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NOTE AND UNIQUE PHENOMENA

Data from a public–industry partnership for enhancing corn nitrogen research

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Abstract

Improving corn (*Zeamays* L.) N managementis pertinent to economic andenvironmental objectives. However, there are limited comprehensive data sources to develop and test N fertilizer decision aid tools across a wide geographic range of soil and weather scenarios. Therefore, a public-industry partnership was formed to conduct standardized corn N rate response field studies throughout the U.S. Midwest. This research was conducted using a standardized protocol at 49 site-years across eight states over the 2014–2016 growing seasons with many soil, plant, and weather related measurements. This note provides the data (found in supplemental files), outlines the data, summarizes key findings, and highlights the strengths and weakness for those who wish to use this dataset.

Abbreviations: EONR, economic optimal nitrogen rates; PRNT, Performance and Refinement of N Fertilization Tools

1 | INTRODUCTION

To improve N management, an extensive amount of data are needed to understand how genetic x environment x management interactions impact corn (*Zea mays* L.) response to N fertilization and optimal application rate requirements. However, collecting enough data has historically been difficult, time-consuming, and expensive. Many efforts have focused on small geographic regions (e.g., within state/provincial boundaries) or the type measurements (e.g., soil, plant, sensor information), sampling times, and sampling and analysis protocols varied within the same study. The lack of common protocols between datasets has limited the ability to aggregate and analyze at a regional scale. This has particularly restricted the evaluation and development of N fertilizer rate recommendation tools across the wide range of growing environments found in the U.S. Midwest and elsewhere. Therefore, a partnership was formed between Corteva Agriscience and eight land-grant universities, and USDA-ARS to enhance understanding of corn N fertilizer response over diverse environmental conditions, and test, improve, and develop N decision aid tools. Because of a primary emphasis on the decision tools, the project was entitled “Performance and Refinement of N Fertilization Tools” or abbreviated PRNT. Here we provide the PRNT data (in supplemental files), outline the data, summarize the key findings, and highlight the strengths and weaknesses of the data in order to better assist those who wish to use this dataset for additional analyses.

Core Ideas

- Data provided from 49 corn N response trials in eight states across the U.S. Midwest.
- Data included a wide range of soil, plant, and weather measurements.
- Published manuscripts show potential methods to improve N management.

2 | DATA OVERVIEW

This dataset contains 49 site-years (2014–2016) of corn grain yield responses to added N fertilizer from eight U.S. Midwest states. Each site-year followed a standardized protocol which included the same 16 N rates, four replicates, two application timings (all at planting or the majority sidedressed; Table 1), N source (ammonium nitrate) from the same fertilizer production plant, site selection criteria (low and high productive soils within each state), data management, collaboration procedures, and explanatory variables. See Table 2 for description of all data sources and Table 3 for a summary of the sampling times. Additional background information and details about the standardized materials and methods, data management, and collaboration protocols are discussed in Kitchen et al. (2017).

To ensure the completeness and reusability of the data, each supplemental file (found in Table 2) contains metadata which explains the variable names, calculations, and provides references to protocols that were used (when applicable). To ensure high data quality, all data underwent a certification process, which followed several steps. First, principal investigators entered data into a common data template and identified suspect measurements that could be explained from field observations or known equipment malfunctions (e.g., clogged rain gauge, combine breakdowns, or weather related crop damage). Second, all principal investigator certified data were submitted to a data manager who then compiled the data. Third, statistical tests (i.e., Cook’s distances) and data comparisons (e.g., weather data compared with measurements from nearby weather stations or gridded data sources) were done and any additional observations were removed with the consent of all the principal investigators. Fourth, all compiled data were evaluated for completeness (e.g., sufficient metadata and data spot checks) by the project manager who then certified the data for use. Of note, during this process we found weather measurements were often incorrect because of

TABLE 1 Nitrogen fertilizer application treatments (ammonium nitrate; 34–0–0) including the rate and timing. Timings included all N applied at planting (“Planting”) and a split application (“Sidedress”) with some N applied at planting and the rest applied at the V9 ± 1 corn growth stage (Abendroth et al., 2011)

