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Improving Corn Nitrogen Recommendations through Spatially Explicit Modeling of Cover Crops and Soil Organic Matter

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Abstract

Effectively managing nitrogen (N) nutrition for corn (*Zea mays* L.) remains a substantial challenge. Poor handling can lead to outcomes ranging from N shortages and reduced crop output to contamination of surface and groundwater resources. For most of the 20th and 21st centuries, N fertilizer guidelines for corn relied on multiplying a targeted yield by a fixed value that indicated the N required per unit of corn grain produced. Even though this strategy frequently proves adequate for nourishing developing plants with minimal ecological harm, it fails to directly incorporate N released from the breakdown of soil organic matter (OM) or the varying processes of N release and uptake associated with residues from earlier cover crops. Conventional N handling methods followed by growers have typically resulted in fairly modest N utilization efficiency. However, precision agriculture tools introduced toward the end of the 20th century promised better N management by accounting for differences across field areas and adjusting application rates to match. Nevertheless, only a small number of operations currently use precision agriculture tools to address N needs. For this study, we examined an innovative N-guideline framework derived from the Soil and Cover Crop Available Nitrogen (SCAN) model. This framework directly accounts for N reserves in OM and cover crop remains. We combined this updated N guideline framework with variable-rate precision agriculture equipment to create location-specific N guidelines across corn fields. We predicted that adopting this N handling strategy would: (i) lower the total N suggested for the corn crop in comparison with a yield goal method, while (ii) preserving corn output at a comparable level to results from the standard yield goal method. Results showed that the SCAN model decreased N amounts at four out of six locations relative to the yield goal method, yet advised increased N use at two out of the six locations. At one location where the SCAN model called for elevated N levels, grain output also rose. In contrast, whenever the SCAN model proposed reduced N amounts compared with the yield goal method, yields generally declined. Further investigation is needed to determine the appropriate agronomic nitrogen efficiency parameter for incorporation into the SCAN model.

Keywords Precision agriculture, Nitrogen, Variable rate application, NDVI, Soil texture, Soil organic matter

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Introduction

Corn (*Zea mays* L.) is among the foremost agronomic crops worldwide, with output exceeding 1 billion tonnes in 2019. Production within the United States (U.S.) contributes almost one-third of that total, surpassing 347 million tonnes in the

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same year [1]. A central difficulty in growing corn is managing plant nitrogen (N) nutrition cost-effectively while protecting the environment. Corn output is regularly restricted by N supply [2], compelling farmers to rely on manufactured fertilizers, livestock manures, nitrogen-fixing cover crops, or various mixtures of these approaches. In large portions of the U.S., suggested N fertilizer quantities are established based on attainable yield targets, after subtracting N credits associated with past manure use or prior legume plantings, such as soybeans (*Glycine max* L.) [3]. Despite the long-term application of these yield-driven N guideline systems, numerous versions fail to include N contributions from other sources explicitly. Apart from N delivered via fertilizers and manure, considerable portions of N absorbed by corn derive from the breakdown of soil organic matter (OM) [4] along with cover crop remains [5]. Investigations reveal that 42% [6] to 83% [7] of the N accumulated by corn comes from sources other than applied fertilizer. Meanwhile, soils can release 18-305 mg N kg−1 [8]. Therefore, the matter involves more than spotting limited N release from OM and cover crop materials; it also requires recognizing substantial N release episodes and modifying N guidelines as appropriate.

Forecasting how much N will become available through mineralization for corn use and then adapting fertilizer inputs to match it is a challenging endeavor. Both the volume and speed of N mineralization depend on soil characteristics and surrounding weather patterns [9-11]. While certain soil features, such as OM levels and texture, can be measured with relative ease and remain stable across seasons, reliable forecasts of weather-related factors remain quite difficult. Consequently, numerous scientists have created mathematical simulations designed to estimate N release from cover crop materials and OM [12-15]. The simulation developed by White *et al.* [16] uses multiple biogeochemical formulas that draw on soil and cover crop details easily obtained through standard laboratory testing to estimate corn yield without added fertilizer. This simulation differs from prior versions in two important respects: (i) it is adjusted to forecast unfertilized corn yield for a given location, which connects to the volume of N released rather than calculating the mineralized N pool directly, and (ii) it relies on biogeochemical processes instead of statistical relationships. Although the model from White *et al.* [16] appears encouraging, knowledge remains limited for converting unfertilized yield estimates into precise determinations of the amount of additional N fertilizer needed to meet the desired corn yield target.

Better N handling is among the expected gains from precision agriculture equipment, yet this objective has not been fully realized to date. Corn's reaction to N fertilizer shows clear differences across the same field, making variable-rate N delivery a strong precision agriculture option for advancing N management [17]. Even so, roughly 20% of farms use variable-rate delivery as part of their precision agriculture methods [18]. Live crop canopy sensors capable of recording normalized difference vegetation index (NDVI) help enable variable-rate N delivery by linking NDVI readings to the crop's N condition and adjusting fertilizer rates accordingly [19]. These NDVI sensors are typically used when delivering fertilizer at variable rates to main crops. Still, recent findings indicate that NDVI data can also forecast N quantities stored in cover crop growth that may later be released and become accessible once the cover crop ends [20]. A further precision agriculture technique uses mapping of soil electrical conductivity (EC) inside fields to form separate soil fertility management areas [21]. Differences in soil EC are linked to clay content [22], a relevant aspect given its association with traits such as moisture retention, cation exchange capacity, and organic matter levels. Soil texture also influences N mineralization rate in the White *et al.* [16] model, suggesting that soil EC maps might contribute to location-specific N guidelines.

During this trial, we assessed a fresh pilot-scale strategy for producing variable-rate N guidelines in corn cultivation. The strategy drew on precision agriculture equipment to gather location-specific data for input into the model introduced by White *et al.* [16]. We used an NDVI sensor to assess cover crop N levels, an electromagnetic induction (EMI) sensor to record soil EC and delineate separate soil management areas, past yield monitor records from combines to define yield areas, and variable-rate fertilizer equipment to apply differing N rates. Our predictions included: (i) the updated N guideline process and delivery approach would decrease N quantities relative to conventional yield-driven guidelines, and (ii) the updated guideline process would keep corn output near the levels seen with the yield-driven approach.

Materials and Methods

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Site descriptions

Experiments were conducted in 2019 and 2020 at various sites throughout Pennsylvania. Four trial locations were included in 2019: Chambersburg (39°53′ N, 77°37′ W), Danville (40°55′ N, 76°37′ W), Rock Springs (40°43′ N, 77°55′ W), and Warriors Mark (40°38′ N, 78°9′ W). The same locations at Danville and Rock Springs hosted repeated trials in 2020. Separate fields were chosen for the 2020 season at Danville and Rock Springs to support normal crop rotation sequences. This choice led to different soil classifications in 2020 compared with 2019 at those two locations. Chambersburg, Danville, and Warriors Mark operated as privately managed farms. Soil classifications showed major differences among locations, with soils belonging to the ultisol, alfisol, and inceptisol categories. Soil at Chambersburg was classified as Hagerstown silt loam (Fine, mixed, semiactive, mesic Typic Hapludalf). Soils at the 2019 Danville location included mixtures of Berks and Hartleton silt loams (Loamy-skeletal, mixed, active, mesic Typic Dystrudept; Loamy-skeletal, mixed, active, mesic Typic Hapludult). Soils at the 2020 Danville location included mixtures of Calvin, Klinesville, and Leck Kill silt loams (Loamy-skeletal, mixed, active, mesic Typic Dystrudept; Loamy-skeletal, mixed, active, mesic Lithic Dystrudept; Fine-loamy, mixed, semiactive, mesic Typic Hapludults). Soils at the 2019 Rock Springs location contained mixtures of Hagerstown and Opequon silty clay loams (Fine, mixed, semiactive, mesic Typic Hapludalf; Clayey, mixed, active, mesic Lithic Hapludalf). Soils at the 2020 Rock Springs location contained mixtures of Murrill, Hagerstown, and Opequon silt loams (Fine-loamy, mixed, semiactive, mesic Typic Hapludult; Fine, mixed, semiactive, mesic Typic Hapludalf; Clayey, mixed, active, mesic Lithic Hapludalf). Soils at Warriors Mark included mixtures of Hagerstown and Hublersburg silt loams (Fine, mixed, semiactive, mesic Typic Hapludalf; Clayey, illitic, mesic Typic Hapludults). Soil texture measured at the 0–20 cm depth showed wide variation among locations, ranging from sandy clay loam to clay. Soil organic matter levels extended from 1.69 % at the 2019 Chambersburg location up to 5.72 % at the 2020 Rock Springs location. Field-wide average values for texture and OM were also determined **(Table 1)**.

Table 1. Field-level mean organic matter (OM), sand, silt, and clay content in the 0–20 cm soil depth. Textural class is calculated according to USDA standards.

