Improving Nitrogen Rates

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1 Introduction

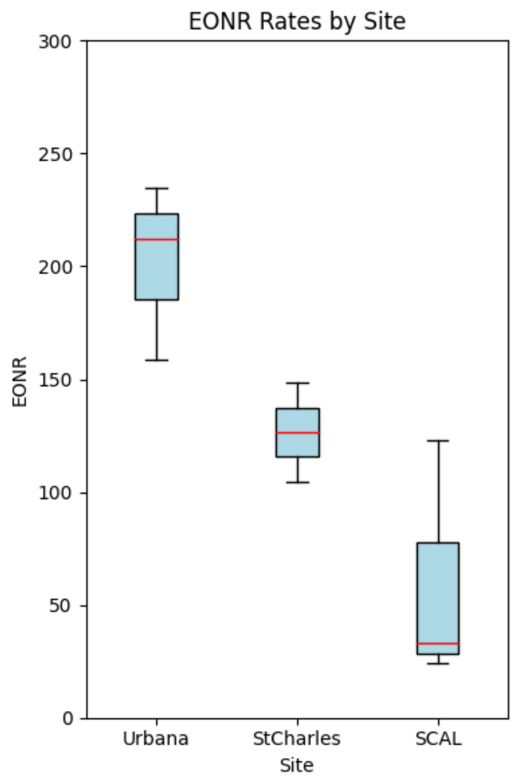
Nitrogen (N) fertilizer is an essential component to maximize crop yields and ensure global food security but excess N fertilizer can have adverse environmental impacts. This underscores the importance and significance of matching N fertilization to crop needs as closely as practicable such that farmer profitability can be improved while simultaneously reducing environmental impacts. Excess N application beyond what the plant can use becomes prone to leaching into waterways as nitrate (NO_3^-) or denitrification as nitrous oxide (N_2O), a greenhouse gas whose emissions are 300 times more harmful than CO_2.

2 Contributing Factors to Overapplication of N

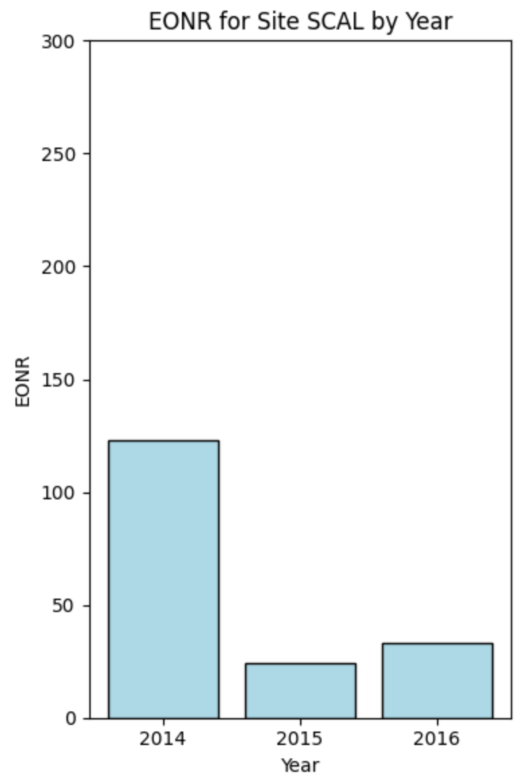
Overapplication of N is frequently observed (Zhang et al., 2015). Two overarching realities which contribute to the overapplication of N are spatiotemporal variability and asymmetric economic risk.

2.1 Spatiotempoeral Variability.

N is dynamic in both spatial and temporal dimensions. This means that two nearby fields in the same growing season can have substantially different optimum N requirements, and the same field in different growing seasons can also have substantially different optimum N requirements (Scharf, 2015). Figure 1 comes from a nitrogen dataset (Ransom et al., 2021) collected across 8 midwest U.S. states and 3 years totaling 46 site-years. It highlights the variability in Economic Optimum Nitrogen Rate (EONR) for 3 example sites across 3 years (Figure 1a) and the variability for a single site across 3 years (Figure 1b).



(a) Boxplot showing EONR rates by site for 3 example sites for the years 2014-2016



(b) Barchart showing EONR rates for a single site "SCAL" for the years 2014-2016

Figure 1: Illustration of spatiotemporal variability in EONR rates.

