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A SIMPLIFIED OPTICAL SENSOR-BASED APPROACH FOR VARIABLE RATE NITROGEN RECOMMENDATION USING VEGETATION INDICES AND YIELD POTENTIAL

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Abstract

Variable rate nitrogen (VRN) management using active optical sensors has been widely studied as a strategy to improve nitrogen use efficiency and reduce environmental impacts. Most current methodologies are based on complex multi-step models that estimate in-season yield from vegetation indices, crop stage, and multiple equations, which often result in unrealistic yield predictions and limit adoption by farmers and consultants. This study presents a simplified and robust approach for VRN recommendation using optical sensors, focusing on ease of implementation and greater alignment with local yield potential. The proposed methodology is derived from classical nitrogen recommendation frameworks based on N-rich strips and sensor-based indices but introduces two key innovations. First, instead of estimating absolute yield directly from sensor data, the approach constrains yield estimation by fixing a realistic yield potential for the N-rich strip based on local knowledge, historical data, and regional benchmarks. Second, the method replaces intermediate variables such as days after emergence and in-season estimated yield (INSEY) with a direct relationship between a vegetation index and grain yield. Using experimental data from winter wheat, an exponential model was established linking the Normalized Difference Red Edge (NDRE) index directly to yield. This relationship was then algebraically inverted, allowing yield differences between the N-rich strip and the surrounding area to be estimated solely from NDRE differences. These yield differences are subsequently converted into nitrogen fertilizer requirements using crop-specific nitrogen removal coefficients and user-defined nitrogen use efficiency. All equations were combined into a single, simplified formula that calculates nitrogen rate as a function of expected yield potential, NDRE measured in the N-rich strip, NDRE measured in the target area, nitrogen extraction, and efficiency parameters. A field experiment was conducted during the 2025 winter wheat season in Arapoti, Paraná, Brazil, evaluating three cultivars under six nitrogen management strategies. Results demonstrated that the sensor-based treatment achieved yield levels comparable to conventional management while applying variable nitrogen rates. The methodology was further adapted for commercial field applications by integrating spatial NDRE data with buffer-based comparisons between the N-rich strip and adjacent strips, and its applicability was demonstrated in a 53-ha commercial barley field. The proposed method represents a practical and scalable alternative for VRN management, with strong potential to enhance adoption of optical sensor technologies in precision agriculture.

Keywords: *precision agriculture; remote sensing; optical sensor; nitrogen use efficiency; N-rich strip; site-specific management*

Introduction

Nitrogen (N) is a key nutrient for crop development and is directly associated with biomass accumulation and grain yield. However, nitrogen management remains a major challenge in agricultural systems due to low nitrogen use efficiency (NUE), high fertilizer costs, and environmental losses through leaching, volatilization, and runoff (Raun and Johnson 1999; Cassman et al. 2002). Globally, cereal production systems recover less than 40% of the applied nitrogen, indicating substantial room for improvement (Raun and Johnson 1999). Enhancing nitrogen management is therefore essential to increase both economic returns and environmental sustainability in cereal production systems (Fageria and Baligar 2005).

Conventional nitrogen management is commonly based on uniform fertilizer applications and predefined yield goals, assuming field homogeneity. However, spatial variability in soil properties, weather conditions, and crop development results in heterogeneous nitrogen demand within fields. Consequently, uniform applications often lead to inefficient nitrogen use, with over-application in some areas and deficiency in others (Mulla 2013). This spatial mismatch between supply and demand has been recognized as one of the primary causes of low NUE in cereal systems worldwide.

Precision agriculture has introduced site-specific approaches to address this variability, particularly using optical sensors to assess crop vigor and nitrogen status in real time. Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) have been widely used to estimate biomass and yield potential (Rouse et al. 1973; Tucker 1979), supporting in-season nitrogen management strategies (Raun et al. 2001). More recently, the Normalized Difference Red Edge (NDRE) index has gained attention due to its greater sensitivity to chlorophyll content and reduced saturation at high biomass levels compared to NDVI (Eitel et al. 2011).

Among sensor-based approaches, nitrogen recommendation algorithms developed at Oklahoma State University, based on the concept of in-season estimated yield (INSEY), have been among the most widely referenced. These algorithms combine vegetation indices with growing degree days to estimate yield potential and guide nitrogen applications (Raun et al. 2001; Raun et al. 2002). The use of nitrogen-rich reference strips (N-rich strips) allows normalization of sensor readings by providing a benchmark of non-limiting nitrogen conditions within the same field environment.

Although effective under experimental conditions, these methods often require multiple input variables, calibration steps, and specific field setups. Their dependence on growing degree days and intermediate yield estimation models increase operational complexity and may limit their adoption under commercial farming conditions (Solari et al. 2008). Furthermore, the use of intermediate variables such as INSEY introduces additional sources of uncertainty, particularly under variable environmental conditions. Issues such as vegetation index saturation, sensitivity to crop growth stage, and variability in sensor response can affect the robustness of yield prediction and nitrogen recommendation, reducing consistency at the field scale.

In a comprehensive review, Colaço and Bramley (2018) analyzed the outcomes from sensor-based nitrogen management across multiple studies and concluded that, while nitrogen savings of 5–45% were commonly reported with little effect on grain yield, there was a lack of consistent evidence of economic benefits. The average reported profit increase was approximately US$ 30 ha^{-1}, and about 25% of studies reported economic losses from sensor-based applications. The authors highlighted that neither simple redistribution functions nor complex calibrated algorithms were consistently successful across a range of field conditions and called for new approaches to sensor-based site-specific nitrogen management. A subsequent multi-method assessment by Colaço et al. (2024), evaluating 13 nitrogen recommendation strategies across 21 on-farm strip trials in wheat and barley, reinforced these findings, and only data-driven empirical approaches substantially outperformed farmer management, illustrating that a practical and robust recommendation framework remains an open problem.

The difficulty in achieving consistent outcomes has been partly attributed to the complexity of existing models. As the number of intermediate steps and calibration parameters increases, so does the potential for error propagation and site-specific mismatch. Previous work by Povh and Molin (2008) demonstrated the potential of optical sensors for nitrogen management in wheat and corn but also highlighted the challenge of generating robust recommendation models from limited experimental datasets. These findings reinforced the need for simplified approaches that maintain agronomic validity while reducing implementation barriers.