Site	Clay (%)	Silt (%)	Sand (%)	Textural class	OM (%)
2019 Chambersburg	33.5	49.9	16.7	Silty clay loam	2.37
2019 Danville	28.0	38.4	33.6	Clay loam	2.51
2019 Rock Springs	42.5	40.9	16.7	Silty clay	2.92
2019 Warriors Mark	34.5	49.9	15.6	Silty clay loam	2.21
2020 Danville	24.1	45.4	30.5	Loam	3.45
2020 Rock Springs	41.7	44.0	14.3	Silty clay	3.92

Agronomic practices

At every site, cover crops were sown in late summer or fall, before corn was established, in both experimental years **(Table 2)**. Cover crop termination near corn planting was achieved via herbicide sprays at all sites across both years **(Table 2)**. In 2019, the herbicide mixes were: atrazine (1-Chloro-3-ethylamino-5-isopropylamino-2,4,6-triazine) at 0.13 kg active ingredient (A.I.) ha−1, metolachlor (2-chloro-N-(2-ethyl-6-methylphenyl)-N-(1-methoxypropan-2-yl)acetamide) at 0.98 kg A.I. ha−1, mesotrione (2-[4-(methylsulfonyl)−2-nitrobenzoyl]−1,3-cyclohexanedione) at 0.98 kg A.I. ha−1, 2,4-D (2-Ethylhexyl Ester of 2,4-Dichlorophenoxyacetic Acid) at 0.27 kg A.I. ha−1, plus glyphosate (N-(phosphonomethyl)glycine) at 1.54 kg A.I. ha−1 for Chambersburg; glyphosate at 1.89 kg A.I. ha−1, saflufenacil (N'-[2-chloro-4-fluoro-5-(3-methyl-2,6-dioxo-4-(trifluoromethyl)−3, 6-dihydro-1(2H)-pyrimidinyl)benzoyl]-N-isopropyl-N-methylsulfamide) at 0.02 kg A.I. ha−1, atrazine at 0.69 kg A.I. ha−1, and metolachlor at 1.59 kg A.I. ha−1 for Danville; glyphosate at 1.40 kg A.I. ha−1, metolachlor at 1.46 kg A.I. ha−1, mesotrione at 0.19 kg A.I. ha−1, and atrazine at 1.46 kg A.I. ha−1 for Rock Springs; pyroxasulfone (3-[[[5-(difluoromethoxy)−1-methyl-3-(trifluoromethyl)−1H-pyrazol-4-

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yl]methyl]sulfonyl]−4,5- dihydro-5,5-dimethylisoxazole) at 0.16 kg A.I. ha−1, glyphosate at 1.26 kg A.I. ha−1, 2,4-D at 0.49 kg A.I. ha−1, atrazine at 1.68 kg A.I. ha−1, and pendimethalin ((3,4-Dimethyl-2,6-dinitro-N-pentan-3-yl-aniline) at 1.06 kg A.I. ha−1 for Warriors Mark. In 2020, the mixes involved glyphosate at 0.84 kg A.I. ha−1, saflufenacil at 0.02 kg A.I. ha−1, rimsulfuron (N-((4,6-dimethoxypyrimidin-2-yl) aminocarbonyl)−3-(ethylsulfonyl)−2-pyridinesulfonamide) at 0.02 kg A.I. ha−1, and Thifensulfuron-methyl (Methyl 3-[[[[(4-methoxy-6-methyl-1,3,5-triazin-2-yl) amino] carbonyl] amino] sulfonyl]−2-thiophenecarboxylate) at 0.01 kg A.I. ha−1 for Danville, while Rock Springs received only glyphosate at 1.12 kg A.I. ha−1. Additional glyphosate was applied throughout the season as needed to control weeds. Every glyphosate product consisted of the isopropylamine salt version.

Table 2. Summary of agronomic practices at the experimental sites. Cover crop seeding rates are presented in parentheses after the cover crop name (e.g., Wheat (*Triticum aestivum*; 64), or Cereal rye (101)). Common names are used after the first mention of each species' Latin name.

Category	3dpi – All plants	3dpi – Test plants	2dpi – All plants	2dpi – Test plants
Total number of plants	54	16	57	16
Total diseased plants	35	10	37	10
Total non-diseased plants	19	6	20	6
Classification outcome	3dpi – All plants	3dpi – Test plants	2dpi – All plants	2dpi – Test plants
Diseased plants: at least one segment classified as diseased	34 (97%)	9 (90%)	36 (97%)	10 (100%)
Non-diseased plants: none of the segments classified as diseased	8 (42%)	3 (50%)	8 (40%)	2 (33%)
Diseased plants: the majority of segments classified as diseased	29 (83%)	8 (80%)	27 (73%)	6 (67%)
Non-diseased plants: the majority of segments classified as diseased	18 (95%)	6 (100%)	20 (100%)	6 (100%)

Corn planting took place at all sites in both years **(Table 2)**. For 2019, the varieties and rates were Pioneer P1422AMXT at 78,332 plants ha−1 at Chambersburg, Pioneer PO216AM at 75,145 plants ha−1 at Danville, Pioneer PO0574 at 79,074 plants ha−1 at Rock Springs, and Pioneer P0843 at 82,780 plants ha−1 at Warriors Mark. For 2020, they were Pioneer P0843 at 75,145 plants ha−1 at Danville and Channel 205–63 VTPRIB at 79,074 plants ha−1 at Rock Springs.

Around corn planting time, starter N fertilizer was applied at each site in both years, consistent with the partner farmers' usual practices **(Table 2)**. In 2019, this was urea at Chambersburg, urea-ammonium nitrate (UAN) solution at Danville, ammonium sulfate at Rock Springs, and UAN at Warriors Mark. In 2020, it was UAN at Danville and ammonium sulfate at Rock Springs. Side-dress N fertilizer later when corn reaches stages V5 to V8, using the N guidelines explained below.

Cover crop biomass and N content

NDVI sensors enabled field mapping to assess cover crop N levels at each site. Two NDVI sensors (Greenseeker RT200, Trimble, Sunnyvale, CA) were attached to the ends of a 4.6 m boom set 1.2 m above ground on a utility terrain vehicle (UTV). Readings occurred every 1 second during travel across the field in 9.1 m strips. Connect to Farmworks Mobile (Farm Works, Hamilton, IN) software with GPS enabled, averaging each NDVI value from the pair of sensors and including location coordinates. Timing was 3 May for 2019 Chambersburg, 16 May for 2019 Danville, 30 April for 2019

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Rock Springs, and 1 May for 2019 Warriors Mark. In 2020, it was 5 May for Danville and 14 April for Rock Springs. Conversion of NDVI values to kg N ha−1 at each point relied on equations from White *et al.* [20].

The resulting cover crop N data was entered into the QGIS (QGIS Development Team) geographic information system (GIS) software via a shapefile. B-spline interpolation in QGIS built a full raster layer showing the field-wide distribution of cover crop N from the point data. Polygons for cover crop biomass N **(Figure 1A)** were then divided into the field into 10 kg N ha−1 steps based on the raster (cells from 5–15 kg N ha−1 became the 10 kg N ha−1 polygon, cells from 15–25 kg N ha−1 became the 20 kg N ha−1 polygon, continuing similarly). Twelve points were picked through stratified random sampling to represent the full spread of biomass N values. Biomass was collected from 0.25 m2 quadrats at those points, then dried, weighed, ground, and analyzed for carbon, nitrogen, and the C:N ratio using an elemental analyzer (EA1110, CE Instruments, Egelsbach, Germany).

