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BENCHMARKING ON-FARM MAIZE NITROGEN BALANCE IN THE WESTERN U.S. CORN BELT

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BENCHMARKING ON-FARM MAIZE NITROGEN BALANCE

IN THE WESTERN U.S. CORN BELT

by

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A nitrogen (N) balance, calculated as the difference between N inputs and grain-N removal, provides an estimate of the potential N losses. We used N balance with other N-related metrics (partial factor productivity for N inputs, and yield-scaled N balance), to benchmark maize yields in relation with N input use in the US Corn Belt. We first used experimental data on grain-N concentration (GNC) to assess variation in this parameter due to biophysical and management factors. Subsequently, we used N balance and N-related metrics to benchmark yields in relation with N inputs in irrigated and rainfed fields in Nebraska using a large database (9,280 field-years). Similarly, we used this database to determine data requirements for robust N balance estimation for a given climate-soil domain and investigated the persistence of N balance. Finally, we used a database (311 field-years) with detailed management practices to identify drivers of N balance variation among fields. Analysis of experimental data indicated average GNC of 1.15%. Analysis of large database showed that irrigated exhibited smaller yield-scaled N balance than rainfed fields. There were fields that achieved high yields with small positive N balance, indicating that productivity and environmental goals can be achieved simultaneously. Important number of fields exhibited persistent large N balance over years which was associated with higher N inputs than other fields. There is substantial room to improve yield and/or reduce N balance through agronomic management like N fertilizer reduction and rotation with soybean. Important drivers of variation in N balance

were water regime, sowing date, soil organic matter, timing and split of N fertilizer application. Producers risk perception plays an important role at explaining N balance variation across fields. A robust N balance can be estimated with at least four (irrigated) and six (rainfed) years and 100 fields per year per climate-soil domain, which, together with an existing spatial framework, can serve as basis to develop strategy to collect field-level data to monitor N balance for the entire US Corn Belt region, which, in turn, can help prioritize policy and research investments to ensure productivity with small N losses from agricultural production.

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PREFACE

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1. CONCEPTUAL FRAMEWORK TO BENCHMARK ON-FARM MAIZE YIELD AND NITROGEN BALANCE

I. Crop nitrogen use

Nitrogen (N) is an essential plant nutrient. Typically, a cereal crop has a requirement of 22 kg N uptake ha^{-1} to produce one metric ton of grain. Nitrogen can easily become limiting in crop production since only a small proportion of the N present in soils is readily available for crop uptake (Godwin and Singh, 1998). Since N mineralization from soil organic matter is typically not sufficient to fully meet crop N requirement, producers apply N in the form of synthetic fertilizer or animal manure. The use of N fertilizer and/or manure is one of the pillar to produce high crop yields and meet the increased food demand on existing cropland (Cassman et al., 2002, Tilman et al., 2002). It has been estimated that, by year 2050, N fertilization would annually add 236 × 10^6 MT of N to terrestrial ecosystems (Tilman et al., 2001).

Typically, cereal crops use 50% or less of the applied N for yield production (‘recovery efficiency’) (Craswell and Godwin, 1984, Krupnik et al., 2004; Lassaletta et al., 2014). The portion of the N that is not absorbed by the crop or immobilized to build soil organic matter (SOM) may be lost to the atmosphere through volatilization, denitrification, leaching, and/or run-off. Environmental impact associated with N losses include eutrophication of coastal seas, loss of biodiversity, groundwater pollution with nitrate and nitrite, increases in greenhouse gas emissions (N_2O), and acidification of soils and surface water bodies (Howarth et al., 1996; Holland et al., 1999). Given the critical role of N in sustaining high crop productivity, together with the high potential environmental impact associated with N losses (hereafter referred to as 'N footprint'), a significant improvement in N management is needed so that productivity and environmental goals can be achieve simultaneously (Tilman et al., 2001). Ultimately, achieving synchrony between N supply and crop demand so that there is no excess (*i.e.*, N surplus) or deficiency (*i.e.*, N deficit) is the key to sustain high yields and producer profit without environmental degradation.

II. Nitrogen balance as an indicator of potential N losses

The magnitude of N losses in producers' fields can be considered as an indicator of the potential N footprint. Current approaches to quantify N losses from agricultural systems ranged from direct measurement, typically performed in experimental plots or field trials (*e.g.*, Harmel et al., 2008; Venterea et al., 2012), to *in-silico* modeling studies at regional and global levels (*e.g.*, Van Drecht et al., 2003; Howarth et al., 2006). However, there were issues with estimation of N losses using direct environmental monitoring and modeling. On the one hand, estimating N losses is complex because of the multitude of factors that can influence N losses in the environment and it is expensive, time consuming, and difficult to implement across thousands of producer fields (Connor et al., 2011; Venterea et al., 2011; Linquist et al., 2012a, b; Robertson, 2014). For example, even proxies to N losses, such as the agronomic N use efficiency or N recovery efficiency, require N-omission plots to account for temporal and spatial variation in indigenous soil N supply (Cassman et al.. 1996, 2002; Wortmann et al., 2011; van Groeningen et al., 2010). On the other hand, while process-based models to estimate N losses are promising, there is general consensus that more efforts are needed to improve their predictions (Venterea and Rolston, 2000; Kariyapperuma et al., 2011; Del Grosso et al., 2012; Roelsma and Hendriks, 2014). These models also require a large number of field-level parameters, which are usually not available in producer fields. Hence, there is a need of a simple but robust, cost-effective metric that only requires small number of parameters that are readily available at field-level.