In this context, the present study proposes a simplified nitrogen recommendation approach based on a single equation that integrates user-defined agronomic parameters, such as expected yield potential, nitrogen removal, and nitrogen use efficiency, with sensor-derived vegetation index differences between a nitrogen-rich reference strip and the target application area. The method directly relates vegetation indices (NDVI or NDRE) to crop yield through an exponential response function, eliminating the need for intermediate variables.

The objective of this study was to develop and evaluate a simplified methodology for variable rate nitrogen recommendation based on optical sensor data, and to assess its performance under field conditions using winter wheat as a model crop. Specifically, (i) derive a single equation for nitrogen recommendation that eliminates intermediate variables; (ii) evaluate the sensor-based approach against conventional nitrogen management strategies in a field experiment; and (iii) demonstrate the spatial implementation of the methodology for commercial-scale applications.

Material and Methods

Overview of the Proposed Methodology

This study proposes a simplified methodology for variable rate nitrogen (VRN) recommendation based on optical sensor data. The approach was designed to reduce the complexity of traditional sensor-based nitrogen algorithms by eliminating intermediate variables and consolidating the recommendation process into a single equation. The method integrates agronomic parameters defined by the user with sensor measurements, allowing nitrogen recommendations to be generated directly from vegetation index differences observed in the field.

Theoretical Development

Original methodology and its limitations

The original methodology developed at Oklahoma State University (Raun et al., 2001; 2002) for sensor-based nitrogen recommendation follows a multi-step process. First, the vegetation index (e.g., NDVI, NDRE is used in this study) is divided by the number of days after emergence (DAE) to calculate the in-season estimated yield (INSEY) according to:

$$INSEY = NDRE / DAE \quad (1)$$

Subsequently, an exponential model that relates INSEY to grain yield is used to estimate yield. This example was created using a local dataset of wheat nitrogen rates experiments:

$$Yield = 834 * e^{350 * INSEY} \quad (2)$$

In practice, this approach requires measurement of the DAE, calculation of INSEY for both the N-rich strip and the target area, followed by yield estimation for each zone using Equation 2. The nitrogen rate is then calculated from the yield difference:

$$N_{\mathrm{rate}} = (Yield_{\mathrm{ref}} - Yield_{\mathrm{target}}) * NR / NUE \quad (3)$$

where NR is the nitrogen removal coefficient (kg N per kg of grain) and NUE is the nitrogen use efficiency (unitless, expressed as a fraction). A fundamental limitation of this approach is that the yield estimated by Equation 2 is highly sensitive to the DAE value, which serves as a normalizing factor. In many practical situations, this can lead to unrealistic yield estimations (either excessively high or low) that compromise the accuracy of nitrogen recommendations.

Constraining yield potential: the inverse calculation

The first innovation introduced in the proposed methodology is the concept of fixing the yield potential based on local agronomic knowledge rather than estimating it from sensor data. As a conceptual transition from the original INSEY framework, this idea can be implemented by inverting Equations 1 and 2 to compute a theoretical DAE that would produce a user-defined yield potential (YP) for the N-rich strip:

$$DAE_{\mathrm{calc}} = NDRE_{\mathrm{ref}} / [\ln(YP / 834) / 350] \quad (4)$$

Anchoring the reference yield to YP in this manner ensures that the resulting yield differences and consequently the nitrogen recommendations, remain within realistic agronomic bounds, regardless of the actual DAE measured in the field. However, the workflow still requires sequential passage through Equations 1, 2, and 3, and therefore retains the operational complexity of the original approach. The next section addresses this limitation by replacing the entire INSEY chain with a single exponential relationship linking NDRE directly to grain yield.

Direct relationship between vegetation index and yield

The second innovation eliminates the need for calculating INSEY altogether. By re-examining the original experimental data that generated the INSEY-based model, a new exponential relationship was established directly between the vegetation index (NDRE) and grain yield using the same dataset from Equation 2, presented in Fig 1:

$$Yield = 834 * e^{5.84 * NDRE} \quad (5)$$

The exponential coefficient changed from 350 (when using INSEY, Equation 2) to 5.84 (when using NDRE directly), representing the growth rate of yield response to changes in NDRE. It should be noted that $k = 5.84$ was not calculated with the present dataset, it was derived from a comprehensive set of winter wheat experiments carried out across multiple sites and seasons, which provides robustness to the coefficient and ensures that the model evaluation in this study constitutes independent validation. This direct relationship bypasses the need for DAE estimation and the intermediate INSEY calculation, substantially simplifying the computational process.

Derivation of the combined equation

The derivation of the combined equation proceeds by expressing the reference and target yields in terms of measurable vegetation index values and user-defined agronomic parameters, then substituting them into the nitrogen rate equation (Equation 3) to eliminate all intermediate variables. The process involves three steps, during which Equations 6 and 7 are derived from the direct NDRE–yield model presented in Equation 5.

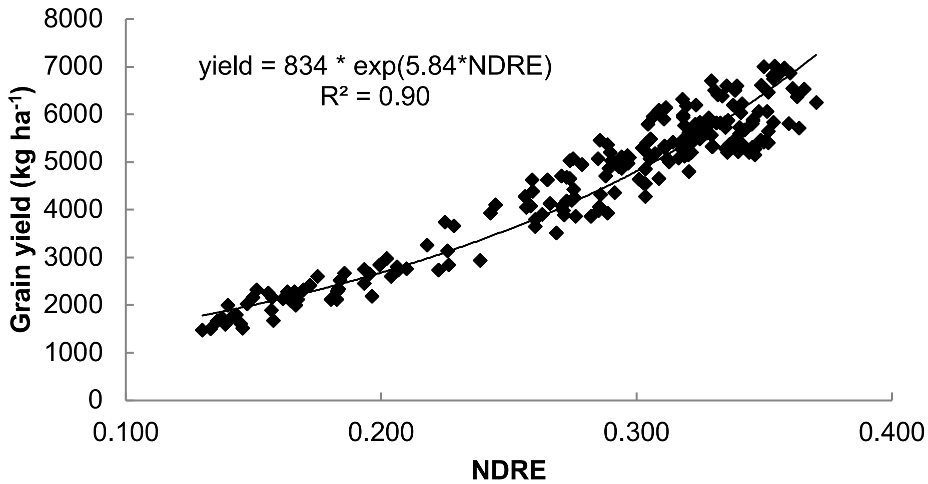

Fig 1. Exponential relationship between NDRE and grain yield of winter wheat, establishing the coefficient k = 5.84 used in the proposed model.