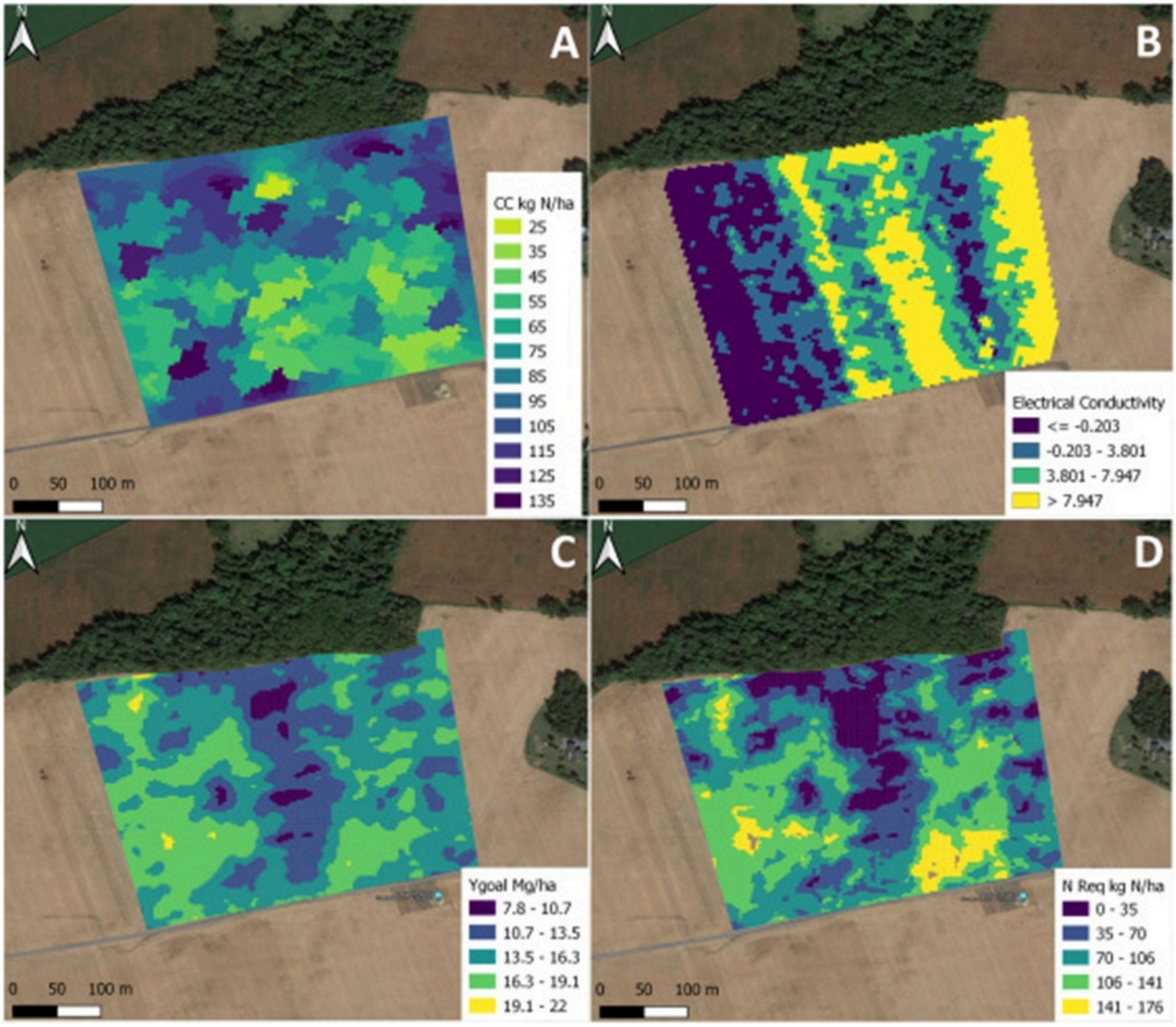

Figure 1. An example of a cover crop N content map created using NDVI data collected at the field and converted to biomass N content using the equations from White *et al.* [20] (A), a soil electrical conductivity map created for one of the sites using measurements from the EMI sensor interpolated to generate a continuous surface (B), a map of previous corn yield (C), and an example of an N prescription map created using the SCAN model (D). These maps were created with data from the 2019 Chambersburg site.

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Soil electrical conductivity

Before cover crop termination, soil electrical conductivity checks occurred at all sites. An EMI sensor (Profiler EMP-400, Geophysical Survey Systems, Inc., Nashua, NH) collected EC data at 15 kHz every 1 s in horizontal dipole orientation. This setup focused sensitivity on topsoil features. A plastic sled, towed by a 3 m nylon cord behind the UTV, prevented metal interference. The sensor fed a handheld PC with GPS, which recorded EC readings and positions as the user crossed the field in 9.1 m passes.

Post-collection, the handheld PC data were loaded into GIS software as a shapefile. B-spline interpolation created a smooth raster map of soil EC over the entire field. Management zones for soil fertility came from splitting this EC data. In 2019, each field had three zones formed by cuts at the 33rd and 66th percentiles of EC values **(Figure 1B)**. Four random points per zone were sampled, with each sample combining 12 1.9 cm cores to a depth of 20 cm within a 5 m radius of the point. In 2020, two zones per field resulted from a split at the 25th percentile, with lower EC values in zone 1 and higher in zone 2. Six random points per zone were sampled as before. Samples were dried, sieved to 2 mm, and sent to the Penn State Agricultural Analytical Services Lab (AASL) for organic matter via loss on ignition [23] and texture via hydrometer [24]. At AASL, OM measurement involved igniting samples at 360 °C for two hours to find percent loss on ignition (LOI), then applying this equation to reach percent OM:

$$\begin{aligned} &OM\ (\%) \\ &= 0.80 \\ &\times\ LOI\ (\%) - 0.23 \end{aligned} \quad (1)$$

Nitrogen recommendation systems

Two different N planning methods generated four specific N application maps at each location. The primary method came from the Penn State Extension Agronomy Guide, identified in this work as the agronomy guide treatment [25]. This yield-focused method also accounts for N contributions from past legume grain or forage crops and manure use. N guidelines under the agronomy guide followed **Eq. 2**:

$$\begin{aligned} &N_{rec} \\ &= \left(Y_{goal}\right. \\ &\times\ 17.86\ kg\ N\ Mg^{-1}\ grain\left.\right) \\ &-\ N_{credit} \end{aligned} \quad (2)$$

Where Nrec is the N guideline in kg N ha−1, Ygoal is the yield target in Mg grain ha−1, and Ncredit is any N adjustment in kg N ha−1 coming from past legumes or manure. Ygoal values are derived from historical corn harvest records supplied by growers at each location. All locations had prior harvests completed with combines fitted with digital yield monitors. Yield records are generated from field yield maps using B-spline interpolation, resulting in a continuous layer. Polygon divisions then split yields into 0.254 Mg ha−1 steps on a 5 × 5 m grid **(Figure 1C)**. Yield values inside each grid cell fed calculations for the N guideline using **Eq. 2**. A manure history existed at the 2019 Chambersburg location, leading to an Ncredit term of 22 kg N ha−1 inside the agronomy guide treatment. A previous legume crop was present at the 2019 Danville location, resulting in an N credit of 16 kg N ha−1 for the agronomy guide treatment.

The alternative N planning method used a set of biogeochemical formulas calibrated from the initial model calibration by White *et al.* [16]. These formulas consider N that could be released from the breakdown of cover crop remains and from soil organic matter. This collection of formulas is called the soil and cover crop available N, or SCAN, model. As in the first method, N quantities received were calculated field-wide on a 5 × 5 m grid **(Figure 1D)**. First, humification efficiency was calculated from soil texture using **Eq. 3**.

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$$\begin{aligned}\varepsilon &= 0.52 \\ &+ (0.0036 \times clay\%) - (0.0097 \times sand\%)\end{aligned} \quad (3)$$

Where ε is the humification efficiency, clay % and sand % are the average clay and sand levels for the soil EC zone linked to that grid cell. Second, corn yield supported by N release from soil organic matter was estimated using **Eq. 4**.

$$\begin{aligned}\Delta YOM &= 9.666 \\ &\times OM\ \% \\ &\times (1 - \varepsilon)\end{aligned} \quad (4)$$

Where ΔYOM is the corn yield in Mg ha−1 supported by N release from soil organic matter, OM % is the average soil organic matter level for the soil EC zone linked to that grid cell, and ε is the microbial carbon use efficiency determined for the grid cell in **Eq. 3**. Third, corn yield supported by N release from cover crop remains came through **Eq. 5**.

$$\Delta Y_{CC} = \alpha \times N_{CC} \times \left(1 - \frac{\varepsilon \times (\mathrm{C{:}N})_{CC}}{10}\right) \quad (5)$$

Where ΔYCC is the corn yield supported by N release from cover crop remains in Mg ha−1, α is a calibration coefficient equal to 0.026 when cover crops release N and 0.085 when they tie up N, NCC is the N quantity in cover crop material in kg ha−1 linked to that grid cell, ε is the microbial carbon use efficiency determined for the grid cell in **Eq. 3**, and (C:N)CC is the C:N ratio of cover crop material linked to that grid cell. Afterward, total corn yield supported by N release from organic matter and cover crop residues was estimated using **Eq. 6**.

$$\begin{aligned}Y_T &= (\Delta Y_{OM} + \Delta Y_{CC}) - 0.000059 \\ &\times (\Delta Y_{OM} + \Delta Y_{CC})^2 - 3.2\end{aligned} \quad (6)$$

Where YT is the total corn yield supported by N release from organic matter and cover crop remains in Mg ha−1, ΔYOM is the corn yield supported by release from soil organic matter determined for the grid cell in **Eq. 3**. ΔYCC is the corn yield supported by release from cover crop remains determined for the grid cell in **Eq. 5**. Formulas 3 through 6 applied here vary slightly from the finalized model in White *et al.* [16], finished after these field trials wrapped up. The model in White *et al.* [16] differs by restricting **Eq. 3** to the sand portion of soil texture and removing an intercept term in **Eq. 6**. These model structure adjustments resulted in modest changes in the calibration coefficients. Nevertheless, both model versions maintain roughly similar effectiveness when forecasting unfertilized corn yield.