Treatment no.	Planting	Sidedress	Total
	———	kg N ha^{-1}	———
1	0	0	0
2	45	0	45
3	90	0	90
4	135	0	135
5	180	0	180
6	225	0	225
7	270	0	270
8	315	0	315
9	45	45	90
10	45	90	135
11	45	135	180
12	45	180	225
13	45	225	270
14	45	270	315
15	90	90	180
16	90	180	270

TABLE 2 List and description of each supplemental files. Shapefiles of the plot boundaries with the corresponding treatments are available in the "Plot_Boundaries_Shapefiles.zip" folder (see supplemental material files) and are organized by year and by state with each site-year a separate shapefile

File ID	File name and extension	Description
1	1.Site_Characterization.xlsx	Physical and chemical soil properties representing each of the four blocks in a study site. Measurements reported for four to six diagnostic horizons down to ~120 cm.
2	2.Soil_ECa.xlsx	Plot averages and raw apparent soil electoral conductivity data using a Veris 3100 (Veris technologies).
3	3.SiteHistoryandManagment.xlsx 3.SiteHistoryandManagment_SI.xlsx	Management of current-year research (e.g., dates of research and management practices, soil fertility tests and supplemental, seeding rates, and herbicide applications), historical records (e.g., crop rotation), and site description (e.g., GPS location, grade of slope, and soil series).
4	4.SoilN.xlsx	Soil nitrate and ammonium measurements taken to depths of 0–30, 30–60, and 60–90 cm.
5	5.Potentially_MineralizableN.xlsx	Potential soil mineralizable N, measured using anaerobic incubations.
6	6.Soil_Respiration.xlsx	Soil respiration (i.e., microbial activity) measured using anaerobic incubations.
7	7.RapidScan.xlsx	Active optical canopy reflectance measurements of Normalized Difference Vegetation Index (NDVI) and Normalized Difference Red Edge (NDRE) at V9±1 growth stage using a handheld RapidSCAN CS-45 (Holland Scientific).
8	8.Yield_Plant_Measurements.xlsx	Grain yield, aboveground tissue biomass, and tissue N concentration measurements.
9	9.EONR_by_site-year.xlsx	Quadratic-plateau coefficients, agronomic optimal N rates, and economic optimal nitrogen rates (EONR). All values were calculated using grain and fertilizer prices of US\$0.158 kg^{-1} (\$4.00 bu acre^{-1}) and \$0.88 kg N^{-1} (\$0.40 lb N^{-1}), respectively.
10	10.Weather.xlsx	Daily temperature (maximum and minimum), precipitation, and solar radiation. Additional columns indicate which observations were replaced and the source of the replacement data.
11	11.Irrigation.xlsx	Irrigation dates and amounts.
12	Plot Boundaries Shapefiles.zip	Shape files containing the boundaries of each plot.
13	Supplemental Descriptions.docx	A summary of reported issues and observations that may affect how each site is used in analyses.

animal interference or dust accumulation on the instrumentation. As a result, solar radiation consistently underestimated other validation datasets and therefore all solar radiation measurements were replaced with modeled data derived using an optimized Bristow–Campbell model (Bristow & Campbell, 1984). In addition, some erroneous temperature and precipitation data were replaced using the highest resolution of available gridded weather information (i.e., GridMET, NOAA MRMS, or Corteva Agriscience's internal weather network). Each replacement was documented. Of note, soil moisture data were excluded from this publication because of our low confidence in the accuracy of the data as a result of issues with instrumentation. All aerial imagery was also excluded because of a lack of standardization and usability as a result of variability in camera types, image resolution, and timing of image capture.

3 | SUMMARY OF FINDINGS

This dataset was used to answer key objectives identified as important when the PRNT project was initiated by the principal investigators, students, and postdoctoral scientists. The major objectives and findings are summarized in Table 4. Additional analyses and publications are underway that are not listed in Table 4. Along with these publications, Corteva Agriscience used this dataset for internal research on N management tools.

