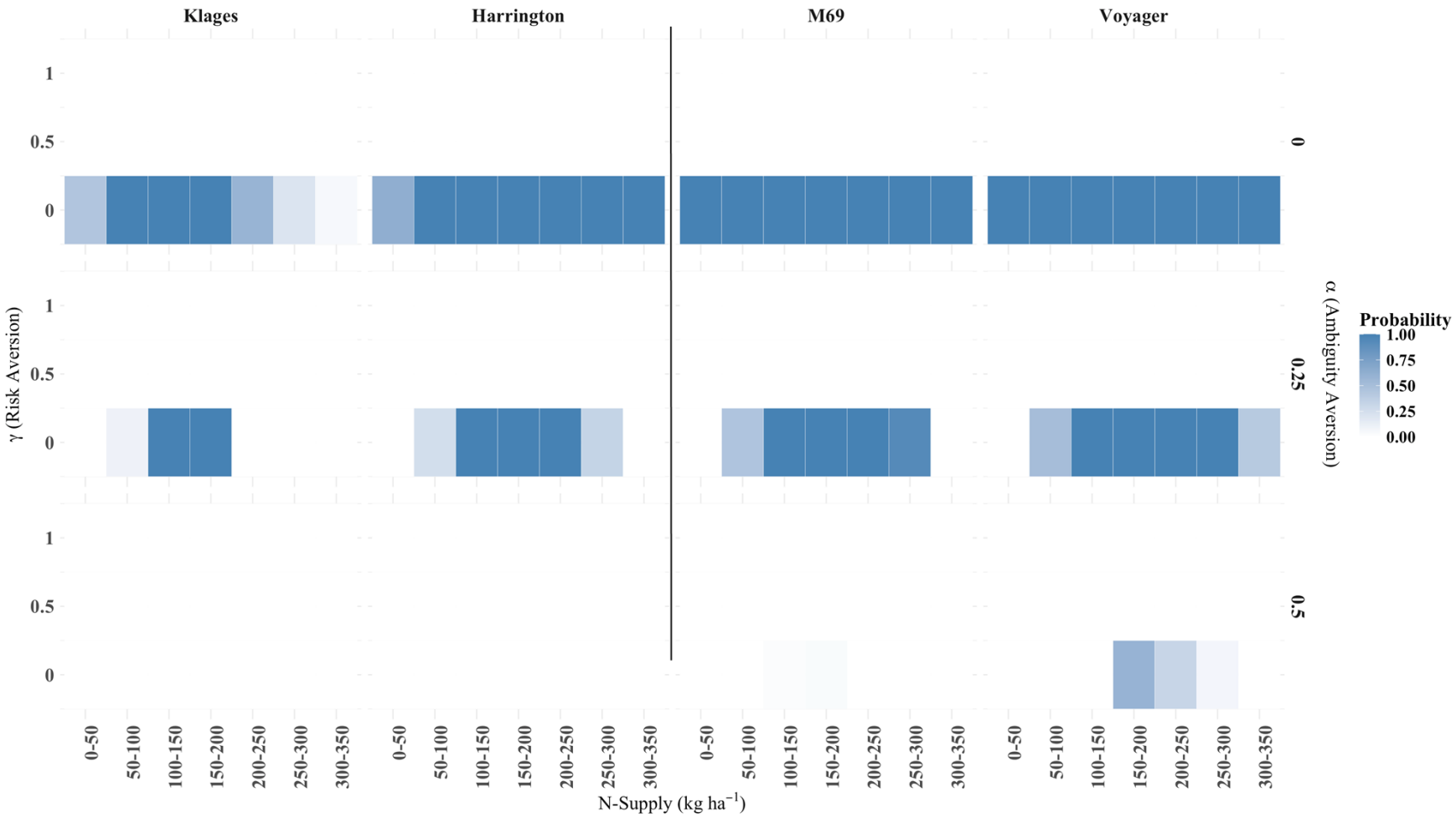
Note: The farmers with a risk aversion coefficient value of 0 are risk-loving, and those with a value of 1 are risk-averse. Similar interpretation for the ambiguity aversion coefficient.