To turn the above formulas into estimates of required N fertilizer for corn, a method underwent evaluation that applies **Eq. 7** for determining the delta yield of corn (difference between the planned yield target and the forecasted unfertilized corn yield) multiplied by the inverse of agronomic nitrogen efficiency (ANE−1, kg N Mg−1 grain). Since the correct value for ANE−1 has not been clearly set for this kind of planning, three ANE−1 options underwent testing: 21.4, 28.6, and 42.9 kg N Mg−1 grain. These values originated from Stanford's [26] "1.2 rule" that calls for 1.2 lbs of N per bushel of grain. The ANE−1 of 21.4 reflects 100% N recovery, 28.6 reflects 75% recovery, and 42.9 reflects 50%.

$$\begin{aligned}N_{req} &= (Y_{goal} - Y_T) \\ &\times ANE^{-1}\end{aligned} \quad (7)$$

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Where Nreq is the added N fertilizer need in kg ha−1, Ygoal is the yield target linked to the grid cell from the yield map, YT is the corn yield supported by release from soil organic matter and cover crop remains, and ANE−1 is the inverse of agronomic N use efficiency, manually adjusted across treatments as noted earlier.

Nitrogen prescription application

Treatments were formed by adjusting the ANE−1 setting inside the SCAN model from the earlier section to span a range of possible figures. Three ANE−1 settings were entered into the SCAN model at each location and compared with the N plan from the agronomy guide formula. A randomized complete block design featuring four replications applied at all locations in both study years. Plot sizes in 2019 measured 312 × 18.3 m at Chambersburg, 96 × 6.1 m at Danville, 285 × 4.6 m at Rock Springs, and 509 × 6.1 m at Warriors Mark. In 2020, plots measured 276 × 6.1 m at Danville and 115 × 4.6 m at Rock Springs. Since some N had already been placed near corn planting, following each farm's usual practices, the remaining N from the planting methods was side-dressed when corn reached stages V5-V8. Variable-rate sprayers delivered the N as UAN at all locations in both years. Side-dress timing in 2019 was 21 June at Chambersburg, 27 June at Danville, 11 June at Rock Springs, and 15 June at Warriors Mark. In 2020, side-dress occurred on 30 June at Danville and on 18 June at Rock Springs.

Corn plant tissue sampling & grain harvest

Plant samples were collected at key growth stages during the season, and calibrations have been established between tissue N levels and plant N adequacy. At all locations in both years, twenty-five full leaf samples at the ear node were gathered from each plot once corn reached the R1 stage to check earleaf N levels. Collection dates in 2019 were 19 July at Chambersburg, 30 July at Danville, 23 July at Rock Springs, and 23 July at Warriors Mark. In 2020, the dates were 29 July at Danville and 23 July at Rock Springs. Samples were then dried and ground before N-level analysis at the AASL.

At all locations in both years, fifteen corn stalk samples were checked for tissue nitrate levels. Stalk pieces measured 20 cm long, taken from 15 cm to 35 cm above ground, once corn reached the R6 stage from each plot. Collection dates in 2019 were 3 September at Chambersburg, 26 September at Danville, 17 September at Rock Springs, and 11 September at Warriors Mark. In 2020, the dates were 18 September at Danville and 9 September at Rock Springs. After gathering, samples were cut into 5-cm pieces, dried, and ground. Extraction of NO3− followed the method of Binford *et al.* [27], with nitrate levels in extracts measured by the vanadium(III) reduction technique [28].

All locations in both years underwent harvest with a mechanical combine, and grain weight from each plot was recorded. A grain subsample from every plot was adjusted to 15.5% moisture for yield calculations. Harvest dates in 2019 were 4 October at Chambersburg, 29 October at Danville, 4 December at Rock Springs, and 21 October at Warriors Mark. In 2020, harvests occurred on 27 October at Danville and on 18 November at Rock Springs.

Economic optimum N rate, partial factor productivity, and partial profit

Following harvest, the economic optimum N rate (EONR) was calculated at each location, along with partial factor productivity (PFP) and partial profit (PP) per treatment. EONR determination involved a quadratic plus plateau N response curve for corn grain yield via PROC NLMIXED in SAS 9.4 (SAS Institute, Cary, NC). The quadratic section derivative was then set equal to the fertilizer: crop price ratio of 5.6 to solve for EONR in kg ha−1. PFP came from dividing grain yield in kg ha−1 by N rate in kg ha−1, resulting in kg grain kg−1 N applied. Partial profit used an N price of $1.97 kg−1 N and a corn price of $197.31 Mg−1 grain, subtracting the cost of applied N from the value of harvested grain.

Statistical analysis

Links between cover crop biomass N amounts predicted from NDVI readings and those measured directly from harvested samples were tested using the PROC REG procedure in SAS. Regression quality received evaluation based on R2, root mean square error (RMSE), slope, intercept, and bias (%). The bias figure came from this formula:

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$$\% \ Bias = 100 \times \frac{\sum_{i=1}^{N} Obs_i - Pred_i}{\sum_{i=1}^{N} Obs_i} \quad (8)$$

Where N is the number of observations in the data set, i is the current observation, Obs is the observed value, and Pred is the predicted value. Thus, negative bias indicates overprediction, and positive bias indicates underprediction.

Clay, sand, and organic matter levels in soil samples were examined using PROC MIXED in SAS to assess whether EC-based soil zones showed statistical differences in these traits via Fisher's LSD mean comparisons (P ≤ 0.05). Average N application amounts for each treatment and site across the two study years were computed. Average advised N rate, corn ear leaf N amount, corn stalk NO3 N− amount, and grain output received examination separately by site and year to avoid impacts from varying weather patterns among locations and seasons using the PROC MIXED procedure in SAS. Identification of statistical distinctions relied on Fisher's LSD within PROC MIXED (P ≤ 0.05). Every dataset followed a normal distribution and needed no modifications before examination.

Results and Discussion

Meteorological conditions

Average growing season (May 1-September 30) temperatures during 2019 were 21.7 C, 19.9 C, 20.0 C, and 19.4 C at the Chambersburg, Danville, Rock Springs, and Warriors Mark locations, respectively. Total growing season rainfall amounted to 410 mm, 568 mm, 428 mm, and 602 mm at the Chambersburg, Danville, Rock Springs, and Warriors Mark locations, respectively. The average growing season temperature in 2020 was 19.8 C and 20.1 C at the Danville and Rock Springs locations, respectively, with total growing season rainfall of 407 mm and 361 mm, respectively [29]. All locations operated without irrigation, relying solely on natural rainfall.

Cover crop N content

Maps showing cover crop N amounts derived from NDVI surveys revealed extensive differences in cover crop biomass N throughout every location **(Figure 1A)**. Biomass N ranges forecasted by NDVI surveys matched well with ranges found through manual collection **(Table 3)**. When information from all locations across both years was combined, the resulting R2 reached 0.512, RMSE reached 29.35, regression slope reached 0.606, and intercept reached 9.05 **(Figure 2)**. Measured C:N ratios from cover crop biomass varied by location and year, staying inside the 19 to 29 interval **(Table 3)**. Cover crop categories at the locations were split into cereal rye alone, combinations including legumes, and combinations excluding legumes, after which % bias calculations occurred for each. Cereal rye alone displayed a % bias of −82.7%, pointing to notable overestimation of cover crop N amounts. Combinations with legumes and without legumes showed percent biases of −27.9% and −21.7%, respectively, suggesting milder overestimation of cover crop N amounts.

Table 3. Cover crop and soil data from the experimental sites. Letters indicate significant differences (P ≤ 0.05) in clay, sand, or organic matter between zones within a site.

Site	Organic matter (%)			Sand (%)			Clay (%)			Electrical conductivity (mS m^{-1})			Cove crop bioma
Empty Cell	Zone 3	Zone 2	Zone 1	Zone 3	Zone 2	Zone 1	Zone 3	Zone 2	Zone 1	Zone 3	Zone 2	Zone 1	C:N ratio

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2019 Chambersburg	2.32	2.58	2.13	20.0	13.5	18.6	33.4	35.6	30.8	6.6–53.9	0.83–6.6	−9.3–0.83	21.2
2019 Danville	2.47	2.50	2.76	34.2	31.9	27.8	28.7	27.0	28.8	5.7–9.3	4.9–5.7	1.9–4.9	28.8
2019 Rock Springs	–	3.46[a]	2.47[b]	–	14.8	18.3	–	49.5[a]	36.6[b]	–	7.3–12.5	2.4–7.3	23.7
2019 Warriors Mark	2.08	2.35	2.21	12.5[b]	13.3[b]	20.1[a]	34.4	35.4	33.8	14.3–21.7	10.3–14.3	6.8–10.3	17.9
2020 Danville	–	3.15[b]	3.76[a]	–	28.6	32.4	–	24.1	24.2	–	10.1–15.4	4.8–10.1	23.3
2020 Rock Springs	–	3.61	4.22	–	13.7	14.9	–	39.9	43.6	–	9.2–13.6	5.8–9.2	19.4

