Novel Scoring Framework for Comprehensive Site-Specific Evaluation of 4R Nitrogen Management Strategies Using Crop Modeling

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Abstract.

Comprehensive nitrogen (N) management, emphasizing the 4Rs nutrient stewardship concept to optimize N fertilizer rate, timing, sources, and placement is essential for sustainable agriculture. However, determination of the optimal N management strategy is complex and context-dependent, influenced by various factors such as weather, management practices, and field characteristics. This complexity necessitates tailored recommendations rather than one-size-fits-all solutions. Crop modeling emerges as a valuable tool for rapidly evaluating alternative management strategies across different contexts, considering their holistic impacts on agronomic, economic, and environmental outcomes. This research aimed to demonstrate the application of calibrated models and scenario analysis to assess alternative N management strategies. Specifically, we proposed a scoring system to comprehensively evaluate agronomic, economic, environmental, and logistical impacts of N management strategies relative to standard fertilizer timing practices prevalent in the study region. We conducted simulations for ten fertilizer timing scenarios using the Agricultural Production Systems sIMulator (APSIM) model over 24 historic weather years at two field sites in southeast Nebraska. Analysis of the simulations were used to derive the economic optimum N rate (EONR), yield at EONR (YEONR), and N leaching at EONR. We introduced a logistic index to assess the practical feasibility of proposed management changes, considering the available days for fertilization relative to the days needed for a standard farm size. A comprehensive scoring metric facilitated tradeoff exploration among multiple performance indicators. Results revealed that split application with 40% applied as spring preplant and 60% applied at V12 reduced EONR by 14% and N loss by 46% compared to standard practices (fall application). Furthermore, all scenarios including spring application timing showed an improvement in the logistic index. The comprehensive scoring matrix revealed that the fertilizer timing with the greatest potential of reducing EONR and N loss also had increased (but not the greatest) logistical index compared to the standard management. Looking forward, interdisciplinary collaboration and advancements in process-based modeling can enhance the scope and robustness of our *scoring matrix. Establishing clear thresholds for score assignment and defining minimum calibration standards can improve the repeatability and scalability of the proposed approach. Overall, our framework presented a valuable tool for informing region-specific fertilizer management decisions, promoting holistic approaches that balance agronomic, economic, and environmental considerations.*

Keywords.
Nitrogen; 4Rs; digital decision support; APSIM; crop modeling; corn; scoring metric

Introduction

Effective management of nitrogen (N) is critical for sustaining crop productivity (Cassman, 1999; N. D. Mueller et al., 2012), minimizing adverse environmental impacts (Bowles et al., 2018; Sobota et al., 2015), and enhancing farm profitability (Koch et al., 2004; Rajsic et al., 2009) but remains challenging due to spatial and temporal variability in crop yield potential, soil N supplying capacity, and N loss rates. As such, extensive research has been dedicated to developing means to determine the optimum N rate for specific locations and years (Cassman et al., 2002; Mamo et al., 2003; Puntel et al., 2019).

Furthermore, a comprehensive approach to N management involves considering all facets of N management. This holistic perspective is reflected in the “4Rs” nutrient management concept, which advocates for the right rate, right time, right source, and right place for fertilizer application (Bruulsema et al., 2009; International Fertilizer Industry Association, 2009). The 4R framework serves as an educational tool and decision-making guide and acknowledges the interconnectedness and context specificity of optimal N management practices, which can vary based on crop management strategies, geographic region, and climatic conditions.

For instance, while many studies generally recommend in-season N management for its ability to synchronize fertilizer application with plant demand (Cassman et al., 2002; Raun & Johnson, 1999; Solari et al., 2008) and utilize tools like plant and soil analysis, imagery, sensors, and models for informed decisions (Ransom et al., 2020), these recommendations must be context-specific. In some cases, in-season sidedress applications have been demonstrated to produce higher yields than preplant applications for irrigated corn grown on sandy soils (Rehm & Wiese, 1975). However, in-season sidedress applications have also been associated with increased N rates resulting in larger N balances and greater N losses (McLellan et al., 2018; Tenorio et al., 2021). Moreover, in non-irrigated environments, such applications may reduce yields and profits due to insufficient incorporation through rainfall or injection (Teten, 2021). These examples underscore the interplay between rate, time, source, and place, highlighting the need for tailored recommendations that consider all 4R principles, specific to the region and management practices (Spackman & Fernández, 2018).

Furthermore, the 4R concept emphasizes the importance of aligning management practices with stakeholders’ diverse goals and interests, necessitating the selection of relevant performance indicators. Although efforts have been made to integrate environmental and economic impacts of N management (Mandrini et al., 2021; Nigon et al., 2019), existing approaches often lack comprehensive assessments of agronomic, economic, environmental, social, and logistical aspects, along with their tradeoffs. As a result, determining the most suitable 4R strategies for a region often sparks debates among stakeholders with divergent priorities.