Step 1 – Constrain the reference yield. Using Equation 5, the yield potential (YP) is assigned to the N-rich strip. By inverting the exponential model, the theoretical NDRE value corresponding to YP is obtained:

$$NDRE_{ref,calc} = ln(YP / 834) / 5.84 \quad (6)$$

Step 2 – Estimate the target NDRE. The difference between the measured NDRE in the N-rich strip and in the target area ($\Delta VI = NDRE_{ref} - NDRE_{target}$) is preserved and applied to the constrained reference value to obtain the adjusted target NDRE:

$$NDRE_{target,calc} = NDRE_{ref,calc} - (NDRE_{ref} - NDRE_{target}) \quad (7)$$

Step 3 – Substitute into the nitrogen rate equation and simplify. Both constrained NDRE values (Equations 6 and 7) are substituted into Equation 5 to obtain the estimated yields for the reference and target areas. The reference yield is, by construction, equal to YP. The target yield is estimated as:

$$Yield_{target} = 834 * e^{k * (NDRE_{ref,calc} - \Delta VI)} = 834 * e^{k * NDRE_{ref,calc}} * e^{-k * \Delta VI} = YP * e^{-k * \Delta VI}$$

Note that the constant 834 and the $NDRE_{ref,calc}$ term cancel out algebraically, since $834 \times e^{k \times NDRE_{ref,calc}} = YP$ by definition (Equation 6 inverted). Substituting the yield difference into the nitrogen rate equation (Equation 3):

$$N_{rate} = (YP - YP * e^{-k * \Delta VI}) \times NR / NUE = (YP * NR / NUE) * (1 - e^{-k * \Delta VI})$$

Since $e^{-k * \Delta VI} = 1/e^{k * \Delta VI}$, the expression simplifies to the final combined equation:

$$\boldsymbol{N_{rate} = (YP * NR / NUE) * (1 - 1 / e^{k * \Delta VI})} \quad (8)$$

where:

N_{rate} = recommended nitrogen rate (kg ha^{-1})

YP = expected yield potential (kg ha^{-1})

NR = nitrogen removal coefficient (kg N per kg of grain)

NUE = nitrogen use efficiency (unitless fraction)

ΔVI = $VI_{ref} - VI_{target}$ (vegetation index difference)

k = exponential response coefficient (5.84 for NDRE)

The first component of Equation 8, (YP * NR / NUE), represents the total nitrogen requirement based on expected crop demand. The second component, ($1 - 1/e^{k * \Delta VI}$), represents the relative yield gap between the nitrogen-rich reference and the target area. This term is derived from the exponential relationship between vegetation index and crop yield, where the coefficient *k* governs the rate of response. When ΔVI = 0 (i.e., the target area has the same vegetation index as the N-rich strip), the second component equals zero, resulting in no nitrogen recommendation, consistent with a fully supplied crop. As ΔVI increases, the relative yield gap increases, and consequently the recommended nitrogen rate increases proportionally.

Field Experiment

A field experiment was conducted during the 2025 winter season in Arapoti, Paraná State, Brazil (24.1939° S, 49.8746° W). The experimental area was characterized by a soil with 23% clay content and 2.2% organic matter, representing conditions with high potential for nitrogen response. The region has a subtropical climate (Cfa, Köppen classification) with mean annual rainfall of approximately 1,400 mm.

Three winter wheat cultivars were evaluated: TBIO Audaz, TBIO Toruk, and TBIO Ponteiro. These cultivars were selected to represent a range of genetic backgrounds and yield potentials commonly used in the southern Brazilian wheat production system.

The experimental design consisted of a randomized complete block design with four replications, arranged in a split-plot scheme with cultivars as main plots and nitrogen management strategies as subplots. Six nitrogen treatments were evaluated for each cultivar, all sharing a common starter application of 30 kg N ha^{-1} at sowing:

T1 – Control: 30 kg N ha^{-1} at sowing (base application only, no topdressing);

T2 – N-rich 90: 30+90 kg N ha^{-1} applied at sowing (total of 120 kg N ha^{-1});

T3 – N-rich 120: 30+120 kg N ha^{-1} applied at sowing (total of 150 kg N ha^{-1});

T4 – Conventional: 30 kg N ha^{-1} at sowing + 90 kg N ha^{-1} at tillering;

T5 – Delayed: 30 kg N ha^{-1} at sowing + 90 kg N ha^{-1} at stem elongation;

T6 – Sensor-based: 30 kg N ha^{-1} at sowing + variable nitrogen rate at stem elongation, calculated using the proposed model (Equation 8).

Two N-rich treatments were established: T2 (30+90 kg N ha^{-1}) and T3 (30+120 kg N ha^{-1}), both applied entirely at sowing. The T2 rate (120 kg N ha^{-1} total) was adopted as the reference for all sensor-based calculations, as it represents the most used nitrogen rate in commercial wheat production in the region. The higher rate in T3 (150 kg N ha^{-1} total) was included to evaluate whether additional nitrogen supply beyond regional practice would result in further yield gains; the implications of using either rate as the N-rich reference on the recommended nitrogen dose are discussed in the Results section. All nitrogen was applied as urea (45% N).

Sensor-Based Nitrogen Calculation

The nitrogen rate for the sensor-based treatment (T6) was calculated using Equation 8 with the following user-defined parameters: yield potential (YP) = 4,000 kg ha^{-1}; nitrogen removal (NR) = 0.028 kg N per kg of grain (Pauletti, 2004); and nitrogen use efficiency (NUE) = 0.60 (60%). Vegetation index data were collected at the stem elongation growth stage using a RapidSCAN CS-45 handheld active crop canopy sensor (Holland Scientific, Lincoln, NE, USA). This sensor incorporates a polychromatic light source and three optical measurement channels centered at 670 nm (red), 730 nm (red-edge), and 780 nm (near-infrared), providing sunlight-independent reflectance measurements. The sensor computes height-independent spectral reflectance values, referred to as Pseudo Solar Reflectance (PSR), and outputs NDVI and NDRE as default vegetation indices. Measurements were taken at a sensor-to-canopy distance of approximately 0.7 m, with data georeferenced by the sensor's built-in GPS. Recent multi-cultivar evaluations in winter wheat have shown that NDRE derived from the RapidSCAN CS-45 achieved the best performance among leaf and canopy optical indices for estimating N status across growth stages, supporting its use as the reference vegetation index in the present study (Jiang et al., 2021). NDRE measurements were obtained in the N-rich reference strips (T2, average NDRE) and in the target plots assigned to the sensor-based treatment (T6). The exponential coefficient used in the model was k = 5.84, derived from the relationship between NDRE and grain yield (Fig 1). The resulting variable nitrogen rates applied to each cultivar are presented in the results.