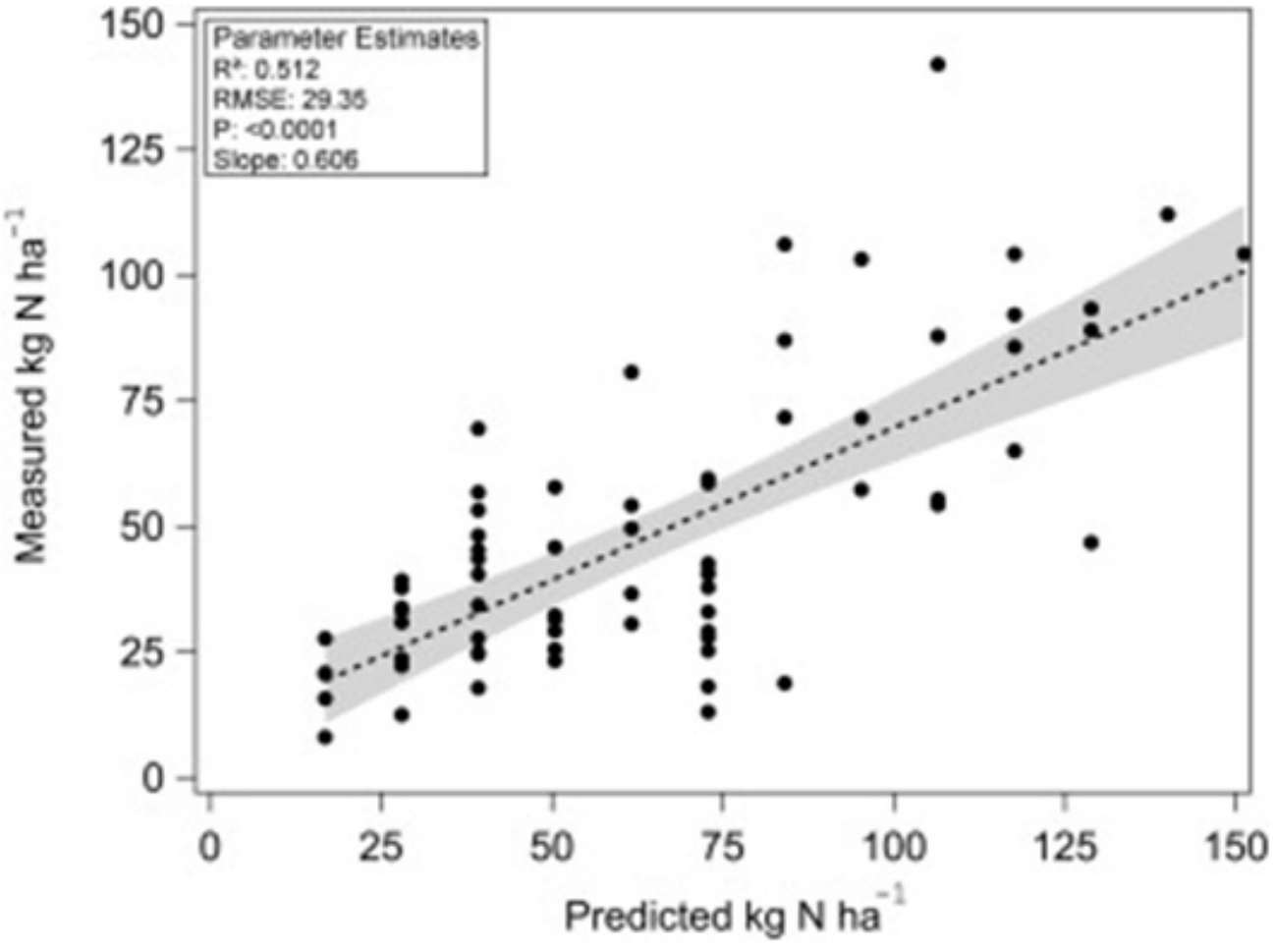

Figure 2. Results from regression analysis of cover crop biomass N predicted from NDVI sensors versus cover crop biomass N measured from collected biomass and elemental analysis.

Soil electrical conductivity

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Created soil EC maps showed high variation at each location **(Figure 1B)**. Soil EC maps helped form zones spanning specific EC ranges at each location **(Table 3)**.

A statistical review found no meaningful differences in sand, clay, or organic matter content across the mapped soil zones at Chambersburg and Danville in 2019, or at Rock Springs in 2020. At Rock Springs in 2019, meaningful differences were observed in clay (P = 0.0013) and organic matter (P = 0.0037) content, but none in sand content across the mapped soil zones. At Warriors Mark in 2019, a meaningful distinction emerged in sand content (P = 0.0162), but none in clay or organic matter content. In 2020 at Danville, a meaningful distinction in organic matter (P = 0.0468) emerged, but none in sand or clay content across the mapped soil zones.

N Recommendations

Average N guidelines showed clear contrasts between the efficiency settings and the agronomy guide approach at nearly all locations **(Table 4)**. The agronomy guide approach delivered the largest N quantity at Rock Springs and Danville for both 2019 and 2020. The ANE−1 42.9 kg N Mg−1 grain setting delivered the largest N quantity at Chambersburg and Warriors Mark in 2019. The ANE−1 21.4 kg N Mg−1 grain setting delivered the lowest N quantity at every location across both years, except Chambersburg in 2019, where it proposed a quantity near that of the agronomy guide. In several situations, the ANE−1 21.4 kg N Mg−1 grain setting proposed a smaller N quantity than what had already gone down at planting time, resulting in zero extra N during side-dress.

Table 4. Mean N fertilizer prescription rates, economic optimum N rate (EONR), leaf N content at R1, corn stalk NO3− content at R6, and corn grain yield. The agronomy guide treatment is abbreviated “Ag. guide”. The units for the varying ANE−1 values (kg N Mg−1 grain) have been omitted for brevity. Stalk Nitrogen rates were calculated from the total N prescribed for each plot divided by the area of the plot. Differing letters indicate significant differences (P ≤ 0.05) among treatments at a site. 1Sites with EONR of “N/A” had yield response curves that did not fit a quadratic plus plateau model.

Site	**Yield (Mg ha^{-1})**				**Stalk NO_3^--N content (mg kg^{-1})**				**Leaf N content (% dry wt.)**				**E((k h**
Empty Cell	**ANE^{-1} 21.4**	**ANE^{-1} 28.6**	**ANE^{-1} 42.9**	**Ag. guide**	**ANE^{-1} 21.4**	**ANE^{-1} 28.6**	**ANE^{-1} 42.9**	**Ag. guide**	**ANE^{-1} 21.4**	**ANE^{-1} 28.6**	**ANE^{-1} 42.9**	**Ag. guide**	
2019 Chambersburg	7.9^{c}	8.8^{ab}	9.5^{a}	8.7^{b}	40^{b}	35^{b}	208^{a}	58^{b}	2.58^{a}	2.59^{a}	2.82^{a}	2.59^{a}	2
2019 Danville	5.8^{b}	5.8^{b}	7.9^{ab}	10.1^{a}	9^{a}	25^{a}	12^{a}	874^{a}	1.79^{b}	2.16^{b}	2.22^{b}	3.00^{a}	2
2019 Rock Springs	7.1^{d}	9.0^{c}	10.3^{b}	12.1^{a}	31^{a}	56^{a}	47^{a}	141^{a}	2.29^{c}	2.55^{b}	2.74^{b}	3.02^{a}	N
2019 Warriors Mark	10.6^{b}	11.5^{b}	12.9^{a}	12.9^{a}	64^{b}	154^{b}	658^{a}	275^{b}	2.63^{c}	2.94^{b}	3.18^{a}	3.10^{ab}	2
2020 Danville	4.9^{a}	5.0^{a}	4.9^{a}	5.6^{a}	91^{b}	5^{b}	87^{b}	1115^{a}	2.44^{a}	2.52^{a}	2.57^{a}	2.69^{a}	N
2020 Rock Springs	5.1^{a}	5.5^{a}	5.3^{a}	5.5^{a}	1^{b}	284^{b}	103^{b}	1342^{a}	2.37^{b}	2.83^{a}	2.99^{a}	3.13^{a}	N

Corn plant tissue N content and grain yield

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Overall, the largest N guideline produced the largest earleaf N concentration during the R1 development stage, though distinctions did not consistently prove meaningful **(Table 4)**. N concentrations recorded at R1 stayed under Penn State Extension's sufficiency interval of 2.75–3.50 % N for the majority of treatments [30]. Only the largest N quantity brought N content within the sufficiency interval at each location, except for the 2019 Warriors Mark and 2020 Rock Springs locations, which featured three treatments within the sufficiency interval. No treatments at the 2020 Rock Springs location entered the sufficiency interval.