Figure A.2: Cultivar-wise probability of the positive utility for different groups of γ(0, 0.5, 1) and α(0, 0.25, 0.50) malt barley producers including scenarios with and without soil tests based on the N-supply bins for the production function as a Linear plateau model



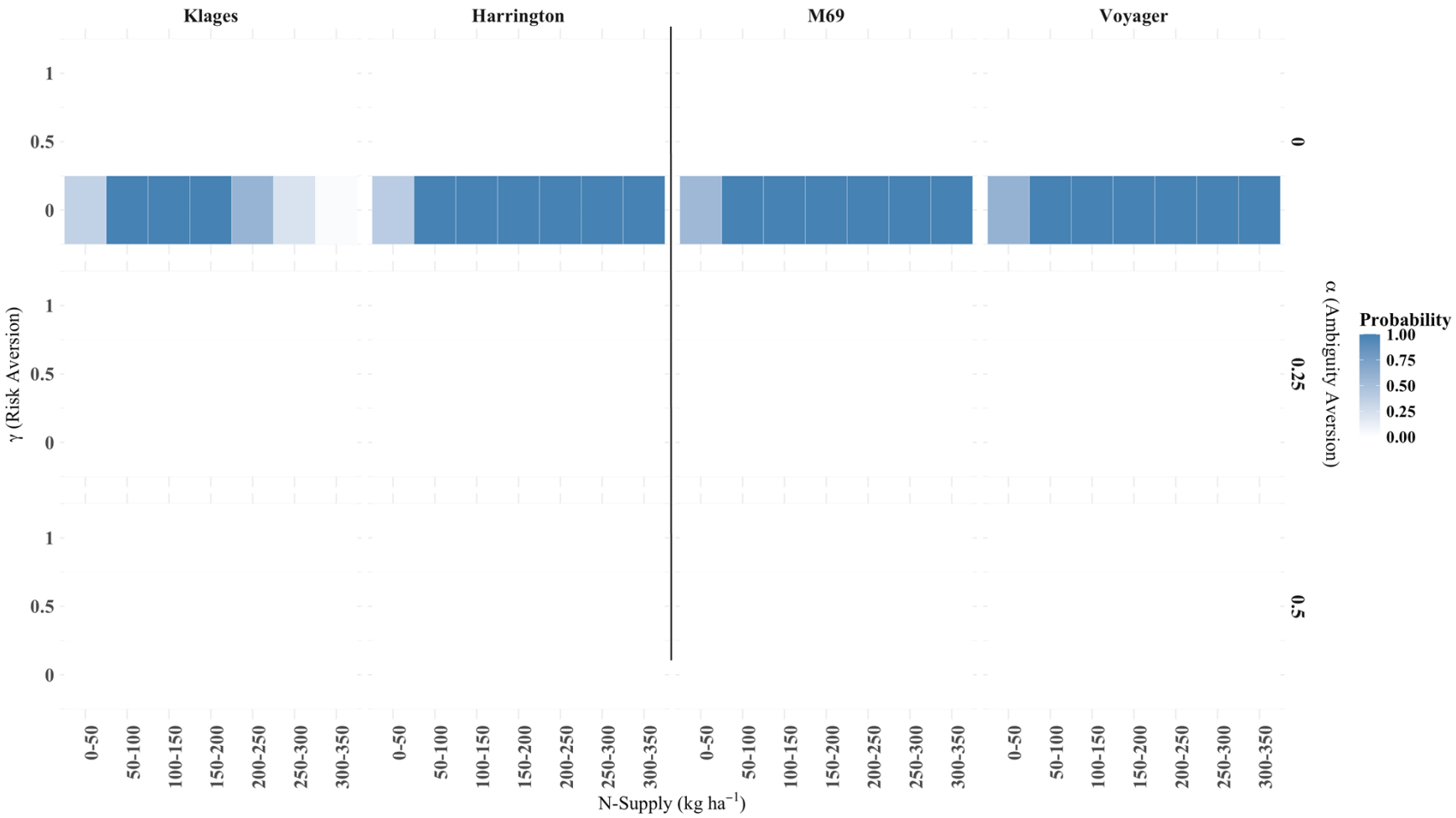
Note: The farmers with a risk aversion coefficient value of 0 are risk-loving, and those with a value of 1 are risk-averse. Similar interpretation for the ambiguity aversion coefficient.