Traditionally, determining the optimal N practices across various regions and weather scenarios has relied on costly and time-consuming imposed treatment experiments. Decision-makers typically rely on fragmented interpretations of these research studies that may not comprehensively evaluate the 4Rs or consider multiple performance indicators simultaneously. In some cases, research results have been aggregated and ranked to guide management recommendations and inform decisions (Iowa State University Science Team, 2012; Mandrini et al., 2021; Nigon et al., 2019). However, such approaches have limitations in assessing the interconnected nature of management changes and their impact on diverse performance indicators. Additionally, the availability of research results covering a vast selection of N management strategies under various managements in various regions may be limited. Considering these challenges, employing crop modeling offers a promising avenue for evaluating the long-term effects of alternative N management strategies for specific geographic regions.

By creating a means of recommending tailored 4Rs by region through crop modeling, the inter-annual weather variations, and context specific considerations can greatly benefit decision and policy makers. Therefore, this paper aims to achieve two primary objectives: (1) demonstrate the application of a calibrated model in assessing alternative N management strategies in southeast Nebraska and (2) introduce a scoring system designed to comprehensively evaluate the agronomic, economic, environmental, and logistical impacts of alternative management strategies relative to standard practices prevalent in the region over time.

Materials and Methods

Nitrogen management scenarios with calibrated APSIM model

A calibrated Agricultural Production Systems sIMulator (APSIM) model (Figure 1a; Thompson et al., 2024, accepted with revisions) was used to test ten N fertilization timing scenarios (Table 1) over 24 weather years (1999 to 2022) within 4 field-zone locations and 36 N rates in southeast Nebraska (Figure 1b). Site DA is in a floodplain landscape position with silt loam soils while site ZH is an upland field with silty clay loam soils. The sites are non-irrigated and in a humid continental climate (warm, rainy summers) with annual precipitation of 726 mm and a mean temperature of 12°C. Fertilization dates were set based on the average observed farmer fertilization dates for the previous 10 years. Fall and spring base applications were simulated with anhydrous ammonia as the fertilizer source while in-season applications were simulated with 32% urea ammonium nitrate (UAN) as the fertilizer source.

Local farmer standard practices (FSP) were defined using survey data. The USDA Economic Research Service reported that in 2018 (most recent available year) N application for corn grown in Nebraska was 185 kg ha^{-1} (Fertilizer Use and Price, 2019). In 2023, a statewide survey reported that for MLRA 106 (n=41) where the study occurred, anhydrous application was the most common product (62%), fall was the most common timing (38%), and the average rate applied was 174 kg ha^{-1} (Nebraska State Digital Agriculture Survey; IRB Number 20230122510EX, data unpublished). Therefore, we defined the FSP in this region as fall anhydrous ammonia application at a rate of 174 kg ha^{-1}.

Transitioning to a spring anhydrous ammonia application is considered an improved practice which requires minimal infrastructure adjustments and thus represents the most straightforward scenario change. Scenarios that apply the majority of fertilizer pre-plant (75% fall or spring base applications with 25% during the growing season) are regarded as improved strategies that are more risk-adverse. Conversely, scenarios with greater fertilization in-season (40% fall or spring base applications with 60% in-season) are generally considered best management practices (S. M. Mueller et al., 2017; Scharf et al., 2002), but often demand a higher level of risk tolerance from growers, given the delay in application of a larger portion of the total N fertilizer (Sawyer et al., 2016). Scenarios which apply in-season N at V5 can be accomplished with standard ground application equipment while scenarios which apply in-season N at V12 require more specialized equipment such as a high-clearance applicator or airplane. The apsimx package (Miguez, 2022) in R was used to run simulations of the calibrated model on the UNL Holland Computing Center virtual machines (Figure 1c).