Outcomes for corn stalk NO3 N− mirrored the pattern seen at R1, as the largest N guideline normally produced the largest NO3 N−concentration, but meaningful distinctions between treatments occurred even less often. Most treatments recorded NO3 N−concentration inside the low category, under 700 mg NO3 $N^{-}kg^{-1}$, following Penn State's corn stalk nitrate test guidelines [31]. Just three occurrences placed treatments inside the AASL optimum category of 700–2000 mg NO3 $N^{-}kg^{-1}$, specifically the agronomy guide treatments at 2019 Danville, 2020 Danville, and 2020 Rock Springs.

Grain output usually increased with higher N rates at each location in 2019, though differences between treatments did not always reach significance. In 2020, N quantity exerted a weaker influence on grain output due to extreme drought throughout the season, resulting in a 30–75% reduction relative to the intended target.

Economic optimum N rate, partial factor productivity, and partial profit

EONR calculations were possible at three of six locations, where yield response to N fertilizer followed a quadratic-plateau pattern. At the 2019 Chambersburg location, EONR sat between average N quantities used under the ANE−1 42.9 kg N Mg−1 grain and ANE−1 28.6 kg N Mg−1 grain settings. At the 2019 Danville and 2019 Warriors Mark locations, EONR sat between average N quantities used under the agronomy guide approach and the ANE−1 42.9 kg N Mg−1 grain setting. Reliable EONR calculation failed for Rock Springs 2019, Danville 2020, and Rock Springs 2020 because yield response patterns did not match a quadratic plus plateau form. Yield reaction at those three locations followed a straight line, rising with higher N quantity at 2019 Rock Springs while showing no change with higher N quantity at Danville 2020 and Rock Springs 2020.

Partial factor productivity covered a broad spectrum from 32 kg grain kg−1 N to 96 kg grain kg−1 N across locations and treatments **(Table 5)**. PFP figures generally increased as N decreased at a given location. At least one SCAN model setting outperformed the agronomy guide approach in PFP at all locations except one.

Table 5. Partial factor productivity (PFP, kg grain kg−1 N) and partial profit (PP, $ ha−1) for treatments at each site. The agronomy guide treatment is abbreviated "Ag. guide," and the units for each ANE−1 (kg N Mg−1 grain) have been omitted. Differing letters indicate significantly different means ($P < 0.05$).

Site	PP ($ ha^{-1})				PFP (kg grain kg^{-1} N)			
Empty Cell	**ANE^{-1} 21.4**	**ANE^{-1} 28.6**	**ANE^{-1} 42.9**	**Ag. guide**	**ANE^{-1} 21.4**	**ANE^{-1} 28.6**	**ANE^{-1} 42.9**	**Ag. guide**
2019 Chambersburg	1316.72^{ab}	1392.56^{ab}	1276.10^{b}	1502.98^{a}	64^{b}	51^{c}	34^{d}	72^{a}
2019 Danville	978.49^{b}	1022.77^{b}	1322.14^{ab}	1556.25^{a}	78^{a}	72^{a}	69^{a}	45^{b}
2019 Rock Springs	1279.44^{c}	1595.97^{b}	1743.28^{b}	1995.15^{a}	96^{a}	86^{a}	71^{b}	67^{b}
2019 Warriors Mark	1840.93^{b}	1952.24^{ab}	2071.18^{a}	2126.65^{a}	87^{a}	70^{b}	54^{c}	62^{b}
2020 Danville	872.50^{a}	825.25^{a}	853.47^{a}	779.56^{a}	84^{a}	76^{a}	67^{a}	34^{b}

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2020 Rock Springs	906.23[a]	946.66[a]	945.72[a]	742.80[a]	89[a]	80[ab]	69[b]	32[c]

Partial profit similarly ranged from $742.80 ha−1 to $2126.65 ha−1 across treatments and locations **(Table 5)**. The agronomy guide approach generated the largest PP figure at all locations in 2019, even though distinctions did not consistently prove meaningful. For example, in 2019, Danville and 2019 Warriors Mark, PP values were close between the agronomy guide approach and the ANE−1 42.9 kg N Mg−1 grain setting.

The SCAN model offers an innovative approach to setting N guidelines for corn cultivation. Earlier investigations have applied NDVI sensors [32, 33], soil maps [34], yield maps [34, 35], and simulation models [35] to enhance N handling in corn fields. As far as we know, no prior work has merged these tools in the exact manner presented here. Our results showed that NDVI was a reliable means of detecting variations in cover crop biomass N, similar to how other studies have used NDVI to assess N conditions in main crops such as corn [7] and wheat [36]. Soil EC readings proved only modestly helpful in distinguishing between soil texture and OM levels, consistent with prior research [34]. Ultimately, the SCAN model lowered N quantities relative to the agronomy guide in the majority of cases. Fresh strategies for N guidelines in corn, such as the one examined, can contribute to more effective and environmentally sound cropping systems.

Regressions comparing cover crop N from manual collection and elemental testing with NDVI estimates showed substantial variation in biomass N across locations and cover crop categories. White *et al.* [20] noted that connections between cover crop N content and NDVI readings differed according to cover crop species. We determined bias (%) across three cover crop categories outlined by White *et al.* [20] in our trial: cereal rye monocultures, legume-containing combinations, and legume-excluding combinations. Bias reached much higher levels in cereal rye monocultures (−82.7%) than in the combinations, which both remained below 30%. As a result, biomass N was overestimated in cereal rye monocultures. Comparable species-driven variations in NDVI versus cover crop biomass links have been reported in other studies [37]. Such patterns could create particular difficulties inside the SCAN model because cover crop biomass N plays a key role in estimating corn yield supported by cover crop remains.

Forecasts of biomass N based on NDVI could have been influenced by the specific sensor used. White *et al.* [20] relied on a portable NDVI sensor (Greenseeker HCS-100, Trimble) operating at a red wavelength of 660 nm and an NIR wavelength of 780 nm. In contrast, our trial used two vehicle-mounted NDVI sensors (Greenseeker RT200, Trimble, Sunnyvale, CA) operating at a red wavelength of 650 nm and an NIR wavelength of 770 nm. Variations in these red and NIR wavelengths between sensors might explain the bias noticed in cover crop N content forecasts. Prior studies have documented how NDVI readings respond to shifts in wavelengths [38, 39]. Discrepancies in NDVI outputs between sensor designs could account for the absence of a 1:1 match between cover crop N from elemental testing and cover crop N from NDVI. This situation also highlights the requirement for calibration curves, similar to those developed by White *et al.* [20], tailored to each unique red-NIR wavelength pairing.

A further reason for the mismatch between NDVI-predicted cover crop N and measured values is that cover crop collections did not always occur at the exact NDVI recording spots. Rather, the full NDVI surface was generated by interpolation across recording locations. Consequently, it seems probable that NDVI readings did not align exactly with cover crop sampling positions. We suspect this interpolation step contributed partly to the missing 1:1 correspondence between elemental analysis results and NDVI-derived cover crop N.

Growers already have accessible tools to produce cover crop NDVI maps that could enable spatial forecasts of cover crop N in their fields. Options include vehicle-mounted NDVI sensors of the type applied here, drone-based imaging [40], and satellite-based imaging [41]. Satellite NDVI measurements appear particularly encouraging for this application, as they are widely available through paid services and require no on-farm specialized gear. Moreover, satellite data provides a complete NDVI surface without requiring interpolation between discrete points, as performed in our work. Irrespective of the NDVI source, the present study underscores the need to develop calibration formulas for the different wavelength sets used in NDVI collection.

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Formation of soil zones based on electrical conductivity yielded limited benefits across the fields involved in this trial. Statistical reviews showed soil texture elements differed between zones at only two locations: 2019 Warriors Mark and 2019 Rock Springs. Soil electrical conductivity is influenced by soil salinity, percent saturation, water content, bulk density, clay content, clay mineralogy, organic matter, cation exchange capacity, and temperature [42]. Thus, elements beyond those required by SCAN formulas may have driven EC differences inside each field. Furthermore, EMI sensors like the one deployed here can exhibit drift [43], which may have led to inaccurate readings at our 2019 Chambersburg location, where negative EC values were observed.

The identified soil zones did not consistently show differences in OM. Percent organic matter differed significantly between zones at two out of six locations: 2019 Rock Springs and 2020 Danville. Peralta and Costa [44] observed strong connections between soil EC and percent organic matter while defining management zones, yet they did not investigate soil texture as an EC driver. Although organic matter quantities frequently change with soil texture due to clay minerals that help stabilize soil organic matter, the lack of texture differences across soil zones in our trial may also have led to a lack of OM differences. Recently commercialized sensors now allow optical detection of soil to forecast soil organic matter quantities, including the Precision Planting SmartFirmer and Veris Technologies OpticMapper. Such emerging sensors could support future efforts to define soil zones varying in organic matter that integrate into precision N handling strategies like the one evaluated here.