4 | STRENGTHS AND WEAKNESSES OF THIS DATASET

This dataset is one of a few that contains corn grain yield response to N fertilization using standardized protocols over a large regional area. Because of the standardized protocols, the large number of data sources, and metadata, this dataset will aggregate well with other data—which could further expand our understanding of corn N management. Extensive efforts have been made to overcome typical gaps found in other published datasets that would limit their use for future analysis or synthesis analysis (Eagle et al., 2017; White & van Evert, 2008).

TABLE 3 The sampling times for data listed in Table 2 (referenced using File ID numbers in parentheses). Within the table, "X" indicates sampling at all 49 sites and the "O" indicates sampling at a subset of the sites. Not all measurements were taken for all treatments (Table 1). There were minor exceptions to this timeline for a few site-years and data sources; see the actual data for more details

Data Type	At or before planting	V5	V9	VT	R4	PM	Harvest	Post-harvest
Site characterization								
Profile characterization (1)	X							
Apparent soil electrical conductivity (2)	X							
Site management								
Current and past cropping system and fertility management history (3)	X							
Soil samples								
Background soil fertility (4)	X							
Nitrate-N (4)	X	X	O	X	O			X
Ammonium-N (4)	X							
Potential mineralizable N (5)	X	X						
Soil respiration (6)	X	X						
Plant samples								
Active optical canopy reflectance (7)			X					
Biomass (8)		X	O	X	O	X		
N concentration (8)		X	O	X	O	X		
Grain samples								
Yield (8)							X	
N concentration (8)						X		
Economic optimal N rates (9)								X
Weather								
Photosynthetically active radiation (10)	[——	——	——	——	——	——	——	——]
Temperature (10)	[——	——	——	——	——	——	——	——]
Precipitation (10)	[——	——	——	——	——	——	——	——]
Irrigation (11)	[——	——	——	——	——	——	——]	

Like most research, a few sites encountered various weather-related problems which dramatically affected corn response to N fertilization. Major issues were noted within the dataset and separately in a summary document. Those interested in using these data for further analysis are advised to familiarize themselves with these issues and are encouraged to consider working with authors that have first-hand knowledge of the study. The most prominent issues are listed here:

- A 2015 Nebraska site showed a limited response to N which was believed to result from the previous soybean [*Glycine max* (L.) Merr.] crop being severely damaged from hail, resulting in grain left on the soil—which was a source of mineralizable N.
- Intensive precipitation events caused ponding with substantial N lost from the 2015 Missouri sites and extensive anoxic plant stress from the anaerobic conditions in the root zone.
- An errant 45 kg N ha^{-1} was applied on all treatments on a 2016 North Dakota site. For some analyses, adjustments taking this error into account were done (e.g., EONR).
- A high wind event late in the vegetative growth development stages resulted in lodging at one of the 2016 Iowa sites for all treatments, but especially affected treatments that received high N rates at planting.

5 | FUTURE USE OF THIS DATASET

While there were considerable investigations with this dataset and documented through publications, other objectives could be explored. For example, these data could be used for validating or developing simulation models, relating remote sensing satellite imagery to plant growth and N need, or evaluating how soil sensing measurements relate to N management. As

TABLE 4 List of published journal articles and theses using this dataset with their major objectives and key findings