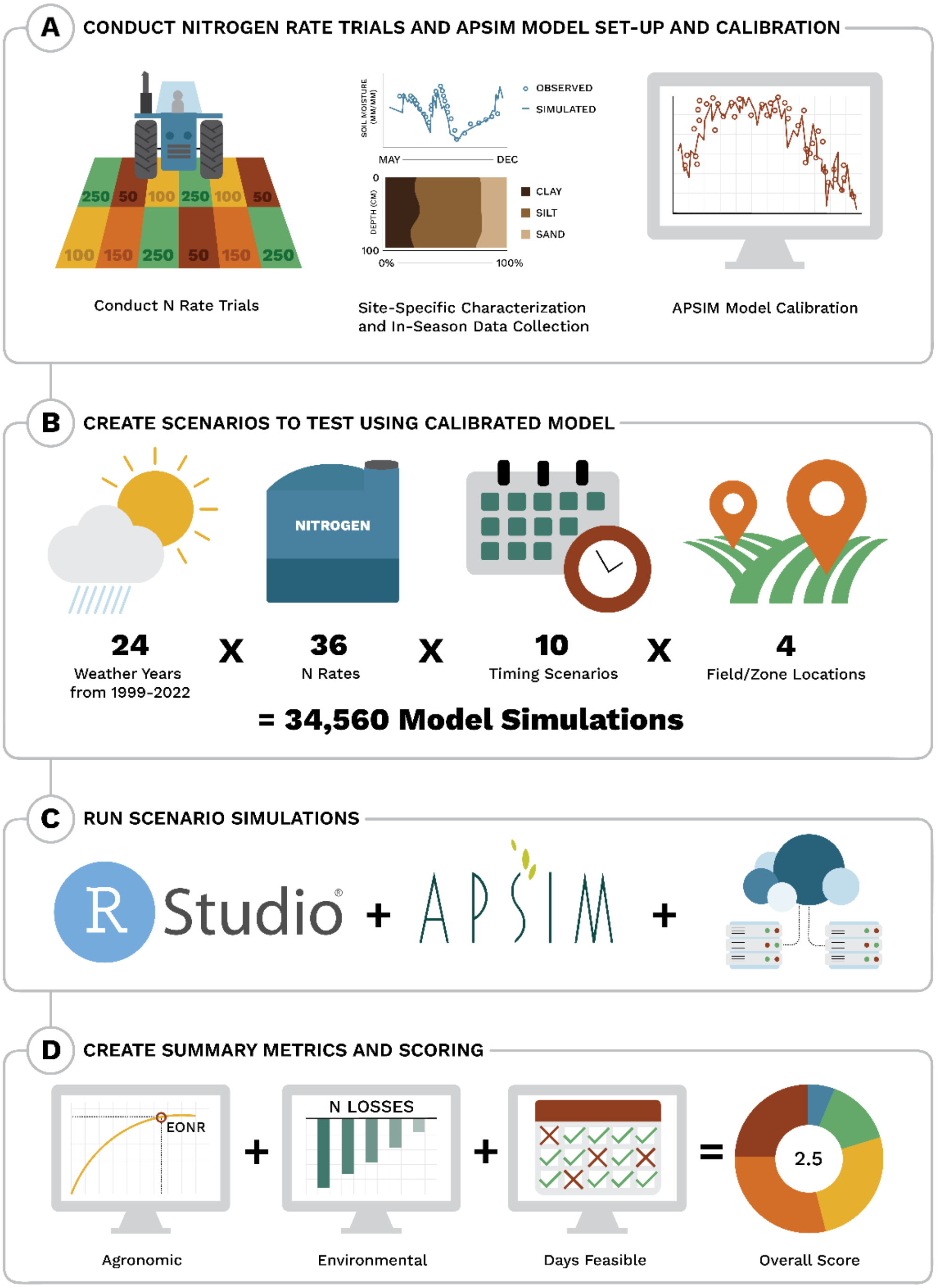

Figure 1. Framework for assessing impact of nitrogen management strategies using crop modeling, including (a) conducting N rate trials, collecting data, and calibrating the crop model, (b) creating nitrogen fertilization scenarios to test using the calibrated model considering varying weather and field locations, (c) running scenario simulations, and (d) analyzing the impact of each scenario on agronomic, environmental, and logistical considerations and assigning scores. Artwork by Tim Svoboda and Faith Junck.

Table 1. Fertilizer application timing scenarios evaluated by crop model simulation.

Scenario Name	Base Application Date	Base App-lication (%)	In-Season Application Date	In-Season Application (%)
Fall	November 30	100	None	None
Fall V5 25 Split	November 30	75	May 30 (DA)/June 2 (ZH)	25
Fall V12 25 Split	November 30	75	June 25 (DA)/June 22 (ZH)	25
Fall V5 60 Split	November 30	40	May 30 (DA)/June 2 (ZH)	60
Fall V12 60 Split	November 30	40	June 25 (DA)/June 22 (ZH)	60
Spring	March 15	100	None	None
Spring V5 25 Split	March 15	75	May 30 (DA)/June 2 (ZH)	25
Spring V12 25 Split	March 15	75	June 25 (DA)/June 22 (ZH)	25
Spring V5 60 Split	March 15	40	May 30 (DA)/June 2 (ZH)	60
Spring V12 60 Split	March 15	40	June 25 (DA)/June 22 (ZH)	60

Nitrogen management scenario analysis and scoring

Nitrogen Fertilization Scenario Scoring Matrix

To evaluate agronomic, environmental, and logistical impacts of a given timing scenario, we devised a scoring matrix which ranked the impact of timing on EONR, N loss, and logistics with higher scores indicating greater benefit and feasibility for the timing practice. Scores were benchmarked relative to the FSP (100% fall anhydrous) using the intervals shown in Table 2. The overall score was calculated as the sum of the EONR, N loss, and logistics scores (Figure 1d). Details of the agronomic (YEONR and EONR), environmental (N loss), and logistics analyses follow. Given the lack of differences in metrics within field zones, our analysis predominantly focuses on field-level differences. Additionally, for instances where field-specific responses were minimal, outcomes were consolidated across sites.