The SCAN model reduced N levels relative to the agronomy guide, independent of the ANE−1 setting, at four of six locations **(Table 4)**. Nevertheless, the ANE−1 42.9 kg N Mg−1 grain setting produced a larger N quantity than the agronomy guide at the 2019 Chambersburg and 2019 Warriors Mark locations. This outcome stemmed from comparatively high clay and low sand levels in soils at those locations, which raised the humification efficiency term, ε, and consequently lowered YCC and YOM. As ε rises, **Eqs. 3 and 5** demand progressively lower cover crop C:N ratios and higher soil OM, respectively, to sustain corn yield. Hence, even with relatively low cover crop C:N ratios, soil texture effects overpowered the computations of YCC and YOM at these two locations. At the four locations where SCAN consistently reduced N quantities, yield suffered negative effects from the ANE−1 28.6 kg N Mg−1 grain and ANE−1 21.4 kg N Mg−1 grain settings in 2019, but not in 2020 when N did not limit corn yield.

The highest PFP figures appeared under the SCAN model settings, yet the highest PP figures generally appeared under the agronomy guide approach. Although PFP helps pinpoint the most efficient N use, it often fails to align with the most profitable management system due to lower yields and returns [45]. The ANE−1 42.9 kg N Mg−1 grain setting achieved yield comparable to or exceeding the agronomy guide at five out of six locations and PFP comparable to or exceeding the agronomy guide at four out of six locations. This setting produced PP comparable to that of the agronomy guide at 4 of 6 locations. It generated lower PP than the agronomy guide at the 2019 Chambersburg location, where it advised surplus N, and at the 2019 Rock Springs location, where it advised insufficient N, resulting in PP equal to the agronomy guide PP. Based on these outcomes, adopting ANE−1 at 42.9 kg N Mg−1 grain inside the SCAN model represents the strongest choice among those examined in this trial. Further investigation is required to determine the optimal handling of ANE−1 values inside the SCAN framework.

It bears noting that the agronomy guide approach in this trial also incorporated variable-rate fertilizer delivery. We can merely guess how a conventional uniform-rate N application, based on the agronomy guide, would have performed compared with the SCAN model with variable-rate delivery for plant tissue N or yield. Still, using the yield maps used to compute YGoal in **Eq. 2**, we determined average N guidelines from the agronomy guide for each location to establish the uniform rate. Guidelines at 2019 locations reached 119, 203, 170, and 210 kg N ha−1 at Chambersburg, Danville, Rock Springs, and Warriors Mark, respectively. Guidelines at 2020 locations reached 232 and 187 kg N ha−1 at Danville and Rock Springs, respectively. These quantities followed a pattern similar to that applied in the trial, with four of six locations showing higher N guidelines under the agronomy guide than under the SCAN model. Bragagnolo *et al.* [46] reported that variable-rate N delivery boosted nitrogen use efficiency and nitrogen absorption relative to uniform-rate delivery without altering total N applied. Martins *et al.* [47] reported that variable-rate delivery decreased N requirements for corn while securing yield equivalent to uniform-rate N delivery. Even so, it remains impossible to determine whether uniform-rate N

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delivery based on an average yield target would have matched the performance of the variable-rate agronomy guide prescription applied here.

Our plant tissue collections indicated that even the largest N quantities tested did not consistently produce tissue N levels inside Penn State Extension's optimum interval [25]. This pattern stood out most clearly in corn stalk NO3− samples, where merely three of twenty-four averages fell inside the optimum interval. Optimum or sufficiency intervals for plant tissue nutrients differ across organizations. For example, Iowa State Extension suggests a stalk NO3− sufficiency interval of 250–2000 mg kg−1 [48]. Although many accept that corn stalk NO3− testing is unreliable for detecting shortages, the same does not hold for earleaf tissue testing. Only nine of the twenty-four averages for leaf N content entered the recognized optimum interval. In most instances, lower leaf N content produced lower yields than treatments within the optimum interval, reinforcing earleaf N content as a useful marker of crop performance.

Environmental factors harmed the trial locations in 2020. Average growing-season temperatures remained almost the same between 2019 and 2020 at the Danville and Rock Springs locations: 19.9 and 19.8 C at Danville, and 20.0 and 20.1 C at Rock Springs. Growing-season rainfall, however, dropped by 28% in 2020 versus 2019 at Danville and by 16% at Rock Springs. Growing season rainfall at Rock Springs stood 25 % lower in 2020 than in 2019 before a 40-mm rain event on the final day of the defined growing season.

Conclusion

In this trial, we evaluated an innovative N guideline system for corn cultivation, the SCAN model, that applied biogeochemical formulas to directly account for N mineralization from OM and cover crop remains. Our updated guideline system lowered the advised N quantity relative to a standard yield-driven method from the Penn State agronomy guide in most cases when ANE−1 was 28.6 kg N Mg−1 grain or lower. Yet lowering the N rate relative to the agronomy guide decreased yield in most cases, except at the 2020 locations, where drought limited yield. Adoption of an ANE−1 value of 42.9 kg N Mg−1 grain resulted in yields comparable to or higher than the agronomy guide at all locations except one. We further found that NDVI measurements of cover crop biomass N are influenced by the wavelengths used by the NDVI sensor. This finding implies that calibration procedures are essential for every wavelength pairing when forecasting biomass N via NDVI. Moreover, we observed that soil EC offered useful information for building zones based on OM and texture in only limited instances, and field-wide averages of these traits might prove more practical. Upcoming studies should focus on determining suitable ANE−1 values for the SCAN model to ensure corn yields remain steady or improve under this strategy. Although we did not examine every possible ANE−1 level, this project suggests that 42.9 kg N Mg−1 grain may serve as a lower limit for ANE−1, as yield regularly declined when values dropped below it. Our outcomes supply guidance for future investigators exploring soil characteristics to develop variable-rate N guidelines for corn.

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Conflict of interest

None

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Ethics statement

None

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References

1. FAOSTAT. Food and Agriculture Organization statistics. Food and Agriculture Organization of the United Nations, Rome. 2020. http://www.fao.org/faostat/en/#data/QC (accessed 26 Jan. 2021).

2. Teixeira EI, George M, Herreman T, Brown H, Fletcher A, Chakwizira E, et al. The impact of water and nitrogen limitation on maize biomass and resource-use efficiencies for radiation, water and nitrogen. Field Crops Res. 2014;168:109-18. https://doi.org/10.1016/j.fcr.2014.08.002.

3. Morris TF, Murrell TS, Beegle DB, Camberato JJ, Ferguson RB, Grove J, et al. Strengths and limitations of nitrogen rate recommendations for corn and opportunities for improvement. Agron J. 2018;110:1-37. https://doi.org/10.2134/agronj2017.02.0112.

4. Osterholz WR, Rinot O, Liebman M, Castellano MJ. Can mineralization of soil organic nitrogen meet maize nitrogen demand? Plant Soil. 2017;415:73-84. https://doi.org/10.1007/s11104-016-3137-1.

5. Andrews JS, Sanders ZP, Cabrera ML, Saha UK, Hill NS. Nitrogen dynamics in living mulch and annual cover crop corn production systems. Agron J. 2018;110:1309-17. https://doi.org/10.2134/agronj2017.10.0609.

6. Liang BC, MacKenzie AF. Corn yield, nitrogen uptake and nitrogen use efficiency as influenced by nitrogen fertilization. Can J Soil Sci. 1994;74:235-40. https://doi.org/10.4141/cjss94-032.

7. Stevens WB, Hoeft RG, Mulvaney RL. Fate of nitrogen-15 in a long-term nitrogen rate study: II. Nitrogen uptake efficiency. Agron J. 2005;97:1046-53. https://doi.org/10.2134/agronj2003.0313.

8. Stanford G, Smith SJ. Nitrogen mineralization potentials of soils. Soil Sci Soc Am J. 1972;36:465-72. https://doi.org/10.2136/sssaj1972.03615995003600030029x.

9. Bregliani MM, Ros GH, Temminghoff EJM, van Riemsdijk WH. Nitrogen mineralization in soils related to initial extractable organic nitrogen: Effect of temperature and time. Commun Soil Sci Plant Anal. 2010;41:1383-98. https://doi.org/10.1080/00103621003759387.

10. Isaac ME, Timmer VR. Comparing in situ methods for measuring nitrogen mineralization under mock precipitation regimes. Can J Soil Sci. 2007;87:39-42. https://doi.org/10.4141/S06-024.

11. Reich PB, Grigal DF, Aber JD, Gower ST. Nitrogen mineralization and productivity in 50 hardwood and conifer stands on diverse soils. Ecology. 1997;78:335-47. [0335:NMAPIH]2.0.CO;2. https://doi.org/10.1890/0012-9658(1997)078.

12. Cabrera ML, Kissel DE. Evaluation of a method to predict nitrogen mineralized from soil organic matter under field conditions. Soil Sci Soc Am J. 1988;52:1027-31. https://doi.org/10.2136/sssaj1988.03615995005200040024x.

13. Cassity-Duffey K, Cabrera M, Gaskin J, Franklin D, Kissel D, Saha U. Nitrogen mineralization from organic materials and fertilizers: Predicting N release. Soil Sci Soc Am J. 2020;84:522-33. https://doi.org/10.1002/saj2.20037.