Number	Citation	Objectives and main findings
1	Bandura, 2017	**Objective**: Evaluate the effect of N application timing on EONR, N use efficiency, profitability, and residual soil nitrate. Also determine the residual soil nitrate and N use efficiency values at economic optimal nitrogen rates (EONR). **Key results**: Differences in EONR as a result of N application timings were most prominent with contrasting soil drainage classes, texture, and organic matter. Nitrogen application timings had the greatest influence on when N was lost but had less influence on plant N uptake and N use efficiency. Achieving a single N use efficacy value for all production systems is not plausible. Applying N rates at EONR did not increase the potential risk of N loss to the environment.
2	Bean et al., 2018b	**Objective**: Evaluate across the U.S. Midwest Corn Belt region the performance of three locally derived active optical reflectance sensor algorithms for making in-season corn N fertilizer recommendations. **Key results**: Locally derived algorithms performed poorly on a regional scale. Farmers should use locally derived algorithms or new regional algorithms should be developed using regional based data.
3	Qin et al., 2018	**Objective**: Develop machine learning models to predict EONR at planting and for split application timings. **Key results**: Machine learning models found soil hydrological features useful for predicting EONR ($R^2 \leq .60$). Additional model improvements could occur when better estimates of in-season soil hydrological status, genetic data, and management information are used as predictors.
4	Bean et al., 2018a	**Objective**: Determine if soil and weather measurements could be used with active optical reflectance sensors to improve in-season N recommendations. **Key results**: Active optical reflectance sensor algorithms improved (r^2 of .14–.43) when soil and precipitation-based variables were included—showing the importance of considering site-specific soil and weather measurements in N management decisions.
5	Yost et al., 2018	**Objective**: Determine if N recommendations based on the Haney Soil Health Test or any of the test's components relate to EONR. **Key results**: The Haney Soil Health Test related poorly to EONR. Of the components in the Haney Soil Health Test, soil health score and the Solvita carbon dioxide-burst explained the most variability related to EONR.
6	Shafer, 2019	**Objective**: Evaluate the accuracy and variability of corn internal N efficiency values (i.e., the amount of grain dry matter produced per unit of N at physiological maturity). **Key results**: The internal N efficiency value (often used in yield-based N recommendations) varied considerably, was not related to EONR, and was difficult to predict—contributing to the inaccuracy of yield-goal based N recommendations.
7	Clark et al., 2019a	**Objective**: Evaluate using an anaerobic potentially mineralizable N test with additional variables (i.e., sampling timings, N fertilizer rates, incubation lengths, soil texture, and initial ammonia values) for predicting EONR. **Key results**: The anaerobic potentially mineralizable N poorly predicted EONR ($r^2 \leq .08$) even with improvements from partitioning soils by texture and including initial soil ammonium ($r^2 \leq .33$). This mineralization test does not improve N management compared to already established N rate recommendation tools.
8	Clark et al., 2019b	**Objective**: Determine the effect of soil and weather information on predicting anaerobic potentially mineralizable N. **Key results**: Measurements of soil, weather, and their interactions were good predictors of potentially mineralizable N ($R^2 \leq .69$). Using these measurements as surrogates to mineralization tests could help with fertilizer rate guidelines and not require additional laboratory tests.
9	Ransom et al., 2019	**Objective**: Compare statistical and machine learning algorithms for selecting and incorporating soil and weather variables into N recommendation tools. **Key results**: Machine learning algorithms helped select important variables for adjusting N recommendation tools even with a minimal number of observations. Further consideration should be given to using machine learning algorithms for developing or improving N management strategies.

(Continues)

TABLE 4 (Continued)