Table 2. Values used to assign scores of 0 (low change) to 3 (high change) relative to farmer standard practice (FSP) for metrics of economic optimum nitrogen (N) rate (EONR), N loss, and logistics index (LI).

	Change Relative to Farmer Standard Practice (FSP)	Score
EONR* (kg ha^{-1})	30 to -30	0
	-30 to -60	1
	-60 to -90	2
	-90 to -120	3
N Loss (kg ha^{-1})	15 to -15	0
	-15 to -45	1
	-45 to -75	2
	-75 to -105	3
LI	<1	0
	1 to 3	1
	3 to 5	2
	>5	3

*For EONR, values that were within +/- 30 kg ha^{-1} were considered reasonably close based on modeling error associated with EONR (Ransom et al., 2023) and were assigned a score of 0.

Agronomic

The EONR was derived from fitting regressions through the yield response to N rate for each simulation of site-zone, year, and scenario using R software (R Core Team, 2020). Yield response to N was described using a quadratic plateau model,

$$y = a + bx + cx^2, x < x_o \tag{1}$$

$$y = a + bx_o + cx_o{}^2, x \geq x_o \tag{2}$$

or linear plateau model,

$$y = a + bx, x < x_0 \tag{3}$$

$$y = a + bx_0, x > x_0 \tag{4}$$

where y is yield (kg ha^{-1}), x is the N rate (kg ha^{-1}), a is the y-intercept, b is the linear coefficient, c is the quadratic coefficient, and xo is the inflection point or join point. The statistical model with lowest Akaike information criterion (AIC) was selected with the same statistical model (quadratic or linear plateau) chosen for all fertilizer timings in a given year and field-zone (Baum et al., 2023; Miguez & Poffenbarger, 2022). A fixed price ratio of 4.5:1 N:corn grain price (US\$ kg^{-1} N: US\$ kg^{-1} grain) was used to be representative of the study year (Bullock & Bullock, 2000). For the quadratic plateau model, EONR was calculated from the N response equations by setting the first derivative of the fitting response curve equal to the price ratio. When the inflection point of the quadratic model exceeded the maximum N rate applied, the EONR was assumed to be the maximum rate. For the linear plateau model, EONR was the inflection point between the linear portion and the plateaued portion of the model. YEONR was predicted by using the EONR as the N rate and solving for y.

Environmental

Annual N losses for each scenario were determined by selecting the simulated annual N loss at the N rate that corresponded to the calculated EONR for a given field-zone, year, and timing scenario.

Logistics

To determine the feasibility of the various application timing scenarios, we calculated a logistic index (LI). First an unweighted logistic index (LI_{uw}) was calculated as,

$$LI_{uw} = D_f / D_n \tag{5}$$

where D_f is the number of days with conditions feasible for application and D_n is the number of days needed to complete applications for an average sized farm. Values greater than or equal to one indicate the application is feasible while values less than one indicate there are not enough days with acceptable conditions to complete the application. To calculate D_f we considered a one-month timeframe around the fall and spring application dates and two-week timeframe around the V5 and V12 application dates, with target application dates from the model scenarios (Table 1). For a day to be considered acceptable for fertilization, soil temperature at 2.54 cm must be above freezing, soil moisture at 30 cm must be below 105% of the modeled field capacity, and for fall application, soil temperature at 10.16 cm must be below 10°C (Frederick & Broadbent, 1966; Sawyer, 1985). To determine the D_n we first calculated the effective field capacity (ASAE EP496.2 DEC99 Agricultural Machinery Management, 1999) as,

$$C_a = \frac{swE_f}{10} \tag{6}$$

where C_a is the area capacity in ha h^{-1}, s is field speed in km h^{-1}, w is implement working width in m, and E_f is field efficiency as a decimal. The working days needed to complete fertilization (D_n) was then determined as,

$$D_n = Farm\ Size\ /\ C_a\ /\ Working\ Hours\ per\ Day \tag{7}$$

where D_n is days needed rounded to the nearest whole number; farm size is in ha, C_a is area capacity in ha/h, and hours per day are the estimated working hours available per day.

The LI_{uw} values were first calculated for each timing scenario (Fall, Spring, V5, and V12) and then weighted based on the percent of fertilizer to be applied in each of the timing scenarios shown in Table 1 to get the final, weighted LI as follows,

$$LI = (LI_B \times P_B) + (LI_S\ \times P_S)/\ 2 \tag{8}$$

where LI_B is the logistic index of the base N application (fall or spring), LI_S is the logistic index of the in-season N application (V5 or V12), P_B is the proportion of the N applied as a base application (fall or spring) and P_S is the proportion of the N applied as an in-season application (V5 or V12).