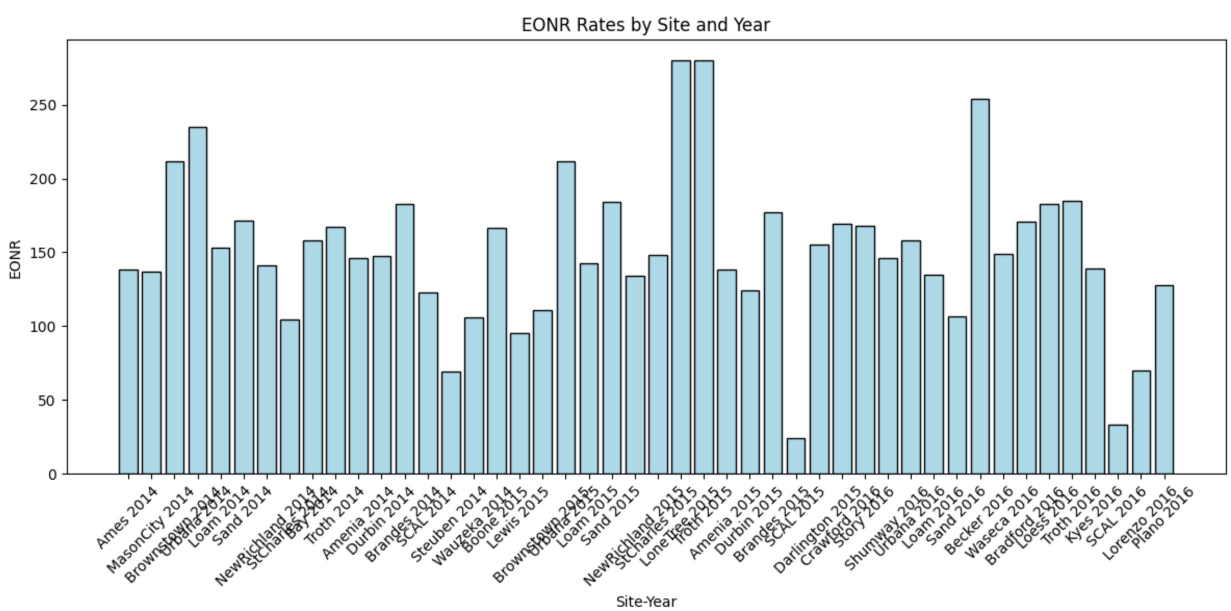
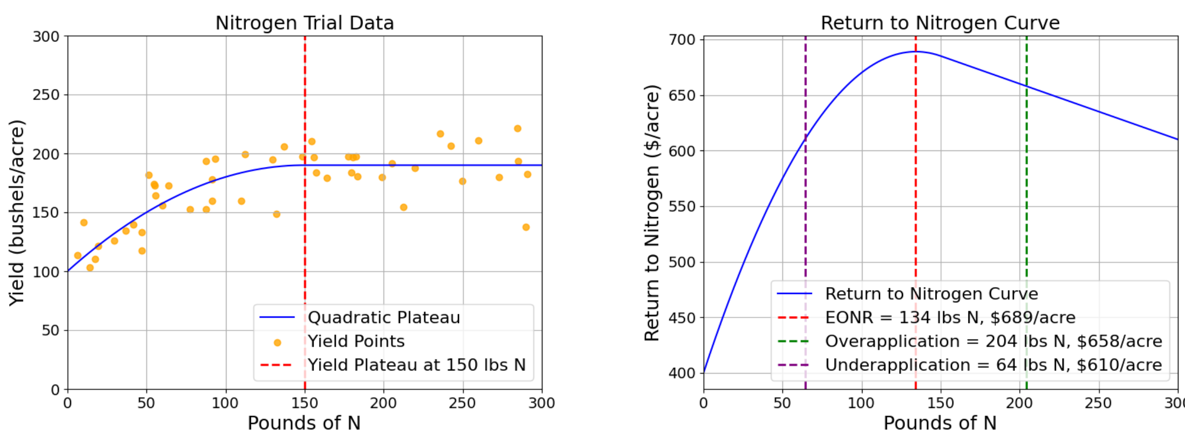


Figure 2: Illustration of spatiotemporal variability across 46 site-years.

Figure 2 highlights the variability by site-year across the entire dataset. This variability represents both epistemic and aleatory uncertainty. Epistemic uncertainty refers to uncertainty arising from lack of information. Aleatory uncertainty refers to outcomes which are inherently unknowable. Epistemic uncertainty associated with N in the soil is influenced by attributes such as soil texture, soil moisture, organic matter, drainage, past weather, and crop N demand. Aleatory uncertainty is driven by the fact that future weather conditions for the remainder of the growing season are unknown at the point of application of N fertilizer.

2.2 Asymmetric Economic Risk

Since N rates are highly variable in spatiotemporal dimensions, the EONR rate for a given field in a given year is not known a priori. Figure 3a shows the process of transforming noisy yield data from N trials into a quadratic plateau function. Figure 3b shows the asymmetric risk of underapplication versus overapplication of N. In this example, a 70 pound overapplication results in a \$31 penalty from optimum, whereas a 70 pound underapplication results in a \$79 penalty from optimum. This is because the slope of the return to N curve on the right side of optimum is due to the cost of N fertilizer without any associated yield gain and is shallower than the slope of the left side of the curve which is steeper due to yield penalties associated with insufficient N.



(a) Transforming yield data points at various nitrogen rates into a quadratic plateau function.

(b) Illustration of asymmetric risk of of underapplication versus overapplication.

Figure 3: Illustration of asymmetric risk of of underapplication versus overapplication.

Because of the spatiotemporal uncertainty in optimum N rates combined with asymmetric economic risk, application of N fertilizers in the U.S. is often seen as a risk-reducing action , leading to overapplication

(Houser, 2022). This overapplication results in reduction in profitability for farmers and to environmental consequences such as hypoxic zones in Lake Erie and the Gulf of Mexico which lead to harmful impacts on aquatic life. Overapplication has other adverse environmental impacts including nitrous oxide greenhouse gas emissions that are 300 times more harmful than CO_2 and the carbon footprint associated with the industrial production of ammonia through the Haber-Bosch process.