Data Collection and Measurements

The following variables were measured across all experimental units: (i) NDRE at the stem elongation stage, collected using an active optical sensor; (ii) grain yield (kg ha^{-1}), determined from mechanized harvesting of each plot, adjusted to 13% moisture content; (iii) test weight (PH, kg hL^{-1}); (iv) thousand kernel weight (TKW, g); and (v) plant population at emergence and at harvest (plants ha^{-1}).

Spatial Implementation for Commercial Applications

For practical field-scale applications, the methodology was adapted to work with spatially distributed vegetation index data. The implementation follows a five-step procedure:

Step 1: Establishment of the N-rich strip, positioned to cross areas of both high and low yield potential within the field;

Step 2: Spatial comparison between the NDRE of the N-rich strip and adjacent strips using a buffer-based approach. For each position along the strip, the NDRE difference (ΔVI) between the reference and neighboring points is calculated;

Step 3: Construction of a scatter plot relating field NDRE values (x-axis) to the corresponding ΔVI values (y-axis), with a trend line fitted to characterize the site-specific relationship between crop condition and nitrogen response;

Step 4: Application of Equation 8 to each point along the trend line to generate a site-specific linear recommendation model that relates NDRE directly to nitrogen rate (N = a × NDRE + b);

Step 5: Application of the site-specific linear model to the full-field NDRE map to generate a spatially continuous variable rate nitrogen prescription map.

Statistical Analysis

Grain yield data were subjected to analysis of variance (ANOVA) using a split-plot model with cultivar as the main plot factor and nitrogen treatment as the subplot factor. When significant treatment effects were detected ($p < 0.05$), means were compared using Tukey's significant difference (HSD) test at 5% significance level. Descriptive statistics were used to summarize NDRE values and other crop parameters across treatments and cultivars. All statistical analyses were performed using R software (R Core Team, 2024).

Results and Discussion

Crop Response to Nitrogen Treatments

The experimental design was analyzed as a split-plot in a randomized complete block design, with cultivar as the main plot and nitrogen management strategy as the subplot factor. The analysis of variance (Table 1) revealed a significant effect of cultivar ($p < 0.01$) and nitrogen management ($p < 0.01$) on grain yield, while the interaction between the two factors was not significant. This indicates that the cultivar ranking was consistent across nitrogen strategies and, conversely, the relative performance of nitrogen treatments did not depend on the cultivar used. Therefore, yield results are presented as main effects averaged across the other factor.

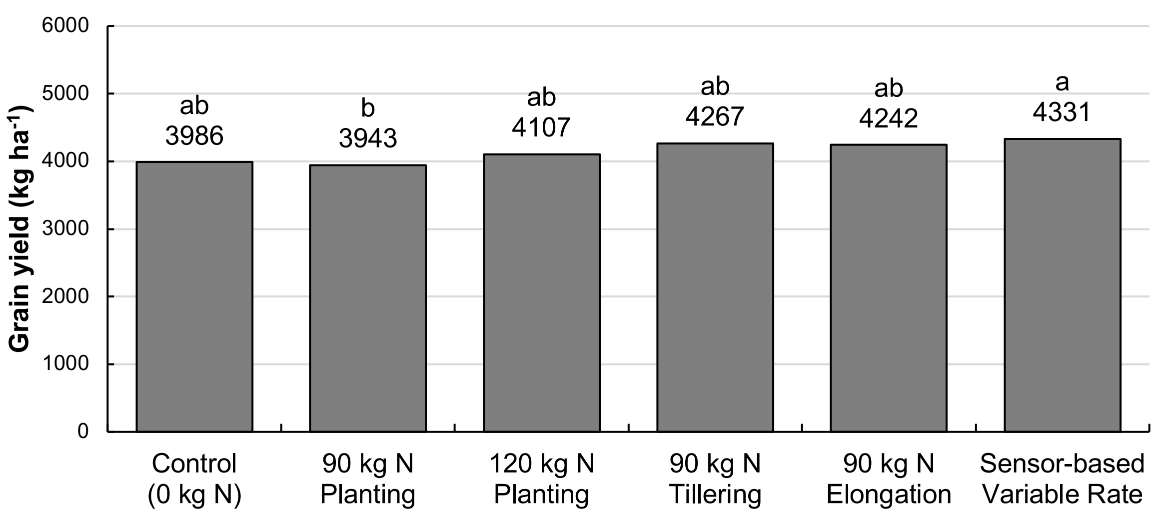

Fig 2. Mean grain yield (kg ha⁻¹) across six nitrogen management strategies, averaged over three wheat cultivars. All treatments received a common base application of 30 kg N ha⁻¹ at sowing; the rates shown on the x-axis refer to the additional nitrogen applied, either at planting, tillering, stem elongation, or as a sensor-based variable rate. Bars sharing the same letter are not significantly different according to Tukey's HSD test ($p \leq 0.05$) applied to the subplot error term

The wheat cultivars showed distinct yield performance. TBIO Ponteiro achieved the highest average yield (4,430 kg ha^{-1}), significantly higher than TBIO Audaz (4,090 kg ha^{-1}) and TBIO Toruk (3,920 kg ha^{-1}), which did not differ statistically from each other (Table 1 and Fig 2). PH and TKW also differed among cultivars. Although the interaction with nitrogen management was significant for these traits, their detailed analysis is beyond the scope of this study, which focuses on the sensor-based nitrogen methodology.