Results

In the following sections, we presented the influence of N fertilizer timing scenarios on agronomics (YEONR and EONR), N losses, and the feasibility metric (LI). We then showed results from a comprehensive scoring matrix which summarized the improvement in EONR, N loss, and LI compared to the FSP into an overall score.

Agronomic (YEONR and EONR)

Mean simulated YEONR was similar between sites (15,497 kg ha^{-1}). For a given location and year, the difference in YEONR due to timing scenarios was on average 34 kg ha^{-1} and the maximum difference was 112 kg ha^{-1}, indicating that maximum yields can be obtained for all timing scenarios by adjusting N rates.

Mean simulated EONR was not statistically different between fields (p=0.307) and averaged 116 kg ha^{-1}. EONR ranged from 27 to 250 kg ha^{-1} for DA (silt loam floodplain) and 32 to 286 kg ha^{-1} for ZH (silty clay loam upland). Impact of timing scenarios on EONR was statistically significant (P=0.061) and similar between the silt loam floodplain (DA) and silty clay loam upland field (ZH). Across years and sites, moving from the FSP timing of fall application to spring application resulted in a 6.6% reduction in EONR. Moving from FSP timing to a split application with 75% in the fall and 25% in season represented a 5.5% decrease in N requirement. Similarly, moving from 100% spring application to a split application with 75% in the spring and 25% in season represented a 3.8% decrease in EONR. Moving from fall application to a split application with 40% applied in the spring and 60% applied in season resulted in 14.3% reduction in N required. Adjusting timing of the in-season application by moving from V5 to the later season V12 resulted in a 2.4% reduction in N required.

Environmental (N Loss)

Annual N loss was statistically different (p=0.0003) between field sites with slightly greater N loss (32.4 ± 18.6 kg ha^{-1}) for the silt loam floodplain compared to the silty clay loam upland site (28.1 ± 17.7 kg ha^{-1}). Annual N loss was also statistically different between timing scenarios (p<0.0001). The greatest N loss occurred for the fall timing (average of 41.6 ± 26.3 kg ha^{-1}) and the least N loss occurred for the 40% applied in spring and 60% applied at V12 (average of 22.5 ± 10.8 kg ha^{-1}). On average, moving from fall to spring resulted in a 20.9% decrease in N loss, while moving from fall to 40% in spring with 60% in season resulted in a 39.7 to 45.9% reduction in N loss for V5 and V12 applications, respectively.

Logistics

Fall or spring fertilization with anhydrous ammonia required more days to complete (6 days) compared to V5 or V12 application with UAN (2 days) due to differences in applicator widths and speeds. Fall application had the greatest number of conditions that had to be met for a day to be considered acceptable, and thus, fertilization was only able to be completed in 50% to 58% of years. However, even if the additional fall condition of not applying when soil temperatures are above 10°C was disregarded, as may be the case in practice, the percent of years in which fall fertilization was feasible did not increase. The silt loam floodplain site with the presence of a shallow water table had fewer years in which fall fertilization was feasible (50%) compared to the silty clay loam upland (58%). All other timings evaluated (Spring, V5, and V12) were able to accomplish the N fertilization in most or all the years evaluated. Spring fertilization in 2019 was infeasible at both sites in accordance with observed heavy rainfall and early spring flooding that was experienced at the sites. Only the V12 timeframe was able to be completed for both sites in all years evaluated.

Scoring Matrix

The timings that included a fall application had overall scores ranging from 0.09 to 0.7, indicating negligible improvement by adding a sidedress application when compared to the FSP (100% applied in fall; Figure 2). Timing scenarios that included spring applications had higher scores (ranging from 0.88 to 1.48). When comparing fall versus spring base applications with the same sidedress timing and proportions, the spring base rate resulted in a 2 to 10 times greater score compared to the fall base rate. The highest overall score (sum of EONR, N Loss, and LI) was for the timing with 40% in the spring and 60% at V12 (Spring V12 60Split) with an average overall score of 1.48 and nearly 75% of years having at least a one category improvement compared to FSP (Figure 2). The overall score for Spring V12 60Split was primarily due to improvements in N losses (score of 0.63) and LI (score of 0.58). The next highest overall score was for the spring timing, with an average score of 1.36. The spring timing and a greater number of years with at least a one category improvement (nearly 90%) compared to the timing with 40% in the spring and 60% at V12 (Spring V12 60Split). A high LI score (1.17) was the biggest contributor to the overall score for the spring timing.