3 Heuristics and Biases in N Application Rates

There are several well-studied heuristics and biases which can provide an understanding for the underlying reasons for why farmers overapply N fertilizer.

3.1 Prospect Theory and the Certainty Effect

The first underlying reason comes from Prospect Theory (Kahneman and Tversky, 1979), which states that people are risk-averse when seeking to preserve good outcomes. Since N application is a risk-reducing input in the U.S., farmers overapply it to reduce risk in preserving a good outcome of a high yield. An extension of this is the Certainty Effect (Samuelson and Zeckhauser, 1988) which observes that people are willing to pay more for the elimination of a risk compared to its reduction. In this context, it is asserted that farmers are willing to apply high N rates to be virtually certain that N is not yield limiting. This is supported by an interview with a farmer who had as a primary N management objective, "Get enough N for crop potential."

To use an example, Prospect Theory and the Certainty Effect tells us to expect that farmers will prefer an N rate (e.g., 200 lbs/acre) that they believe provides 100% confidence that N rates will be sufficient over one (e.g., 170 lbs per acre) that provides 80% confidence, even if the latter has greater expected utility.

3.2 Optimism and Overconfidence Bias

Overconfidence bias was originally described by Alpert and Raiffa (Alpert and Raiffa, 1982). This can be due to selective recall that interprets new information in ways that confirm one's prior beliefs. Overconfidence bias can also arise from a need to appear competent to others and to ourselves. In general, people seem to be overconfident in areas where they perceive some level of control, described by Langer (1975) as the illusion of control. This can lead to individuals being overly optimistic such that they overestimate the odds of positive events happening to them. As a result, they use this optimism to rationalize or justify their actions, a bias known as motivated reasoning (Kunda, 1990).

In the context of N management, this plays out because a farmer perceives some level of control of corn yields based on how much N is applied. This illusion of control leads to optimism of overly high yields, thus causing the justification for high N rates.

We see evidence of these biases in a study that evaluated the perception of farmers on the marginal productivity of N (MPN) (Agarwal et al., 2016). Marginal productivity describes the additional corn yield in bushels per acre for each additional unit of N. Respondents were asked a series of questions regarding their expected yields given varying amounts of N applied. The study found that all farmers overestimated MPN, though more experienced farmers and farmers who primarily rely on Iowa State Extension had more realistic expectations of MPN. The logical result of optimistic thinking of MPN is to apply N at higher rates than are optimal. Optimism and overconfidence bias can often serve to cause one's mental models to diverge from reality rather than converge towards it. This brings us to our next bias.

3.3 Inaccurate Mental Models

We represent our understanding of the external world as mental models and use these mental models to predict the outcomes of actions. Mental models, though typically incomplete, help us to understand the world around us and make appropriate decisions. Dynamic Decision Making (DDM) is a research area that studies how people control dynamic and complex real-world systems (Brehmer, 1992). To the degree that our mental model diverges from reality, our ability to predict the outcome of our actions is diminished. Dynamic and complex systems are difficult to predict because they contain both epistemic and aleatory uncertainty.

While overconfidence bias was originally described by Alpert and Raiffa (Alpert and Raiffa, 1982), it has more recently been studied with respect to subjective probability distributions (SPD) (Soll et al., 2024). Whereas prior studies have primarily focused on epistemic uncertainty only, focusing on a respondent's ability to estimate a knowable piece of information (e.g. "How much does a 747 airplane weigh?"), Soll examines how people deal with the combination of aleatory and epistemic uncertainties. In general, people tend to underestimate their epistemic uncertainty. In other words, they are too confident in the accuracy of their predictions, a behavior known as overprecision (Lichtenstein et al., 1982). Soll further unpacks overprecision behavior in the context of SPD and describes it in terms of concentration (how closely the standard deviation of one's subjective distribution compares to the empirical distribution) and calibration (how well subjective probabilities match actual probabilities across a range of questions).

We can hypothesize from Soll et al. (2024) what the difference between an empirical probability distribution and the subjective probability distribution of farmers might look like in Figure 4. Compared to the empirical probability distribution (in red), farmers' judgments would directionally be expected to be both poorly calibrated due to optimism bias (represented as the mean shift from 150 to 200 pounds per acre) and overly concentrated due to overconfidence bias (represented as the reduced standard deviation from 51.70 to 25.85) as shown in green.