Table 1. Split-plot analysis of variance and mean comparison for grain yield, test weight (PH), thousand kernel weight (TKW), and NDRE across three wheat cultivars and six nitrogen management strategies. Means followed by the same letter within each factor do not differ by Tukey test (α = 0.05). ** significant at p < 0.01; * significant at p < 0.05; ns = not significant

Source of variation	Yield	PH	TKW	NDRE
	(kg ha^{-1})	(kg hL^{-1})	(g)	
Cultivar (A)	**	**	**	**
N Management (B)	**	**	**	**
A × B	ns	*	*	ns
CV(a) / CV(b) %	6.4 / 7.0	2.5 / 1.5	4.3 / 2.6	5.2 / 6.1
TBIO Audaz	4,090 b	80.53 a	29.99 b	0.286 b
TBIO Toruk	3,920 b	78.80 b	31.63 a	0.292 b
TBIO Ponteiro	4,430 a	75.09 c	31.62 a	0.355 a
N Management	**Total N**	**Yield**		
Control	30	3,986 ab		
N-rich 90	120	3,943 b		
N-rich 120	150	4,107 ab		
Conventional (Tillering)	120	4,267 ab		
Delayed (Elongation)	120	4,242 ab		
Sensor-based	64 (57–75)	4,331 a		

Note: All treatments received 30 kg N ha^{-1} at sowing as base application. N rates in T6 (Sensor-based) varied by cultivar: 29 (TBIO Audaz), 45 (TBIO Toruk), and 27 (TBIO Ponteiro) kg N ha^{-1}

Effect of Nitrogen Management on Grain Yield

Regarding nitrogen management strategies, the sensor-based treatment achieved the highest average yield (4,331 kg ha^{-1}), followed by the conventional application at tillering (4,267 kg ha^{-1}) and the delayed application at stem elongation (4,242 kg ha^{-1}). The N-rich treatments with applications done at sowing (N-rich 90 and N-rich 120) and the unfertilized control showed intermediate to lower yields. The Tukey test indicated that the sensor-based treatment was significantly higher than the N-rich 90 treatment, while the remaining treatments formed overlapping groups (Table 1, Fig 3).

These results demonstrate that the sensor-based approach, maintained yield levels comparable to or higher than conventional management, despite using substantially less nitrogen. The sensor-based treatment applied an average of 34 kg ha^{-1} of additional nitrogen (ranging from 27 to 45 kg ha^{-1} depending on the cultivar), compared to 90 kg ha^{-1} in the conventional and delayed treatments, representing a nitrogen saving of 50 to 70%.

Effect of Nitrogen Application Timing

The comparison between nitrogen application at tillering (T4) and at stem elongation (T5) provided important insights into crop response dynamics. For TBIO Audaz, the delayed treatment (T5: 4,313 kg ha^{-1}) showed numerically higher yields than the conventional tillering application (T4: 4,150 kg ha^{-1}), suggesting that nitrogen application can be postponed without yield penalty under the conditions evaluated. For TBIO Ponteiro, a similar pattern was observed (T5: 4,547 vs. T4: 4,485 kg ha^{-1}). For TBIO Toruk, however, the delayed application resulted in lower yields (T5: 3,866 vs. T4: 4,166 kg ha^{-1}), indicating cultivar-dependent responses to application timing.

This finding is particularly relevant for sensor-based nitrogen management, as it confirms that, for at least some cultivars, nitrogen decisions can be postponed until the stem elongation stage (when real-time crop information from optical sensors is available) without significant yield loss. This flexibility enhances the practical applicability of sensor-based approaches, allowing nitrogen rates to be adjusted based on actual crop conditions rather than predetermined schedules.

Performance of the Sensor-Based Approach

The sensor-based treatment, which used the proposed simplified model with k = 5.84, generated differentiated nitrogen recommendations based on NDRE differences between the N-rich reference and the target areas. The recommended rates varied by cultivar: 29 kg ha^{-1} for TBIO Audaz, 45 kg ha^{-1} for TBIO Toruk, and 27 kg ha^{-1} for TBIO Ponteiro, reflecting the different nitrogen demands captured by the vegetation index.

In terms of agronomic nitrogen use efficiency, the sensor-based approach achieved 10.1 kg of grain per kg of additional N applied (averaged across cultivars), compared to 3.1 kg kg^{-1} for the conventional treatment and a negligible response for the N-rich 90 treatment applied at sowing. This indicates that the model was able to identify the actual crop nitrogen demand and adjust the fertilizer rate, avoiding excess application. The results suggest that the proposed model could maintain or improve yield levels while providing a more flexible and resource-efficient nitrogen management strategy. These results are consistent with the magnitudes reported by Aula et al. (2020) in a review of peer-reviewed studies on active optical sensors for winter wheat N management, where sensor-based approaches improved NUE by an average of 10.4% and saved up to 53 kg N ha^{-1} relative to conventional practice, while preserving yield levels.

Model Behavior and Agronomic Interpretation

The proposed model is based on an exponential relationship between vegetation index and yield, where the coefficient k = 5.84 represents the growth rate of crop response. This structure allows the estimation of relative yield differences directly from vegetation index measurements, without the need for intermediate variables such as INSEY or growing degree days.

The use of vegetation index differences (ΔVI) between the N-rich strip and the target area proved to be a robust indicator of crop nitrogen status. This approach captures the relative crop response to nitrogen, which is more stable across environments compared to absolute index values. By combining this relative response with user-defined parameters (yield potential, nitrogen removal, and efficiency), the model translates crop variability into actionable nitrogen recommendations through a single equation.

The choice of nitrogen rate in the N-rich reference strip directly influences the magnitude of ΔVI and, consequently, the recommended topdressing rate. When the higher N-rich rate (T3: 30+120 kg N ha^{-1}) was used as the reference instead of T2 (30+90 kg N ha^{-1}), the recommended nitrogen rates increased from 29, 45, and 27 kg N ha⁻¹ to 47, 61, and 47 kg N ha⁻¹ for TBIO Audaz, TBIO Toruk, and TBIO Ponteiro, respectively (Fig 3). This increase reflects the larger vegetation index difference between the higher reference and the target area, which the model interprets as a greater yield gap to be compensated. This result has practical implications for the establishment of N-rich strips in commercial fields. In areas with high potential for nitrogen response, such as soils with low organic matter or sandy texture, adopting a reference rate above the regional standard may be advisable. A higher N-rich rate ensures that the reference strip more closely approximates the true yield ceiling, thereby improving the model's ability to detect and quantify nitrogen deficiency in the surrounding area. Conversely, if the N-rich rate is insufficient to achieve non-limiting conditions, the model may underestimate the actual crop response and generate lower-than-optimal recommendations.