Across timings evaluated, the improvements in EONR relative to FSP were negligible with scores of 0 to 0.27 (Figure 2). Nitrogen loss scores had a greater improvement relative to FSP. The greatest N loss score was for the timing with 40% in the spring and 60% at V12 (Spring V12 60Split); this timing scenario had an average score of 0.63 and over 50% of years with a one category or greater improvement in N loss (Figure 2). For LI, all timing scenarios with any fall application had negligible improvement in scores (scores of 0 to 0.06; Figure 2). The greatest improvement in logistic index was for the spring application timing which had an average score of 1.17 and over 80% of years with a one category or greater improvement. The timing with 40% in the spring and 60% at V12 (Spring V12 60Split) had an average LI score of 0.58 and over 50% of the years with a one category or greater improvement (Figure 2).

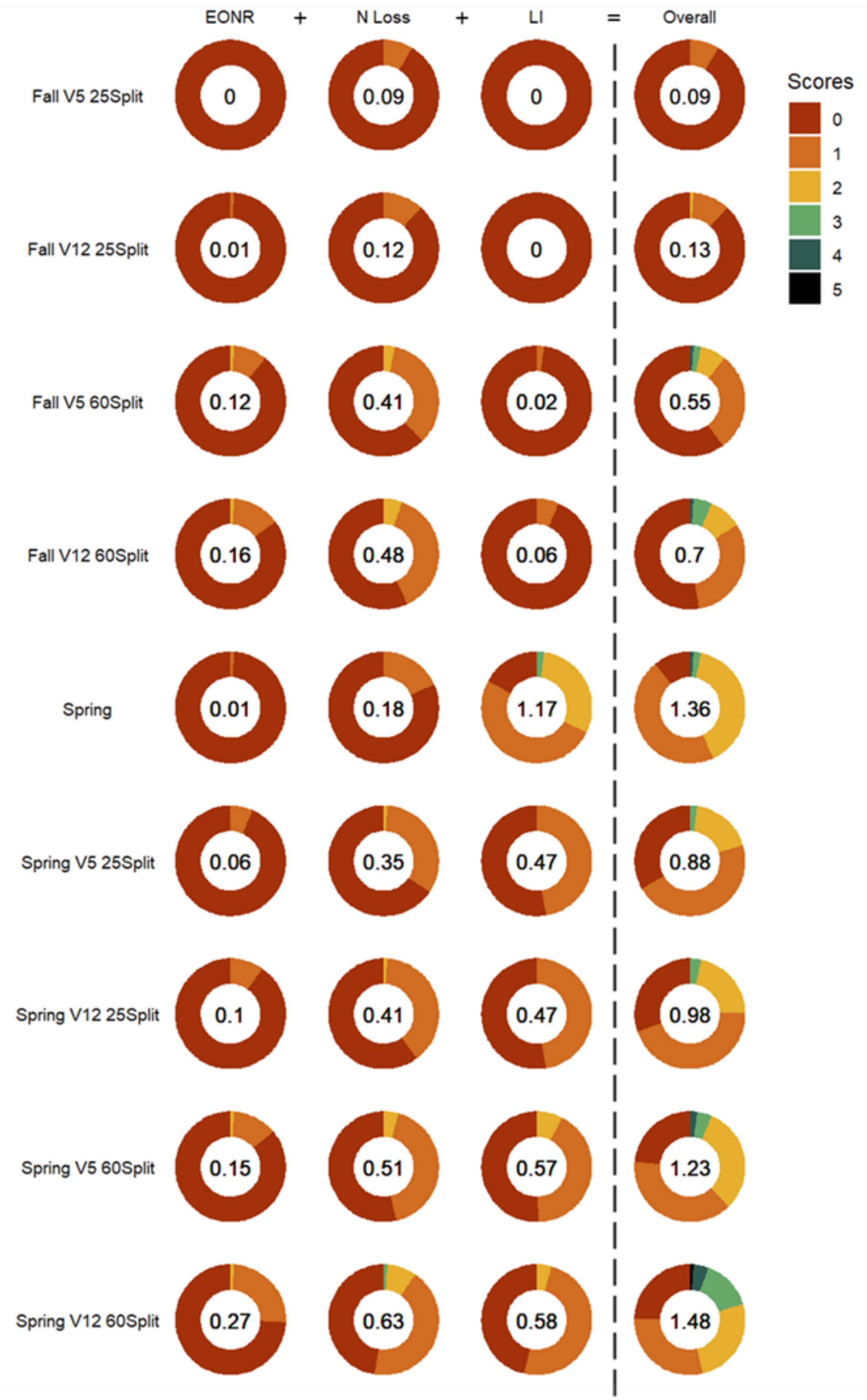

Figure 2. Scoring matrix considering economic optimum nitrogen rate (EONR), nitrogen loss (N Loss), and logistics (LI) for nitrogen timing scenarios evaluated. Scores range from 0 (worst) to 5 (best) and are relative to the farmer standard practice (FSP) timing of fall application. Donut colors show the percent of 24 historic years evaluated with a given score, while the average score across years is printed in the middle of the donut in black text. The overall score is the sum of the EONR, N Loss, and LI scores.