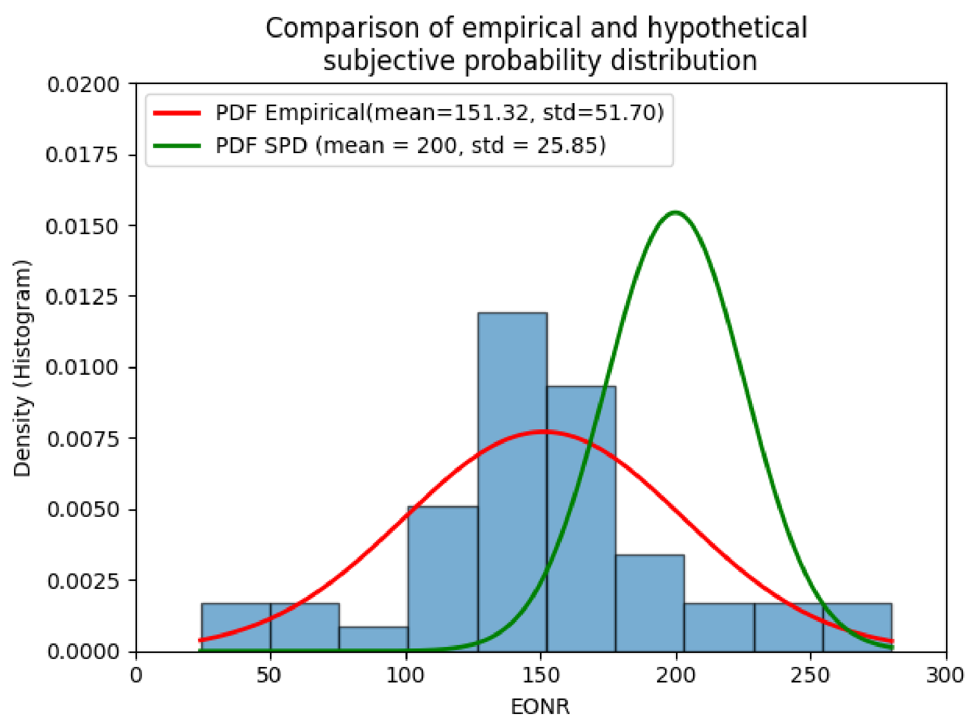


Figure 4: Comparison of empirical probability distribution to hypothetical subjective probability distribution displaying both optimism and overconfidence.

3.4 System 1 Thinking

N dynamics comprise several complex phenomena. This includes multiple loss pathways including ammonia volatilization, nitrate leaching, and denitrification. It also includes crop demand for N and mineralization of organic matter into plant available forms of N. These phenomena are highly interdependent and influenced by temperature, precipitation, soil texture, and microbial activity which have both aleatory and epistemic components.

Marx and Weber (2012) note that in the context of decision making under uncertainty, people often resort to deterministic thinking. Given the tremendous amount of aleatory and epistemic uncertainty that exists around finding the optimum N rate, this seems understandable. If thinking probabilistically about N rates proves to be too difficult, how might farmers arrive at a choice for N fertilization rates?

Sterman (1989) observes that in complex systems, behavior is driven by the anchoring-and-adjustment heuristic. In the absence of timely feedback on the state of inventory, time delays, and future demand forecasts, people resort to anchoring on past decisions and adjusting from there.

When we contextualize this to N management, we observe that farmers only get feedback signals for underapplication of N. These signals show up both during the growing season as yellowing leaves and stunted growth and at harvest as diminished yield. However, there is no feedback signal for overapplication. If the farmer has applied sufficient N to maximize yield, there is no signal to tell them if they have applied 5, 50, or 100 pounds more than needed.

Kahneman popularized the notion of System 1 (intuitive) and System 2 (reflective) thinking. When confronted with a difficult question that requires System 2 thinking, people often answer an easier one instead that only requires System 1 thinking. Put another way, when there is a target attribute that is asked, people respond with a heuristic attribute that is easier to answer (Kahneman and Frederick, 2002).

In a study on N management, Reimer et al. (2020) found that 70% of farmers used System 1 approaches to determine their N management practices and only 30% used System 2 approaches. Since N dynamics are so unpredictable that even the most knowledgeable scientists are challenged to advise on the optimum rate for a given field in a given year, it is reasonable to assume that a farmer is substituting the difficult question ("What rate of N should I apply on this field?") with an easier question.

The positive-negative asymmetry effect (Baumeister et al., 2001) and the status quo bias (Samuelson and Zeckhauser, 1988) provide us insights into what the substitute question might be. The positive-negative asymmetry effect says that in general, “negative information receives more processing and contributes more strongly to the final impression than does positive information.” The status quo bias observes that in decision-making experiments, individuals disproportionately stick with the status quo (Samuelson and Zeckhauser, 1988). When we combine the positive-negative asymmetry effect with status quo bias, we can hypothesize that the substitute question farmers are asking is: “Were X lbs of N sufficient last year?” If they saw evidence of nitrogen deficiency in the prior year such as yellowing leaves, they will likely be inclined to increase their rates. However, if they believe it was sufficient last year, they are likely to stick with the status quo. This is another way of describing the anchoring-and-adjustment heuristic. In this decision making context it might be more precisely described as the anchoring-and-upward-adjustment heuristic since there is no feedback signal associated with lowering N rates.

4 A Decision Support System for Improved N Application Rates

The proposed decision support system that addresses the heuristics and biases present in N fertilizer application can be described in 3 steps: Understand, Calibrate, and Act. While this decision support system primarily makes use of active decision support techniques that focus on changing minds, it also includes elements of passive decision support that changes people's environment to encourage them to make better choices.