14. Gaskin JW, Cabrera ML, Kissel DE, Hitchcock R. Using the cover crop N calculator for adaptive nitrogen fertilizer management: A proof of concept. Renew Agric Food Syst. 2020;35:550-60. https://doi.org/10.1017/S1742170519000152.

15. Sela S, van Es HM, Moebius-Clune BN, Marjerison R, Melkonian J, Moebius-Clune D, et al. Adapt-N outperforms grower-selected nitrogen rates in northeast and Midwestern United States strip trials. Agron J. 2016;108:1726-34. https://doi.org/10.2134/agronj2015.0606.

16. White CM, Finney DM, Kemanian AR, Kaye JP. Modeling the contributions of nitrogen mineralization to yield of corn. Agron J. 2021;113:490-503. https://doi.org/10.1002/agj2.20474.

17. Trevisan RG, Bullock DS, Martin NF. Spatial variability of crop responses to agronomic inputs in on-farm precision experimentation. Precis Agric. 2020. https://doi.org/10.1007/s11119-020-09720-8.

18. Lowenberg-DeBoer J, Erickson B. Setting the record straight on precision agriculture adoption. Agron J. 2019;111:1552-69. https://doi.org/10.2134/agronj2018.12.0779.

19. Cao Q, Miao Y, Feng G, Gao X, Li F, Liu B, et al. Active canopy sensing of winter wheat nitrogen status: An evaluation of two sensor systems. Comput Electron Agric. 2015;112:54-67. https://doi.org/10.1016/j.compag.2014.08.012.

20. White CM, Bradley B, Finney DM, Kaye JP. Predicting cover crop nitrogen content with a handheld normalized difference vegetation index meter. Agric Environ Lett. 2019;4:190031. https://doi.org/10.2134/ael2019.08.0031.

21. Serrano J, Shahidian S, da Silva JM, Stafford JV. Comparing the DUALEM and VÉRIS sensors for mapping soil properties. In: Precision Agriculture '13. Academic Publishers, Wageningen. 2013:25-32. https://doi.org/10.3920/978-90-8686-778-3_1.

22. Corwin DL, Lesch SM. Characterizing soil spatial variability with apparent soil electrical conductivity: Part II. Case study. Comput Electron Agric. 2005;46:135-52. https://doi.org/10.1016/j.compag.2004.11.003.

23. Schulte EE, Hoskins B, Sims JT, Wolf A. Recommended soil organic matter tests. In: Recommended Soil Testing Procedures for the Northeastern United States. Northeast Regional Bulletin #493. 3rd ed. Newark, DE: Agricultural Experiment Station, University of Delaware; 2011. p. 63-74.

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24. Gee GW, Bauder JW. Particle size analysis. In: Klute A, editor. Methods of Soil Analysis. Part 1. Physical and Mineralogical Methods. 2nd ed. Agronomy Monograph No. 9. Madison, WI: American Society of Agronomy; 1986. p. 383-411.

25. Roth GW, White CM. Corn. In: The Agronomy Guide 2019-2020. University Park, PA: Penn State Extension; 2019. p. 61-74.

26. Stanford G. Rationale for optimum nitrogen fertilization in corn production. J Environ Qual. 1973;2:159-66. https://doi.org/10.2134/jeq1973.00472425000200020001x.

27. Binford GD, Blackmer AM, El-Hout NM. Tissue test for excess nitrogen during corn production. Agron J. 1990;82:124-9. https://doi.org/10.2134/agronj1990.00021962008200010027x.

28. Doane TA, Horwáth WR. Spectrophotometric determination of nitrate with a single reagent. Anal Lett. 2003;36:2713-22. https://doi.org/10.1081/AL-120024647.

29. NOAA. 2023 datasets | Climate Data Online (CDO) | National Climatic Data Center (NCDC). National Oceanic and Atmospheric Administration; 2023. https://www.ncdc.noaa.gov/cdo-web/datasets (accessed 18 September 2022).

30. White CM, Spargo JT, Beegle DB. Soil fertility management. In: The Agronomy Guide 2019-2020. University Park, PA: Penn State Extension; 2019. p. 21-52.

31. Beegle DB, Rotz J. Late season cornstalk nitrate test. 2009. https://extension.psu.edu/late-season-cornstalk-nitrate-test (accessed January 18, 2023).

32. Tagarakis AC, Ketterings QM. Proximal sensor-based algorithm for variable rate nitrogen application in maize in northeast U.S.A. Comput Electron Agric. 2018;145:373-8. https://doi.org/10.1016/j.compag.2017.12.031.

33. Tremblay N, Wang Z, Ma BL, Belec C, Vigneault P. A comparison of crop data measured by two commercial sensors for variable-rate nitrogen application. Precis Agric. 2009;10:145-61. https://doi.org/10.1007/s11119-008-9080-2.

34. Basso B, Dumont B, Cammarano D, Pezzuolo A, Marinello F, Sartori L. Environmental and economic benefits of variable rate nitrogen fertilization in a nitrate vulnerable zone. Sci Total Environ. 2016;545-546:227-35. https://doi.org/10.1016/j.scitotenv.2015.12.104.

35. Paz JO, Batchelor WD, Colvin TS, Logsdon SD, Kaspar TC, Karlen DL, et al. Model-based technique to determine variable rate nitrogen for corn. In: Proceedings of the Fourth International Conference on Precision Agriculture. 1999. p. 1279-89. https://doi.org/10.2134/1999.precisionagproc4.c31b.

36. Vian AL, Bredemeier C, Turra MA, da S. Giordano CP, Fochesatto E, da Silva JA, et al. Nitrogen management in wheat based on the normalized difference vegetation index (NDVI). Cienc Rural. 2018;48. https://doi.org/10.1590/0103-8478cr20170743.

37. Prabhakara K, Hively WD, McCarty GW. Evaluating the relationship between biomass, percent groundcover and remote sensing indices across six winter cover crop fields in Maryland, United States. Int J Appl Earth Obs Geoinf. 2015;39:88-102. https://doi.org/10.1016/j.jag.2015.03.002.

38. Gozdowski D, Stępień M, Bodecka E, Rozbicki J, Samborski S. Relationships between satellite derived NDVI and from ground sensors for winter wheat. In: Proceedings of the 46th International Biometrical Colloquium. 2016. https://doi.org/10.13140/RG.2.2.21340.39040.

39. Stamford JD, Vialet-Chabrand S, Cameron I, Lawson T. Development of an accurate low cost NDVI imaging system for assessing plant health. Plant Methods. 2023;19:9. https://doi.org/10.1186/s13007-023-00981-8.

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40. Duan T, Chapman SC, Guo Y, Zheng B. Dynamic monitoring of NDVI in wheat agronomy and breeding trials using an unmanned aerial vehicle. Field Crops Res. 2017;210:71-80. https://doi.org/10.1016/j.fcr.2017.05.025.

41. Gozdowski D, Stępień M, Panek E, Varghese J, Bodecka E, Rozbicki J, et al. Comparison of winter wheat NDVI data derived from Landsat 8 and active optical sensor at field scale. Remote Sens Appl Soc Environ. 2020;20:100409. https://doi.org/10.1016/j.rsase.2020.100409.

42. Corwin DL, Lesch SM. Apparent soil electrical conductivity measurements in agriculture. Comput Electron Agric. 2005;46:11-43. https://doi.org/10.1016/j.compag.2004.10.005.

43. Sudduth KA, Drummond ST, Kitchen NR. Accuracy issues in electromagnetic induction sensing of soil electrical conductivity for precision agriculture. Comput Electron Agric. 2001;31:239-64. https://doi.org/10.1016/S0168-1699(00)00185-X.

44. Peralta NR, Costa JL. Delineation of management zones with soil apparent electrical conductivity to improve nutrient management. Comput Electron Agric. 2013;99:218-26. https://doi.org/10.1016/j.compag.2013.09.014.

45. Wortmann C, Ferguson R, Schepers J, Maharjan B, Krienke B. Overall efficiency of fertilizer nitrogen use for corn production in Nebraska. CropWatch. 2019. https://cropwatch.unl.edu/2019/fertilizer-N-efficiency-Nebraska-corn (accessed January 31, 2023).

46. Bragagnolo J, Amado TJC, Bortolotto RP. Use efficiency of variable rate of nitrogen prescribed by optical sensor in corn. Rev Ceres. 2016;63:103-11. https://doi.org/10.1590/0034-737X201663010014.

47. Martins RN, de Pinto FAC, de Moura AD, da Siqueira WC, de Villar FM. Nitrogen variable rate fertilization in corn crop prescribed by optical sensor. J Plant Nutr. 2020;43:1681-8. https://doi.org/10.1080/01904167.2020.1729805.

48. Sawyer J, Mallarino A. Use of the end-of-season corn stalk nitrate test in Iowa corn production. 2018. https://store.extension.iastate.edu.

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