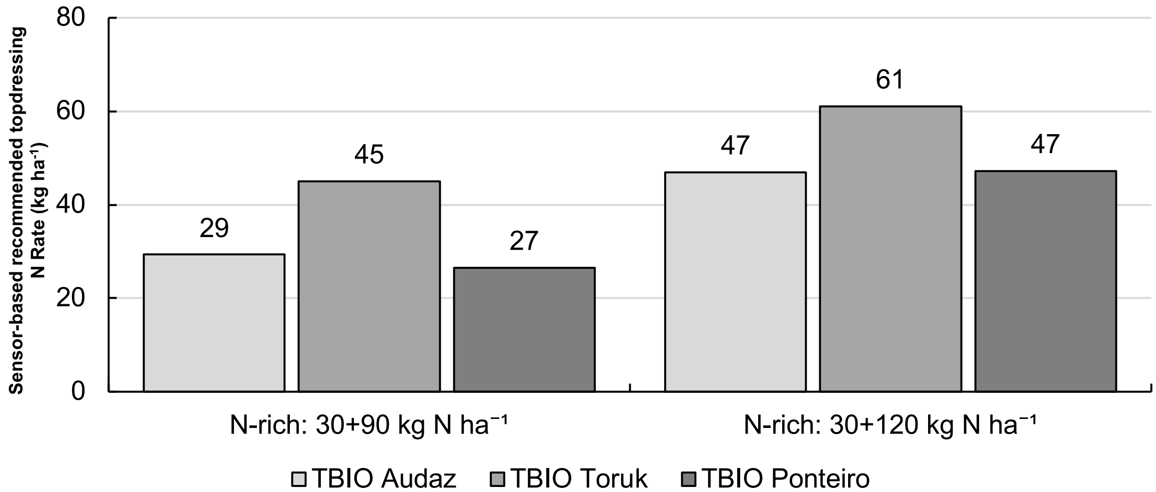

Fig 3. Effect of N-rich reference rate on the recommended topdressing nitrogen rate (Equation 8) for each cultivar. Bars represent the nitrogen rates calculated using VIref from T2 (30+90 kg N ha⁻¹) and T3 (30+120 kg N ha⁻¹) as the N-rich reference, with YP = 4,000 kg ha⁻¹, NR = 0.028, and NUE = 0.60

Comparison with Conventional Sensor-Based Models

Traditional sensor-based nitrogen recommendation approaches, such as those based on the INSEY concept (Raun et al., 2001; 2002), rely on multi-step processes including: (i) calculation of growing degree days or DAE; (ii) normalization of the vegetation index to obtain INSEY; (iii) estimation of yield from the INSEY–yield model; and (iv) calculation of nitrogen requirement from the yield difference. Each step introduces potential sources of error, and the intermediate yield estimation is particularly prone to producing unrealistic values that may not reflect actual field conditions.

In contrast, the proposed approach consolidates all these steps into a single equation (Equation 8) that requires only six input parameters: three user-defined agronomic parameters (YP, NR, NUE), two sensor measurements (VI_{ref} and VI_{target}) and the *k* constant derived from a local model. This simplification reduces computational complexity, eliminates sources of intermediate error, and facilitates real-time implementation. Critically, the user retains control over the yield potential parameter, which anchors the recommendation to local reality rather than relying on potentially unreliable model-based yield estimates.

The approach also addresses a key concern raised by Colaço and Bramley (2018) regarding the inadequacy of N-rich strips as normalizing references due to spatial variability. While the proposed method still relies on N-rich strips, the buffer-based spatial implementation accounts for local variability by comparing each target position with its nearest reference points, rather than using a single field-average reference value. This spatial approach generates a field-specific recommendation model that adapts to local conditions.

Practical Implications

The simplified methodology offers several practical advantages that may contribute to increased adoption of sensor-based nitrogen management. The elimination of growing degree days or days after sensing and intermediate yield estimation removes two of the most operationally complex aspects of existing approaches. Farmers and consultants can define the yield potential based on their knowledge of the field and region, the nitrogen removal coefficient based on crops, and the desired efficiency factor, all parameters that are intuitive and readily available. These simplifications directly address adoption barriers documented for established sensor-based tools such as N-rich strips and the Sensor-Based Nitrogen Rate Calculator, where perceived complexity and compatibility with existing farm practices have been identified as key factors limiting diffusion (Looney et al., 2022).

The spatial implementation workflow further enhances the practical value of the approach by generating field-specific linear models that translate vegetation indices maps directly into nitrogen prescription maps. This process can be integrated with standard precision agriculture software platforms and variable rate application controllers, facilitating the transition from sensor data to actionable field prescriptions. The use of drone or satellite-derived vegetation indices maps as inputs to the spatial workflow also expands the applicability beyond ground-based sensors, potentially enabling larger-scale adoption.

To illustrate the practical applicability of the proposed methodology, the spatial workflow was applied to a 53 ha commercial barley field. For this application, the exponential coefficient k = 3.62 was used, derived from a NDRE–yield relationship developed specifically for barley following the same procedure described for wheat in Fig 1. The N-rich reference strip received 60 kg N ha^{-1} of topdressing, while the resulting variable rate prescription averaged 15 kg N ha^{-1} across the field, representing a 75% reduction in topdressing nitrogen relative to the reference rate. Fig 4 presents the four spatial outputs of the implementation process. The NDRE map (Fig 4a) shows the overall crop vigor across the field, with the N-rich strip highlighted in blue. The buffer-based comparison (Fig 4b) illustrates how each target position was paired with its nearest reference points within the N-rich strip to calculate local ΔVI values. The resulting point-based nitrogen recommendation map (Fig 4c) shows the spatial distribution of recommended rates derived from the model, and the final interpolated prescription map (Fig 4d) presents the variable rate urea application map.