4.1 Understand: Improving Mental Models of N Dynamics

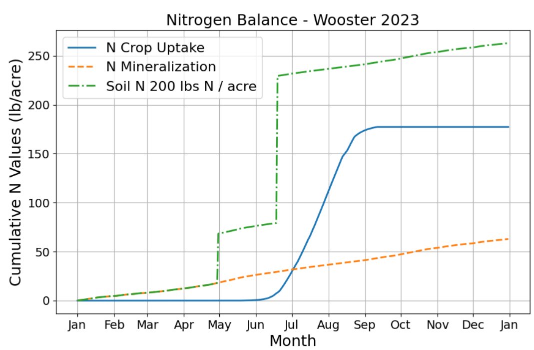
Since figuring out optimum N rates is highly complex, creating a decision support system that can embed the decades of scholarship on N dynamics and the more recent advancements in machine learning (ML) approaches into an accessible form to improve farmers' understanding of N dynamics is an important first step to improved approaches to N management. This has several benefits that address many of the heuristics and biases described in the earlier section.

Firstly, creating an understanding of N dynamics can address inaccurate mental models that often form the basis for poor choices. Saysel (2014) found that feedback of residual nitrogen in a simulation resulted in better fertilization choices . This supports our hypothesis that farmers lack an appropriately accurate mental model informed by data that can explain the N dynamics happening on their fields. Gonzalez (2005) explored the value of outcome feedback, feedback of one's own actions, and feedback of how experts interact with a simulation on improving dynamic decision making and found that expert feedback was the only approach that improved dynamic decision making relative to the control group. While Gonzales does not explicitly reference mental models in the article, it seems that the success of the expert feedback might partly be due to being more effective at improving the mental models of the participants. In our case, we are using a decision support system that embeds expert feedback to enable farmers to make better choices.

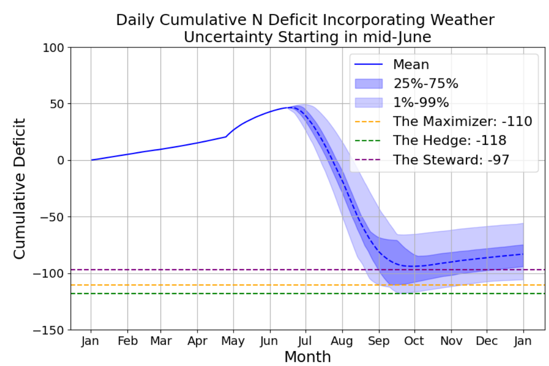
Secondly, it can serve to convince farmers that N dynamics is more complicated than they realized. While this may not seem intuitive, Fishman et al. (2016) found that fertilizer input recommendations were more influential among farmers with less confidence. If the decision support system serves to lower confidence in what they think they know, they may be more receptive to recommendations and less likely to overweight their own judgments, a behavior known as egocentric advice discounting (Bonaccio and Dalal, 2006).

Thirdly, communicating N dynamics in a way that highlights both the epistemic and aleatory uncertainty present in N management choices could help farmers understand the importance of collecting field-specific calibration data to reduce the epistemic uncertainty. Figure 5 shows two charts aimed at improved understanding of N dynamics. Figure 5a shows the N balance for a specific field in a given year describing the amounts of N demand by the crop that year, the amount of N mineralization by the soil, and the total amount of N in the soil at a fertilization rate of 200 pounds N per acre. The data was generated using DNDC, a process-based soil biogeochemical model (Gilhespy et al., 2014).

While this information can be generated using little or no information about a farmer's specific field, it can serve to improve a farmer's mental model, temper their overconfidence, and serve as a "call to action" to collect calibration data to reduce the model uncertainty. These all serve to improve response efficacy, the perceived effectiveness of an action (Floyd et al., 2000). In our case, this step ultimately serves to convince a farmer that it is possible to manage N more effectively.



(a) Chart showing cumulative N crop demand, N mineralization, and N mineralization with 200 pounds of N fertilizer added.



(b) Chart showing aleatory uncertainty effects of weather for a scenario with fertzilier applied on Day 165.

Figure 5: Charts that seek to improve understanding of N dynamics.

4.2 Calibrate: Reducing Epistemic Uncertainty and Increasing Saliency with Field-Specific Data Collection

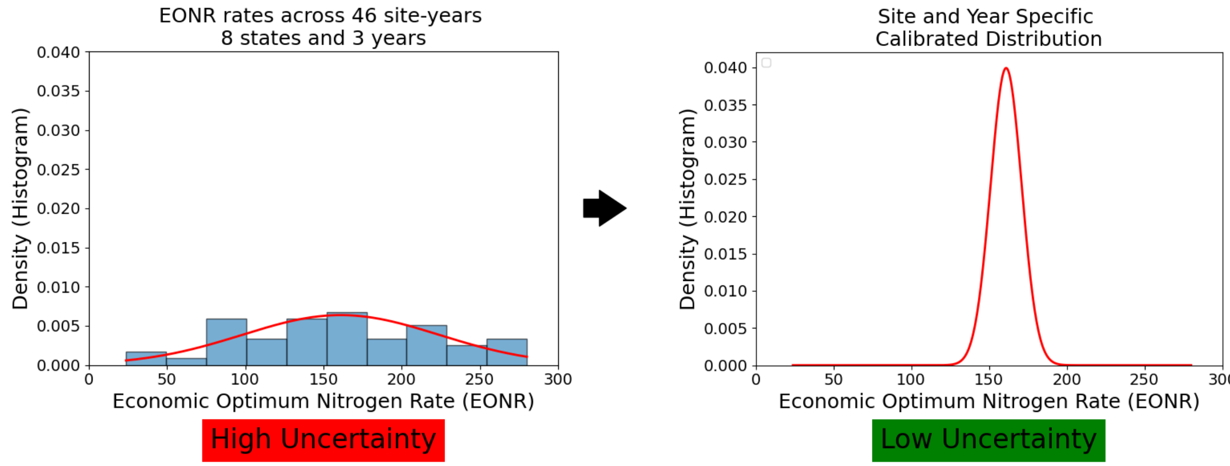
We have established that there is much uncertainty in both spatial and temporal dimensions that leaves us with a wide range of possible optimum N rates for a given field in a given year, and that given the asymmetries in economic risk, this uncertainty promotes overapplication of N. Since this uncertainty encompasses both epistemic and aleatory components, this step of calibration aims to reduce the epistemic uncertainty through the collection of field-specific data. A digital tool is proposed that can lower the time, frustration, and hassle commonly associated with managing agricultural data. Three levels of data collection are proposed that each successively reduce the uncertainty while also increasing the time investment to collect the data.