Figure A.3: Cultivar-wise probability of the positive utility for different groups of γ(0, 0.5, 1) and α(0, 0.25, 0.50) malt barley producers including scenario without soil tests based on the N-supply bins for the production function as a Linear plateau model



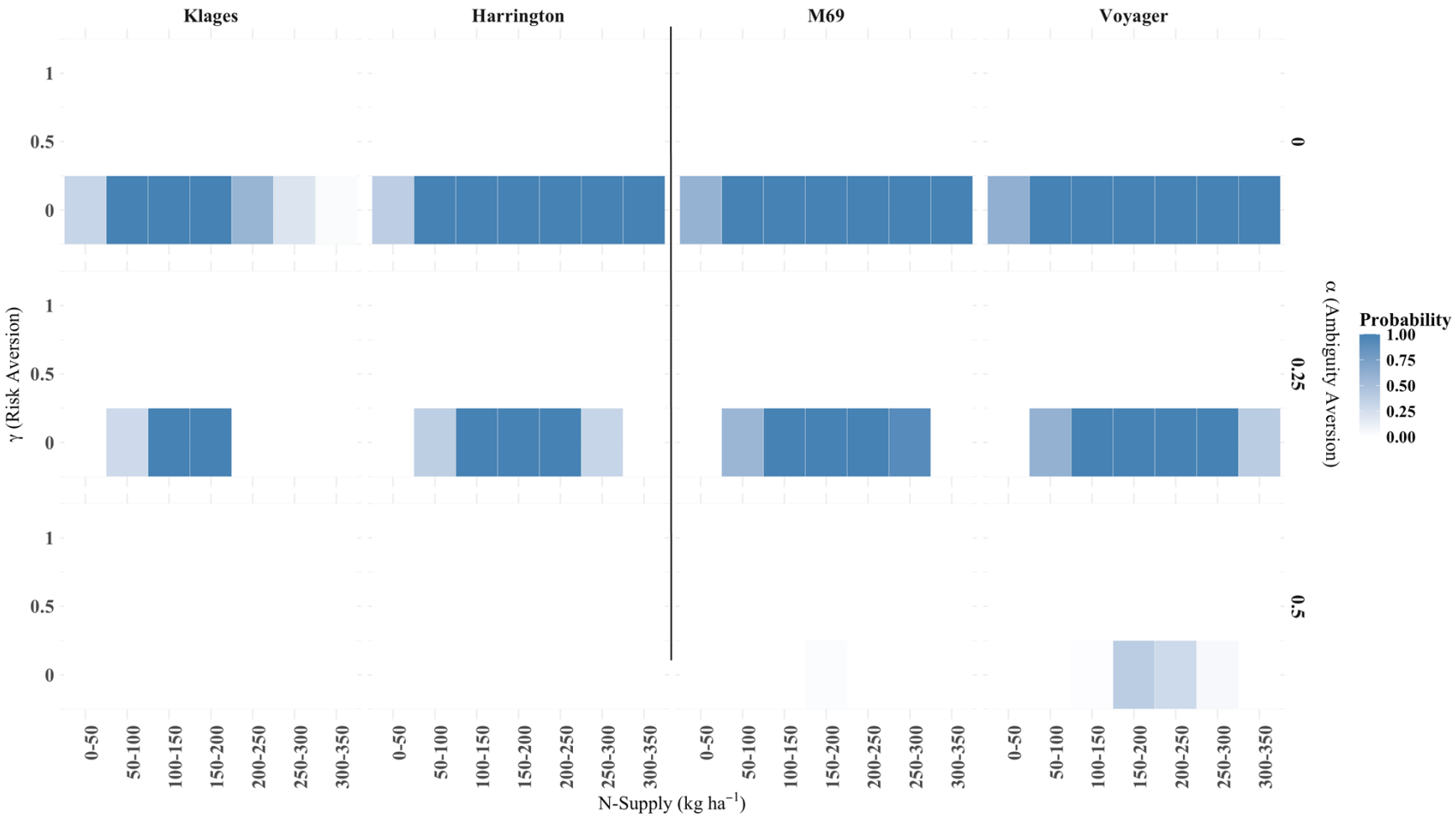
Note: The farmers with a risk aversion coefficient value of 0 are risk-loving, and those with a value of 1 are risk-averse. Similar interpretation for the ambiguity aversion coefficient.