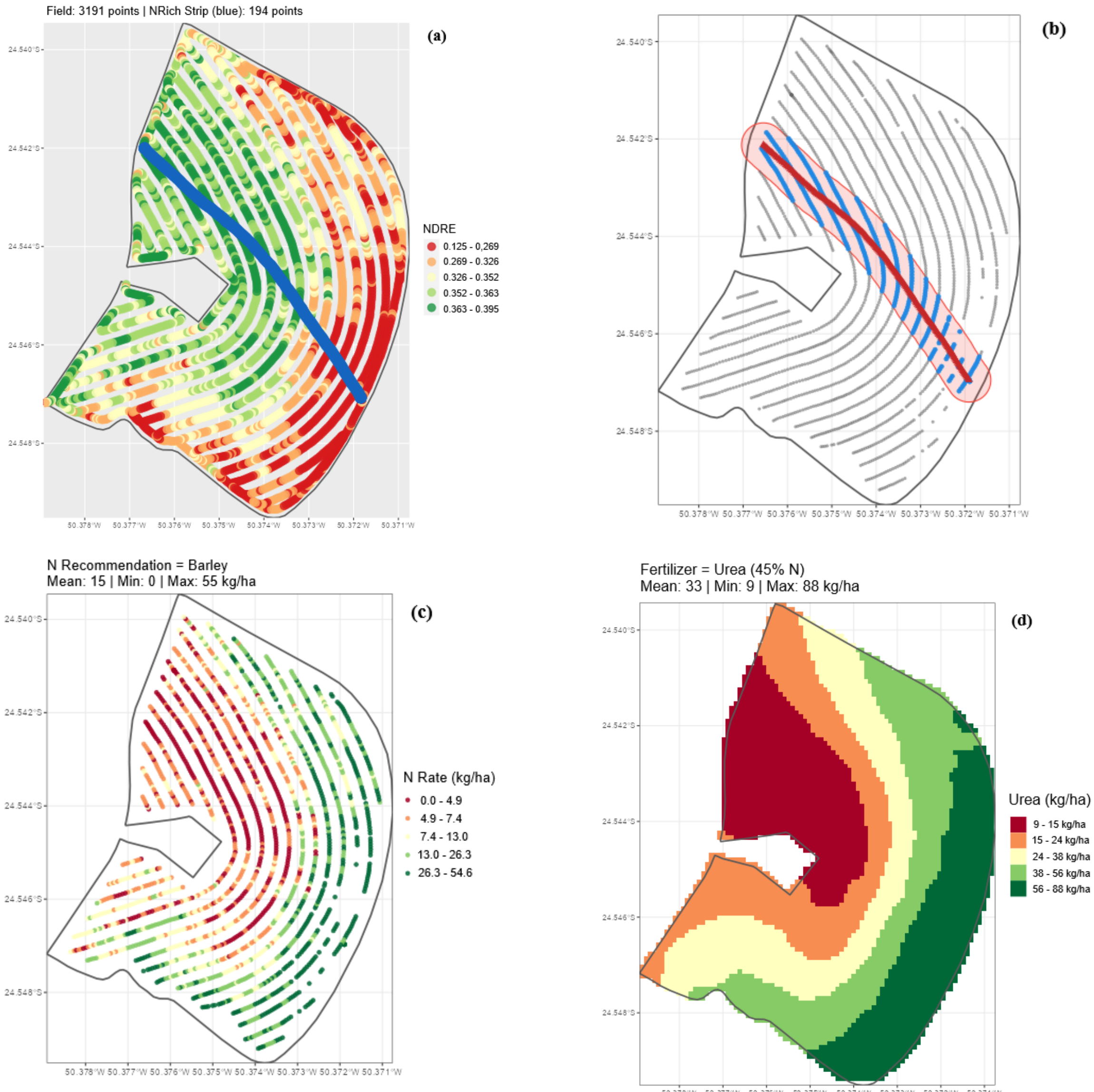

Fig 4. Spatial implementation workflow for variable rate nitrogen recommendation in a commercial barley field: (a) NDRE map with the N-rich strip highlighted in blue; (b) buffer-based comparison between the N-rich strip and adjacent passes; (c) point-based nitrogen map derived from the model; (d) interpolated variable rate nitrogen prescription map

The intermediate analytical steps are presented in Fig 5. The scatter plot of ΔVI as a function of NDRE (Fig 5, top) shows a negative linear trend ($R^2 = 0.43$), in which areas with lower NDRE values exhibit larger vegetation index differences relative to the N-rich strip, indicating greater nitrogen responsiveness in the weaker portions of the field. Although the explained variance is moderate, reflecting the heterogeneity of commercial fields, the trend is sufficient to capture the dominant spatial pattern of crop nitrogen demand and translate it into differentiated recommendations. In other production environments, the inverse relationship can occur, for instance when high-vigor zones coincide with areas of higher yield potential and therefore greater response to additional nitrogen; in such cases, the slope of the local model inverts and the prescription map is redistributed accordingly without altering the underlying methodology. The site-specific recommendation model (Fig 5, bottom) translates this relationship into a linear function of nitrogen rate as a function of NDRE, providing a field-specific equation that can be directly applied to the NDRE map to generate the prescription map.