1. Soil Test and Historic Yield Data - This is information that most farmers already have access to. The vast majority of farmers conduct standard soil tests every 3-4 years that provide the basis for their soil fertility treatments. Additionally, nearly every modern combine comes with a yield monitor that generates a shape file that associates yield with latitude and longitude locations across the field. This information has both the lowest required effort from the farmer and the highest value to reduce the uncertainty associated with optimum N rates. The soil test information provides important information to estimate the mineralization and losses of N in the soil while the historic yield provides an indication of the crop N demand.

2. Replicated N Trials - This is on-farm research where a series of N rates are replicated a number of times to assess the yield response to various N rates. This requires more effort than the first set of data in that N rates at sidedress must be varied across a number of on-farm research plots and yield data at the end of the season must be measured, ideally with a grain cart scale corresponding to each replicated plot. This data provides information to more precisely calibrate the losses and mineralization of N for a given field.

3. Unmanned Aerial System Imagery - This last set of data includes one or more UAS flights over the field to get in-season status of the health of the crop. This information comes in the form of stand count, growth stage, canopy cover, and spectral reflectance that can be ultimately be represented in vegetation indices such as Normalized Difference Vegetation Index (NDVI). This last set of information is valuable because it can predict the N demand of the crop in-season and provide a recommendation for an adjustment of N sidedress rates.

While collecting of calibration data is important to reduce the uncertainty in the model results, it is also important to build trust and confidence with the farmer. Salience is an important influencer for behavior change because our attention is drawn to things that are relevant (Dolan et al., 2012). Gigerenzer and Hoffrage



(a) Chart showing empirical EONR rates from a dataset across a range of sites and years

(b) Chart showing hypothetical distribution with low uncertainty for a specific field and year

Figure 6: Using calibration data to move from high uncertainty to low uncertainty in optimum N rates.

(1995) present studies that show that information provided in frequency formats improves Bayesian reasoning. The theory is that we are more likely to give attention to things that relate to our personal experience rather than things that are presented in a more general and abstract way. The act of collecting calibration data serves to create salience and trust because data from a farmer's own fields has been used by the model to generate results. This is observed in Ooge and Verbert (2021) where data provenance emerged as one of six themes that had an influence on participants' trust in prediction models.

Another important benefit of collecting calibration data is the IKEA effect, which finds that we value things that we have put forth effort to create (Norton et al., 2012). This concept is referred to as "effort justification" and predicts that effort and valuation increase together. In this case, because the farmer has invested time in collecting the data, they value the results of the model more. And presumably, the more levels of data they collect, the more they might value the results.

This step builds on the response efficacy promoted in the previous step to promote self-efficacy, the belief that one is capable of executing an action (Bandura, 1997). Bandura lists several sources of self-efficacy including (from strongest to weakest) mastery experience, vicarious experience, and verbal persuasions from others. This step is conducive to mastery experience because it provides three levels of data collection and uses a digital tool to lower the barriers and make it as easy as possible to collect this data. This allows farmers to start at their current level of proficiency. Because mastery experience is about getting many "at-bats", to use a baseball analogy, farmers can start small, build confidence, and expand to more comprehensive data collection and associated benefits over time.

4.3 Act: Choosing N Rates Informed by Probabilistic and Calibrated Information

The previous steps of Understand and Calibrate are important for equipping the farmer and using their data collection efforts to provide the best possible information unique to their own fields and the elapsed weather conditions. In this step, information takes the form of agronomic, economic and environmental information and includes both active and passive decision support techniques. It uses active decision support techniques via informative charts and tables designed to enable the farmer to make the best choice with the information available to them. However, it also makes use of passive decision support techniques.

Figures 7, 8, and 9 show examples of economic, agronomic, and environmental charts and tables that discretize the continuous range of values into 3 choices with associated identities. These identities are labeled as "The Steward", "The Maximizer", and "The Hedge". These identities could further be described in the decision support system as follows:

1. The Steward seeks to balance economic and environmental considerations and is willing to forgo some amount of profitability to reduce the environmental impacts such as nitrate leaching off of their fields.
2. The Maximizer seeks to maximize profitability.
3. The Hedge seeks to minimize the possibility of insufficient N and is willing to forgo a small amount of expected profit to ensure sufficient N and maximum yields.