Number	Citation	Objectives and main findings
10	Ransom et al., 2020	**Objective**: Evaluate the performance of publicly available N recommendation tools across for prescribing N for planting and split fertilizer applications; and their economic and environmental effects. **Key results**: Of the 31 N rate decision tools tested, no one tool was universally reliable across the U.S. Midwest, but several tools that included soil nitrate tests were among the top performers. The implication of this outcome is that a generalized N recommendation tool may not be possible and that N recommendation tools should be developed based on smaller regions, unless more dynamic variables (e.g., weather) are to be included.
11	Clark et al., 2020a	**Objective**: Determine the effect of N fertilizer timing on soil nitrate, plant N uptake, and corn grain yield. Determine under what soil and weather conditions single- or split-N applications should be used to optimize corn production and minimize potential N loss. **Key results**: Split N applications resulted in similar soil nitrate, plant N uptake, and con grain yield as a single N application with noticeable exceptions based on soil (e.g., soils with high propensity for N loss, or soils that support high N mineralization and improved nutrient and water retentions) and weather measurements (e.g., uniform precipitation around the sidedress timing).
12	Clark et al., 2020b	**Objective**: Evaluate the effect of soil sampling timing, N fertilization, and incubation length on anaerobic potentially mineralizable N. **Key results**: Anaerobic potentially mineralizable N was sensitive to soil properties, weather, sampling time (pre-plant vs. in-season), N fertilization (high vs. low), and incubation period. Therefore, if used for N management, a common protocol should be established.
13	Clark et al., 2020c	**Objective**: Identify the predictability of relative yield and the frequency of over- and under-applying N fertilizer with pre-plant and pre sidedress nitrate tests in conjunction with potentially mineralizable N. **Key results**: Including an estimate of mineralizable N with other soil N tests marginally improved the predictability of relative yield (R^2 increase up to .10). This marginal improvement was not enough to promote the potentially mineralizable N test for predicting N fertilization needs.
14	Clark et al., 2020d	**Objective**: Evaluate the pre-plant and pre-sidedress nitrate tests as predictors of grain yield, N uptake, and EONR when adjusted by soil sampling depth, soil texture, temperature, and potentially mineralizable N from different sampling times and N fertilization rates. **Key results**: Grain yield, N uptake, and EONR were best predicted using the pre-sidedress nitrate test instead of the pre-plant nitrate test. Including mineralization estimates with nitrate tests only marginally improved predictions of grain yield, N uptake, and EONR and, therefore, is not suggested as a method for improving N fertilizer management.
15	Bean et al., 2020	**Objective**: Assess the relationship of soil respiration to EONR. **Key results**: Across all site-years, soil respiration was moderately related to EONR ($r^2 = .21$). When analyzed by year, the relationship improved in 2016 ($r^2 = .50$) but was poorly related in the other 2 yr ($r^2 < .20$). Soil respiration is an inconsistent stand-a-lone predictor of corn N need but has the potential to improve estimations of EONR when coupled with other variables or N recommendation tools.
16	Ransom et al., 2021	**Objective**: Improve publicly available N recommendation tools by integrating soil and weather information. **Key results**: Incorporating site-specific soil and weather information into N recommendation tools is a viable approach for improving regional corn N recommendations [r^2 values increased from $\leq .24$ (unadjusted tools) to $\leq .57$ (adjusted tools with soil and weather information)].
17	Bean et al., 2021	**Objective**: Explore, within the framework of hydrologic soil groups and drainage classifications, which site-specific soil and weather properties best estimated corn N needs. **Key results**: Soil hydrologic and drainage classifications with soil and weather measurements improved corn N need estimations when compared with state-specific N recommendations, especially when EONR <100 kg N ha^{-1}.

noted, the authors are receptive to working with those who want to use this dataset for further analyses.

The major scientific contribution of this dataset would be to continue to assist public and private institutions with developing or validating N fertilizer rate recommendation tools. Nitrogen management remains a major issue and solving it will be made easier when similar field research from different growing conditions (i.e., weather, soil, and management factors) are made available to both public and private sectors. Similar public-industry partnerships like this should be encouraged.

DATA AVAILABILITY STATEMENT

All files are available as supplemental files and in the Dryad repository: https://doi.org/10.5061/dryad.66t1g1k2g.

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AUTHOR CONTRIBUTIONS

Curtis J. Ransom: Data curation; Formal analysis; Investigation; Methodology; Project administration; Writing-original draft; Writing-review & editing. Jason Clark: Data curation; Formal analysis; Investigation; Methodology; Writing-review & editing. Gregory Mac Bean: Data curation; Formal analysis; Investigation; Methodology; Writing-review & editing. Matthew E. Shafer: Data curation; Formal analysis; Investigation; Writing-review & editing. James J. Camberato: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Project administration; Resources; Supervision; Writing-review & editing. Paul R. Carter: Conceptualization; Funding acquisition; Methodology; Project administration; Writing-review & editing. Richard B. Ferguson: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Project administration; Resources; Writing-review & editing. David W. Franzen: Conceptualization; Data curation; Investigation; Methodology; Project administration; Resources; Writing-review & editing. Carrie A.M. Laboski: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Project administration; Resources; Supervision; Writing-review & editing. D. Brenton Myers: Project administration; Resources; Writing-review & editing. Emerson D. Nafziger: Conceptualization; Data curation; Funding acquisition; Investigation; Methodology; Project administration; Resources; Writing-review & editing. John E. Sawyer: Conceptualization; Data curation; Investigation; Methodology; Project administration; Resources; Writing-review & editing. John shanahan: Conceptualization; Funding acquisition; Methodology; Project administration; Resources; Writing-review & editing.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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