Discussion

YEONR, EONR, N Loss, and Logistic Index

We utilized a calibrated model to evaluate the impact of ten N fertilizer timing strategies on a suite of metrics encompassing agronomic, economic, environmental, and logistical considerations. Yield at EONR was similar for all N timing scenarios, indicating that by adjusting N rate, all timing scenarios were able to achieve similar yields. Previous research has noted that moving from fall to spring pre-plant applications resulted in a 4% yield increase and moving from fall to 40% applied as spring preplant and 60% applied as sidedress resulted in a 10% yield increase, suggesting that fall N application was a yield-limiting factor (Iowa State University Science Team, 2012). We did not observe this yield change which may be because our method adjusts N rate at each timing to EONR whereas other studies used fixed fertilizer rates which when applied in the fall may have been insufficient for obtaining optimal yield due to increased time in which the fall applied fertilizer was subject to N losses. In other words, by adjusting the N rate at each timing to EONR, we were able to maintain yield production (YEONR).

EONR decreased by moving from the FSP timing to other timing scenarios, with the greatest reduction (14.3%) for the scenario with 40% applied in the spring and 60% applied at V12. This agrees with proposed best practices which suggest that delaying a greater portion of N fertilizer to the time when the crop is rapidly uptaking N will increase N efficiency (S. M. Mueller et al., 2017; Scharf et al., 2002). It is notable that moving from fall application to spring application resulted in a 6.6% decrease in EONR. This represents the most straightforward timing change as it requires no additional trips through the field, no additional fuel or labor, and no changes to equipment or fertilizer source and thus may be the most likely to be adopted. The reduction in EONR (6.6%) by moving from fall to spring is slightly greater than that proposed by UNL N recommendations for corn which suggest this change results in a 5% decrease in N fertilizer requirements (Shapiro et al., 2019).

Our comparison to FSP focused primarily on the relative differences in EONR between FSP timing and other simulated timings rather than comparing FSP rate with the EONR values obtained at other simulated timings. This is because previous literature has demonstrated the difficulty in accurately predicting EONR (Baum et al., 2023; Mandrini et al., 2021; Puntel et al., 2016; Sela et al., 2018) resulting in less confidence in the absolute values of modeled EONR compared to relative differences between timing scenarios. Our results suggested that the impact of adjusting the FSP rate to EONR was over twice as impactful as adjusting the FSP timing to the timing with the lowest EONR (40% applied in the spring and 60% applied at V12) in reducing fertilizer N need. Thus, if improvements in crop modeling can result in more accurate EONR simulation (Baum et al., 2023), the opportunity to use this method for benchmarking impact of N rate changes compared to standard practice could be even more impactful.

The reduction in N loss by moving from fall to spring application (20.9%) and by moving from fall to 40% in spring and 60% in-season (39.7% to 45.9%) was much greater than that observed in previous research which noted decreases in nitrate-N of 6% and 5% for these timing changes, respectively (Iowa State University Science Team, 2012). However, the previous research (Iowa State University Science Team, 2012) acknowledges large standard deviations (25 for moving from fall to spring and 28 for moving from fall to 40% in spring and 60% in-season) which indicate that some years have potential for much higher or lower N loss reductions by adjusting timing.

From a feasibility standpoint, the LI allowed us to quantify the likelihood of being able to complete field work for fertilization using various timing strategies given specific soils and weather conditions in the region. The silt loam bottom field (DA) had fewer years in which fertilization could be completed (50%) compared to the silty clay loam upland (ZH; 58%) which is expected due to the presence of a water table at DA resulting in wetter soils. These differences highlight the need for tools that can forecast trafficability based on weather and soil (Müller et al., 2014; Obour et al., 2017). The relative increase in feasibility (greater days available for fertilization relative to days required) for moving from fall to spring, indicates that this timing scenario may be more likely to be adopted by farmers. This does raise the question of why this strategy has not been adopted previously. It is possible that fall application is seen as a risk management approach as farmers can first try to apply in the fall, then if the conditions are not favorable, they still have time to try in the spring. This approach effectively allows for more total days for potential fertilization by summing the available days available in the fall and spring. The development of a LI is critical in more comprehensively assessing the potential for proposed management changes to be adopted.