There are several approaches embedded in these charts and tables that may not be immediately obvious. The first is the fact that a continuous range has been broken up into three discrete choices. In reality, the farmer has a theoretically infinite number of choices for how much N to apply. However, Schwartz (2004) notes that too much choice can have two negative effects. It can lead to paralysis leading to inaction, because someone worries about making the wrong choice. It can also lead to regret because someone worries after the fact that they may not have made the optimal choice. By taking a continuous range and breaking it down into three choices, we reduce the possibility of inaction and the potential for regret.

Secondly, is that each of the 3 choices has an identity associated with it. Identity-based motivation is a theory that focuses attention on our motivations to make choices that are congruent with our identities

Marginal Return to N
Incremental Profit at each N rate
"Positive is good, negative is bad"

	Total lbs N / acre							
Year	**100**	**120**	**140**	**160**	**180**	**200**	**220**	**240**
2000	$42	$42	$42	$16	-$9	-$9	-$9	-$9
2001	$55	$55	$55	$36	$23	-$9	-$9	-$9
2002	$44	$44	$44	$44	-$10	-$9	-$9	-$9
2003	$56	$56	$56	$31	$19	-$9	-$9	-$9
2004	$29	$29	$29	-$9	-$9	-$9	-$9	-$9
2005	$50	$50	$50	$49	$48	-$9	-$9	-$9
2006	$48	$48	$48	$55	$9	-$9	-$9	-$9
2007	$28	$28	$28	$9	-$9	-$9	-$9	-$9
2008	$49	$49	$49	$37	$55	$22	$8	-$9
2009	$46	$46	$46	-$9	-$9	-$9	-$9	-$9
2010	$43	$43	$43	$21	-$9	-$9	-$9	-$9
2011	$32	$32	-$9	-$9	-$9	-$9	-$9	-$9
2012	$45	$45	$45	$20	-$9	-$9	-$9	-$9
2013	$43	$43	$43	$31	-$9	-$9	-$9	-$9
2014	$40	$40	$40	$56	$0	-$9	-$9	-$9
2015	$43	$43	$43	$31	-$9	-$9	-$9	-$9
2016	$38	$38	$38	$16	-$9	-$9	-$9	-$9
2017	$46	$46	$46	$36	$17	$8	-$9	-$9
2018	$45	$45	$45	$63	$2	-$9	-$9	-$9
2019	$42	$42	$42	$18	-$9	-$9	-$9	-$9
2020	$46	$46	$46	$48	$2	-$9	-$9	-$9
2021	$45	$45	$45	$53	-$4	-$9	-$9	-$9
2022	$71	$71	$71	$37	$16	-$9	-$9	-$10
2023	$55	$55	$55	$22	$50	-$8	-$8	-$8
Average Marginal Return	**$45**	**$45**	**$43**	**$29**	**$5**	**-$7**	**-$8**	**-$9**
Cumulative Marginal Return	**$45**	**$90**	**$133**	**$162**	**$168**	**$161**	**$153**	**$144**
				The Steward	**The Maximizer**	**The Hedge**		

Figure 7: Summary of temporal variability in Economic Optimum Nitrogen Rate (EONR) for a given field across 24 years.

(Oyserman, 2009). By explicitly assigning an identity (Steward, Maximizer, or Hedge) to each of the 3 choices, it encourages the farmer to make the choice most closely aligned with their identity while still preserving their autonomy to make a different choice. It has been observed that farmers who identify as stewardship-minded are more likely to indicate high barriers to adopting sustainable N management practices (Rudnick et al., 2023). Construal level theory suggests that cognitive dissonance can be rationalized by overemphasizing lower-level mechanics to describe the reasons for a disconnect between one's values and action (Trope and Liberman, 2010). Put another way, individuals characterize their behaviors in terms of lower-level mechanics ("it was too hard") rather than their higher-level meaning ("I chose profit over environmental sustainability"). By explicitly associating these identities with discrete N rates, the hypothesis is that the stewardship-minded farmer will be more likely to choose the stewardship-minded N rate.

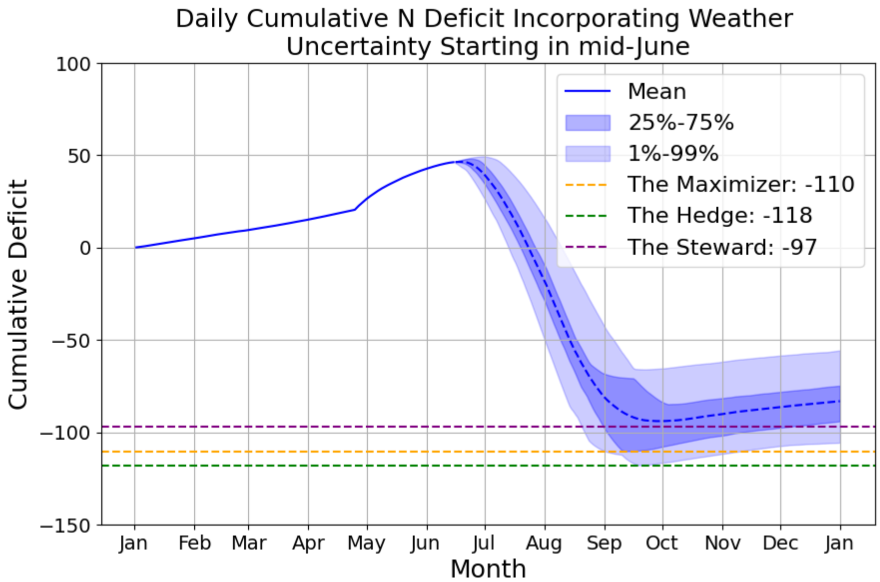


Figure 8: Chart highlighting aleatory uncertainty in N deficit for the remainder of the growing season to inform choice of N rate.