Figure A.4: Cultivar-wise probability of the positive utility for different groups of γ(0, 0.5, 1) and α(0, 0.25, 0.50) malt barley producers including scenarios with and without soil tests based on the N-supply bins for the production function as a Linear plateau model



Note: The farmers with a risk aversion coefficient value of 0 are risk-loving, and those with a value of 1 are risk-averse. Similar interpretation for the ambiguity aversion coefficient.

Figure A.5: Cultivar-wise probability of the positive utility for different groups of γ(0, 0.5, 1) and α(0, 0.25, 0.50) malt barley producers including scenario without soil tests based on the N-supply bins for the production function as a Quadratic plateau model



Note: The farmers with a risk aversion coefficient value of 0 are risk-loving, and those with a value of 1 are risk-averse. Similar interpretation for the ambiguity aversion coefficient.

Figure A.6: Cultivar-wise probability of the positive utility for different groups of γ(0, 0.5, 1) and α(0, 0.25, 0.50) malt barley producers including scenarios with and without soil tests based on the N-supply bins for the production function as a Quadratic plateau model

Table A.1: Calibrated linear production models for yield, cultivar wise

Cultivars	Equations of LP models for Yield
Klages	$\hat{y}_i = \begin{cases} 3002.95 + 38.51\, N_{\text{supply}} & \text{if } N_{\text{supply}} \leq 122.18 \\ 7707.89 & \text{otherwise} \end{cases}$
Harrington	$\hat{y}_i = \begin{cases} 3047.74 + 39.98\, N_{\text{supply}} & \text{if } N_{\text{supply}} \leq 138.21 \\ 8573.40 & \text{otherwise} \end{cases}$
M69	$\hat{y}_i = \begin{cases} 3561.50 + 37.33\, N_{\text{supply}} & \text{if } N_{\text{supply}} \leq 141.27 \\ 8835.80 & \text{otherwise} \end{cases}$
Voyager	$\hat{y}_i = \begin{cases} 4097.20 + 31.71\, N_{\text{supply}} & \text{if } N_{\text{supply}} \leq 163.17 \\ 9270.85 & \text{otherwise} \end{cases}$

Note: The linear plateau models estimated critical nitrogen supply (CNS) from where the yield starts plateauing (i.e., becomes constant). For N_{supply} below CNS, yield was estimated using the given equation; above CNS, yield was constant. For instance, the yield of Klages plateaued above 122.18 kg ha^{-1} at 7707.89 kg ha^{-1}.

Table A.2: Summary Statistics of the simulated variables under study (LP model estimates)

Cultivar Groups	Cultivar	Mean (SD)				
		N-soil	N-fertilizer	N-supply	Yield	Protein
		kg ha^{-1}	kg ha^{-1}	kg ha^{-1}	100 kg ha^{-1}	g kg^{-1}
Historical	Klages	83.82	106.15	190.19	74.44	126.66
		(38.23)	(62.78)	(73.46)	(6.84)	(9.83)
	Harrington	84.04	105.77	189.59	81.45	120.76
		(38.29)	(62.73)	(73.51)	(9.28)	(7.28)
Modern	M69	83.96	106.09	190.05	84.09	115.59
		(38.30)	(62.86)	(73.56)	(9.00)	(8.71)
	Voyager	83.86	105.99	189.85	86.83	114.03
		(38.25)	(62.71)	(73.42)	(10.08)	(8.21)