Strengths, Limitations, and Recommendations of a Proposed Alternative Fertilizer Management Scoring Matrix

The proposed scoring matrix (Figure 2) incorporates agronomic, economic, environmental, and logistical aspects and has potential to rapidly provide site- and region-specific comparisons of alternative management strategies, such as fertilizer timing. The proposed method is flexible and customizable, allowing experts to choose scenarios to evaluate, select metrics to use, define thresholds for assigning scoring, and determine the FSP by which to compare alternatives. For example, in our case, we did not include YEONR or another metric for production as part of our overall scoring matrix (Figure 2) because we found that it did not differ substantially between scenarios evaluated; however, in other cases, experts may find this metric to be relevant (Iowa State University Science Team, 2012). Similarly, in our study, the contrasting sites (silty clay loam upland and silt loam floodplain) were similarly impacted by adjusting fertilizer timing; therefore, one scoring matrix (Figure 2) was used for both sites. However, in regions with greater differences in soil and landscape position, differences may be more profound and may warrant unique scoring matrices to provide more site-specific management recommendations (Scharf et al., 2005). While our work focused primarily on the aspect of fertilizer timing, this method can be applied to other aspects of 4R management including source, placement, and rate and combinations thereof. In the future, we propose that this framework could be scaled within an online tool (Rattalino Edreira et al., 2018) that allows users to select their region and see scores for various metrics of interest, assess tradeoffs, and better understand the impact of different management considerations. To this end, we identified four considerations for enhancing the ability to scale the proposed framework into a robust tool.

First, an interdisciplinary effort is needed to develop comprehensive metrics for all aspects to be considered. For example, in this proof of concept, our assessment of economic impacts is limited to EONR; additional economic metrics could enhance this analysis by exploring ways to capture the varying cost of fertilizer purchased at different times of the year, varying cost of different fertilizer sources, additional cost of fuel for multiple trips across the field, and additional equipment and labor needs. Along this same line, societal metrics could be incorporated to make the scoring matrix more complete.

Second, further development of process-based modeling outputs could strengthen the metrics we included in the framework. For example, our environmental metric considered only N leaching which can be readily simulated by the APSIM model; however, the environmental assessment would be strengthened by including other N losses such as ammonia emissions, which are not well accounted for in current process-based models but have been the subject of recent research (Balasubramanian et al., 2017; Beuning et al., 2008; Liu et al., 2020). Further, modeling of environmental impacts of fuel consumption and exhaust emissions related to additional trips across the field for sidedress applications could be considered (Lovarelli et al., 2018). The incorporation of these aspects into the model would enable a more comprehensive assessment of environmental impacts.

Third, we found a lack of literature defining the impact of various magnitudes of change in the metrics we evaluated was a limitation for score assignment, resulting in somewhat arbitrary assignments of scores (Table 2, Figure 2). Preferably, scores would be assigned based on intervals of practical relevance. For example, previous studies have found that EONR values within 30 kg ha^{-1} are reasonably close based on the modeling error associated with EONR

(Ransom et al., 2023); therefore, this can provide a guideline for determining thresholds for score assignments (Table 2). Similar information on the accepted error around various metrics or the value that causes substantial impact are lacking or fragmented in literature, resulting in challenges in developing a repeatable protocol for score assignment.

Fourth, to promote more rapid adoption of this method, we recommend that a minimum dataset for model calibration be determined. While our study benefited from detailed model calibration, we acknowledge this aspect could pose limitations. Therefore, establishing a minimum required dataset for model calibration and exploring the integration of remote sensing could facilitate rapid expansion of the proposed method into a digital tool (Hunt L. A. and Boote, 1998; Manivasagam & Rozenstein, 2020; Montesino-San Martin et al., 2018).

By addressing these four considerations, we expect our framework to be scalable to offer valuable region-specific N insights, aiding holistic decision-making that incorporates diverse perspectives from various stakeholders. Such tools offer tremendous value for tackling the intricate challenge of fertilizer management, particularly given the competing interests of numerous stakeholders.

Conclusion

Our study presents a customizable framework designed to assess the comprehensive impact of proposed fertilizer management changes, with a focus on the principles of 4R nutrient stewardship. Through model calibration and scenario analysis, we identified a promising N timing scenario (split application with 40% applied as spring preplant and 60% applied at V12) that decreased EONR (14%) and N loss (46%) compared to standard practices in the region. The introduction of a logistic index proved instrumental is assessing the practical feasibility of proposed N management changes, revealing numerous scenarios (all those which included a spring application) capable of improving logistical feasibility compared to the standard practice of fall application. The implementation of a comprehensive scoring matrix facilitated the exploration of tradeoffs among multiple performance indicators, providing valuable insights for decision makers.

Looking ahead, our study identifies several opportunities to enhance the feasibility and applicability of our scoring matrix. Interdisciplinary efforts would enrich the development of comprehensive metrics, while advancements in process-based modeling can broaden the scope of our framework. Additionally, establishing clear thresholds for score assignment and defining minimum calibration datasets can enhance the repeatability and scalability of our approach.

By addressing these challenges, the proposed framework shows great potential as a valuable tool for informing region-specific fertilizer management decisions. Integration of a model-based scoring system into a decision-support system can provide stakeholders with actionable insights, promoting holistic approaches that balance agronomic, economic, and environmental considerations. Our work underscores the importance of applying research and innovation to develop digital tools that can inform more resilient and efficient nutrient management practices.

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