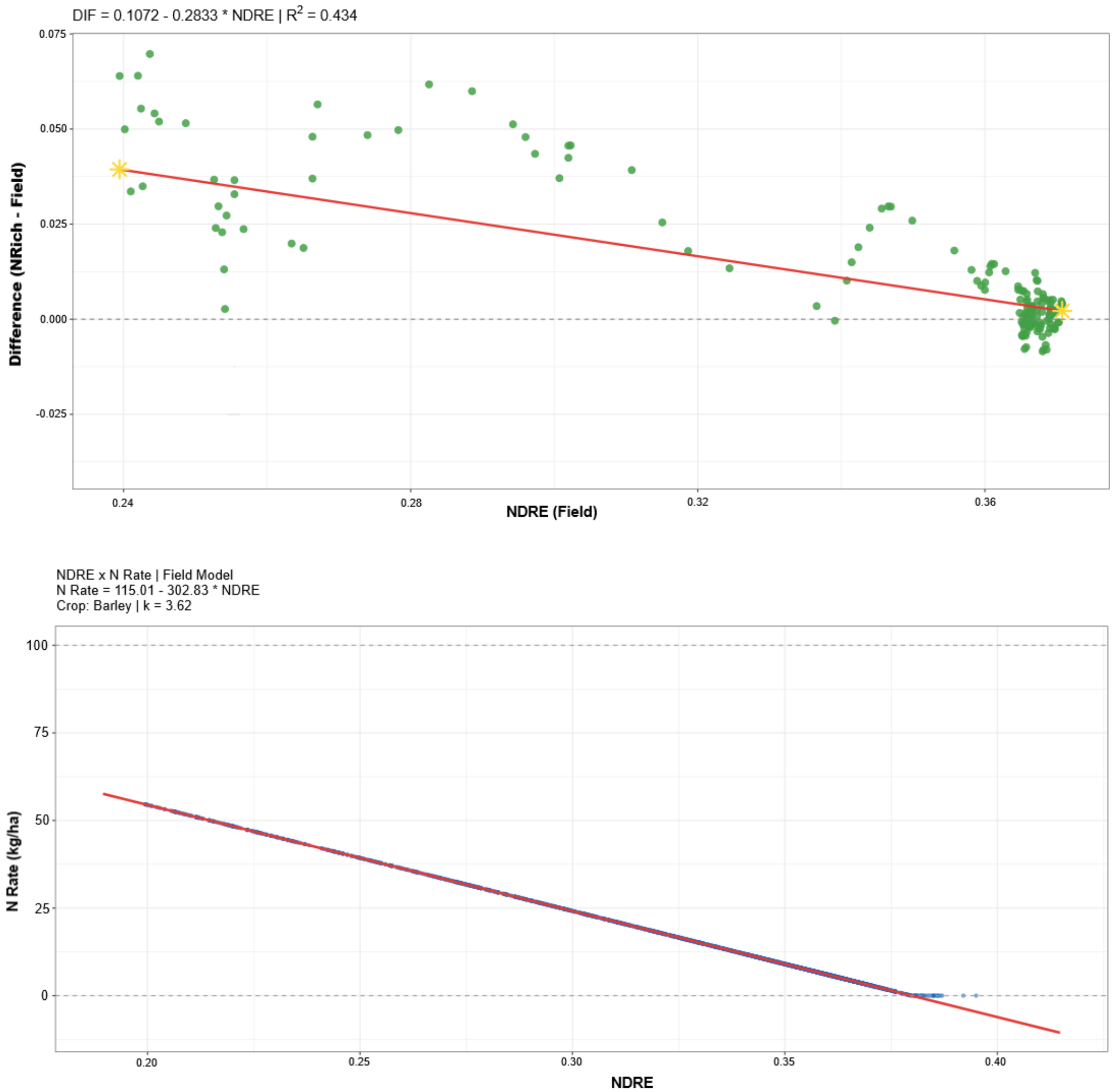

Fig 5. Intermediate steps of the spatial nitrogen recommendation model: (top) scatter plot of ΔVI as a function of NDRE with trend line; (bottom) site-specific nitrogen recommendation model (N rate vs. NDRE)

This example demonstrates that the proposed methodology can be operationally implemented in commercial conditions, generating spatially variable nitrogen recommendations from a single sensing event combined with user-defined agronomic parameters. The workflow from NDRE acquisition to a ready-to-use prescription map requires minimal processing steps and no intermediate yield estimation, reinforcing the practical advantage of the simplified approach.

Limitations and Future Research

While the results of this study are encouraging, several limitations should be acknowledged. First, the field experiment was conducted at a single location and during one growing season primarily as a methodological demonstration. Although the experimental design included three cultivars and multiple nitrogen strategies, the validation of the proposed methodology replicating the process across different environments, soil types, climatic conditions, and crops is essential to confirm its robustness.

Second, the exponential coefficients (k = 5.84 for wheat and k = 3.62 for barley) were derived from datasets specific to each crop and may vary with sensor platform and environmental conditions. Local research is needed to establish appropriate k values for other crops (e.g., corn, rice, soybean) and to determine whether a single coefficient can be used across multiple conditions or whether site-specific calibration is required.

Third, the proposed methodology, like all approaches based on N-rich strips, requires the establishment and maintenance of a reference area with non-limiting nitrogen. It is essential that this strip crosses the field through zones of varying yield, so that the reference adequately captures the range of spatial variability present in the area and enables meaningful comparisons between the N-rich strip and the target zones.

Finally, the economic analysis of the sensor-based approach was not the primary focus of this study. A detailed cost-benefit assessment considering fertilizer savings, technology costs, yield effects, and nitrogen use efficiency would strengthen the case for adoption. As noted by Colaço and Bramley (2018), economic viability is a critical driver for technology adoption, and future studies should include rigorous economic evaluation alongside agronomic performance. Recent multi-year on-farm evidence reinforces this point, Hagn et al. (2025) reported nitrogen savings of up to 38 kg ha^{-1} and a 15% increase in N efficiency with sensor-based variable rate application in winter wheat over four seasons, but also observed that not every field trial showed advantages over uniform management, highlighting that robustness across weather, disease and crop development conditions remains a relevant practical challenge.

Conclusion

The proposed simplified methodology for nitrogen recommendation based on optical sensor data proved effective in supporting nitrogen management decisions under field conditions. The consolidation of multiple intermediate steps into a single equation allows direct estimation of nitrogen rates from user-defined agronomic parameters and vegetation index differences, eliminating multi-step calibration procedures.

The field experiment demonstrated that the sensor-based approach achieved yield levels comparable to conventional nitrogen management (30+90 kg N ha^{-1}) while applying substantially reduced nitrogen rates (27–45 kg N ha^{-1} of topdressing), representing savings of 50–70% in topdressing nitrogen across three wheat cultivars. The vegetation index difference (ΔVI) between the N-rich reference and the target area proved to be a robust indicator of crop nitrogen status, enabling consistent recommendations across cultivars.

The spatial implementation workflow provides a practical pathway for translating sensor data into field-specific variable rate nitrogen prescription maps, compatible with both ground-based sensors and remote sensing platforms. The reduced model complexity, combined with satisfactory agronomic performance, highlights the potential of the proposed approach to improve the practicality and adoption of sensor-based nitrogen management in precision agriculture systems.

Future research should focus on validating the methodology across different crops, environments, and sensor platforms, establishing crop-specific coefficients, and integrating economic analysis to further assess the approach's potential for broad-scale adoption.

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