Table A.3: Cultivar wise profit distribution based on N-supply bins (Linear plateau model estimates and considering scenarios with and without soil tests)

Cultivars	N-supply bin	Avg. Profit	Std. Error	95% CI	
	kg ha^{-1}	$ ha^{-1}			
		Historical cultivars			
	0-50	15.76	0.97	13.78	17.73
	50-100	315.67	0.80	314.03	317.30
	100-150	590.24	0.29	589.64	590.83
Klages	150-200	586.62	0.18	586.26	586.98
	200-250	12.92	0.27	12.37	13.48
	250-300	-21.32	0.19	-21.72	-20.93
	300-350	-42.18	0.24	-42.67	-41.68
	0-50	37.76	1.02	35.68	39.84
	50-100	349.42	0.83	347.74	351.11
	100-150	689.28	0.53	688.19	690.36
Harrington	150-200	759.98	0.18	759.62	760.34
	200-250	722.59	0.18	722.23	722.95
	250-300	286.99	1.83	283.26	290.72
	300-350	70.31	0.24	69.81	70.80
		Modern cultivars			
	0-50	116.44	0.95	114.51	118.38
	50-100	410.09	0.77	408.51	411.66
	100-150	731.45	0.53	730.38	732.52
M69	150-200	812.35	0.18	811.99	812.71
	200-250	775.34	0.18	774.98	775.71
	250-300	698.27	1.06	696.11	700.43
	300-350	104.64	0.24	104.15	105.14
	0-50	182.45	0.80	180.81	184.08
	50-100	427.69	0.65	426.36	429.03
	100-150	702.97	0.49	701.98	703.96
Voyager	150-200	888.86	0.19	888.48	889.24
	200-250	862.06	0.18	861.70	862.42
	250-300	831.02	0.19	830.63	831.42
	300-350	437.03	3.33	430.25	443.81

Table A.4: Cultivar-wise distribution positive utility probabilities (average) based on ambiguity and risk aversion and N-supply bins (Linear plateau model estimates and considering scenarios with and without soil tests)

Cultivars	α	β	All N-supply bins	Selected N-supply bins		
				0-50	150-200	300-350
Historical cultivars						
Klages	0	0	0.64	0.63	1.00	0.06
	0	0.50	0.20	0	0.48	0
	0	1.00	0.18	0	0.47	0
	0.25	0	0.14	0	0.48	0
	0.25	0.50	0.10	0	0.33	0
	0.25	1.00	0	0	0	0
	0.50	0	0	0	0	0
	0.50	0.50	0	0	0	0
	0.50	1.00	0	0	0	0
Harrington	0	0	0.95	0.68	1.00	1.00
	0	0.50	0.29	0	0.48	0
	0	1.00	0.28	0	0.49	0
	0.25	0	0.25	0	0.48	0
	0.25	0.50	0.22	0	0.49	0
	0.25	1.00	0.15	0	0.45	0
	0.50	0	0	0	0	0
	0.50	0.50	0	0	0	0
	0.50	1.00	0	0	0	0
Modern cultivars						
M69	0	0	1.00	1.00	1.00	1.00
	0	0.50	0.39	0.25	0.49	0.11
	0	1.00	0.34	0	0.49	0
	0.25	0	0.31	0	0.47	0
	0.25	0.50	0.27	0	0.48	0
	0.25	1.00	0.25	0	0.48	0
	0.50	0	0	0	0.02	0
	0.50	0.50	0	0	0	0
	0.50	1.00	0	0	0	0
Voyager	0	0	1.00	1.00	1.00	1.00
	0	0.50	0.50	0.42	0.47	0.65
	0	1.00	0.40	0.07	0.48	0.26
	0.25	0	0.35	0	0.47	0.25
	0.25	0.50	0.31	0	0.48	0.24
	0.25	1.00	0.29	0	0.48	0.23
	0.50	0	0.07	0	0.29	0
	0.50	0.50	0	0	0	0
	0.50	1.00	0	0	0	0