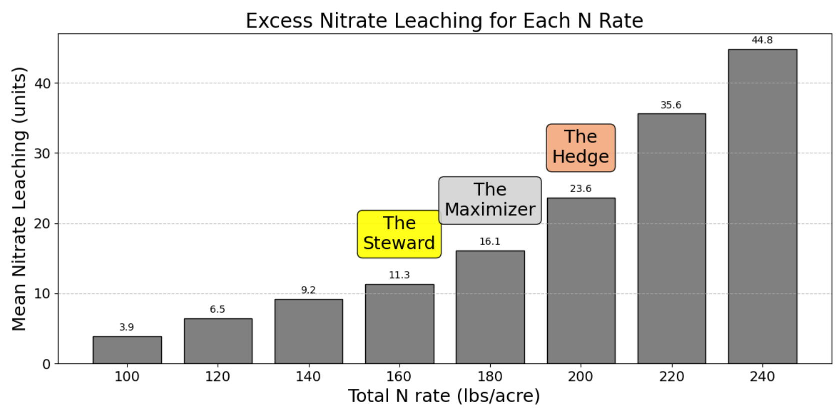


Figure 9: Chart highlighting nitrate leaching rates associated with various N rates.

Thirdly, the description of each identity includes a framing that is intended to be more positive for lower N rates. Li et al. (2021) found that positive framing increased participants' willingness to pay (WTP) for treatments on residential lawns that reduce nitrogen and phoshorus runoff. Positive framing ("You can improve your water quality if you do this") was shown to be more effective for increasing WTP than negative framing ("Your water quality will continue to get worse if you don't do this"). While the identities and descriptions likely need more refinement, the idea would be for the Steward identity and associated description to have the highest positive frame, followed by Maximizer, followed by Hedge.

Fourthly, the three discrete choices in the charts and tables make use of defaults. Samuelson and

Zeckhauser (1988) observes that people disproportionally follow defaults. Three defaults are provided that are all better than the status quo for environmental impact and profitability. A variation on this approach could be to position the Maximizer or the Steward as the default choice, as we might expect these to be the approaches that align most closely with most farmers' stated values. Research suggests that people deduce the quality of the default based on their beliefs about the default setter and adjust their behaviour accordingly (Thomas and Jona, 2018). Therefore, influencing people's perceptions about the motives behind the digital tool and determining which, if any, options are positioned as preferred are important to the success of the decision support system and will require ongoing feedback from farmers to determine the best approach.

This step aims to provide three simple alternatives for a farmer to act in ways that are consistent with how they value profitability, risk, and environmental impact, all while preserving their autonomy to make the final decision on N rates for their fields.

5 Initial Feedback from Farmers

Some of the concepts in this paper have been reviewed with three farmers through a semi-structured interview process. Preliminary findings include the following:

1. When showed a range of charts and tables, all three farmers consistently preferred the versions that were more complex over versions that simplified the information. This preference appeared to be related to two things. First is they were interested in building their understanding of N dynamics and they wanted to see all of the variability. Secondly, they were looking at the results to assess the trustworthiness of the information.

2. When asked about important factors for N application rates, no farmer indicated environmental impact as a consideration. When prompted about whether environmental impact was a factor for them, each one had a similar response, indicating that they are already using reasonable rates and application methods that minimize the potential for losses. However, when showing them various charts, each one found the nitrate leaching chart to be valuable and indicated that it could have an influence on their N rates. However, the reason appeared to be less related to environmental impact, and more related to the fact that they were losing N that they had paid for from their fields.

3. They immediately understood the agronomic charts shown in 5a and 5b and indicated that they would

influence their N rate choices "if they were accurate".

4. One of the farmers indicated that their trust and confidence in the value of a digital tool to help them improve their N rates would be highly influenced by the motivations of the company or organization that created the tool.

Overall, the initial interviews indicated that the concepts proposed in this paper are on the right track.

6 Conclusion

Oftentimes, well-meaning initiatives grounded in engineering and technology are isolated from behavioral science. This isolation limits the potential impact of these efforts because the engineering and technology efforts may not be focused on the right problem, or they may be focused on the right problem but the results are not delivered to people in a thoughtful choice architecture that is aware of people's heuristics and biases and seeks to promote response and self-efficacy.

While the engineering effort to use process-based models, machine learning, and substantial datasets to improve the prediction accuracy of optimum N rates is an ambitious one, the results of this paper indicate that the information can be brought together in a decision support system that can simultaneously improve farmer profitability, reduce environmental impact, and reduce stress. Through the steps of Understand, Calibrate, and Act, the proposed N decision support system can overcome the inherent heuristics and biases that contribute to overapplication of N through promoting increased response and self-efficacy and delivering simple, discrete alternatives that are improvements over the status quo.

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