Sources of N inputs in agricultural systems include synthetic fertilizer, manure, biological N fixation, soil organic matter (SOM) mineralization, dry and wet atmospheric deposition, nitrate-N in shallow water tables, and, in the case of irrigated agriculture, N-NO_3^- in the irrigation water (Skaggs et al., 1995; Connor et al., 2011). N outputs include SOM immobilization, grain N removal, and N losses. As detailed in Chapter 3, quantification of all sources of N inputs for a large population of producer fields is not possible as it would require expensive and laborious measurements. Hence, in our study, we used a partial N balance (simplified here as ‘N balance’) to estimate the potential N losses. The N balance is calculated as the difference between N inputs (from synthetic fertilizer, manure, and groundwater irrigation) and grain N removal. In other words, we focused on those N inputs that account for the largest fraction of total N inputs and that are readily available from producer fields. In addition, we assumed N released from SOM mineralization (which includes the inorganic soil N at sowing) to be similar to soil N immobilization, which is a reasonable assumption for soils in which SOM is near steady state as it is the case in the US Corn Belt (Baker and Griffis, 2005; Verma et al., 2005; Blanco-Canqui and Lal, 2008). The magnitude of the N balance can be taken as an indicator of potential N losses as reported by a number of previous studies (Broadbent and Carlton, 1978, van Groenigen et al, 2010, Venterea et al., 2011, Shcherbak et al., 2014, Pittelkow et al., 2014, Sanz-Cobena et al., 2014, Xu et al., 2016). A negative N balance indicates that crop N removal exceeds the N inputs; hence, if this trend persists over time, there will be progressive soil mining and declining crop productivity. In contrast, a positive N balance indicates that N inputs exceed crop N removal, leading to high potential N losses. Ideally, a near-zero N balance reduces the potential N losses, while maximizing yield and maintaining soil quality over time.

Previous attempts to use the N balance approach to diagnose current use of N fertilizer to produce grain in agricultural systems have been limited due to lack of publicly available field-level data on N inputs and outputs (yield). Due to this limitation, studies that aimed to benchmark yield and N input use have relied on N fertilizer data at coarser spatial aggregation (*e.g.*, county, state, and country) such as the National Agricultural Statistics Service (NASS, https://quickstats.nass.usda.gov/) and FAO database, http://www.fao.org/faostat/en/#data/) (Khanal et al., 2014; Lassaletta et al., 2014; Basso et al., 2019). For example, in the US, the available data on N fertilizer is available for a single average value per state and is reported every 5 years by the USDA-

Economic Research Service (https://www.ers.usda.gov/data-products/fertilizer-use-and-price/). Due to the lack of more detailed data, some studies have attempted to generate predictions of N fertilizer for small regions or even individual fields following tortuous methods (*e.g.*, fertilizer sales records, university-based N recommendations), but such predictions have not been validated on their ability to reproduce actual N fertilizer rates in producer fields (Khanal et al., 2014; Basso et al., 2019).

III. Conceptual framework to benchmark yield and N balance

Benchmarking crop yields against external input use helps to elucidate possible opportunities to increase producer profit while using the same or less amount of input. The aim of benchmarking is to compare production, economic or environmental targets with the performance of the sampled farms to identify performance, devise improved processes, identify priorities and implement improvement programs based on the results (Camp, 1989; Waterfield, 2002). Benchmarking of crop yields, farm inputs and economic factors can provide a rational basis for on-farm decision making and practice change (Franks and Collis, 2003). Previous studies have used this benchmarking approach in assessing productivity and identifying opportunities for improvements (French and Schultz, 1984; Sadras and Angus, 2006; Passioura, 2006; Grassini et al., 2009, 2011; Hochman et al., 2014; Gibson et al., 2019). Along these lines, the N balance framework can help producers benchmark their yield and N balance and compare them against other producers within their region and find means for further improvements.

The Corn Belt is located in the US North Central region, accounting for *ca.* 30% of global maize production. Large variation in N balance is typical among producer fields (Grassini and Cassman, 2012). In principle, this may suggest that there is room to improve N balance, provided that the underlying biophysical and mananagement factors explaining the variation in N balance can be identified. Following Gibson et al. (2019), our study used a benchmarking framework for N balance to assess possible ways to increase yield and/or reduce N balance in producer fields (Figure 1-1). In other words, our study aimed to identify opportunities to achieve high yields and exhibit small N balance simultenously (category A in Figure 1-1). We note that the goal is not to achieve zero N balance because that would lead to mining of soil organic matter over the long term. Instead, the aim is to keep the N balance above a level at which there is sufficient N to convert crop residues into soil organic matter while avoiding high N losses due to excessive N input application.

IV. Research goals

The main goal of the present study was to assess performance of maize systems in US Corn Belt in relation with use of N fertilizer to produce high yields and identify opportunities for improvement. In the present study, we overcome some of the limitations from previous studies aiming to assess N balance in agro-ecosystems by using a (i) large database including field-level data on yield and N inputs collected across multiple field-years, (ii) a simple, yet conceptually robust, N balance approach to estimate potential N losses, and (iii) a spatial framework to define cohort of fields located within similar climate-soil domains and upscale results from field to regional level (technology extrapolation domain [TEDs]; Rattalino Edreira et al., 2018). Similarly, a better assessment of N balance required robust estimation of grain N removal which, in turn, is calculated based on grain yield and grain N concentration (GNC). While maize producers usually know their grain yield, they rarely measure GNC. In this regard, this study assessed variation in GNC as a result of climate, soil, and management practices using experimental data compiled from experiments conducted across the US North Central region to determine the degree to which grain N removal is sensitive due to variation in GNC.

This study initially evaluated the variation in grain N removal due to variation in GNC and aimed to identify factors influencing this variation to have better GNC estimate at field level (Chapter 2). Then, the N balance framework was used in bechmarking yield against N input level using a large producer database containing 9,280 field-year observations (Chapter 3). Subsequently, the same large database was used to quantify data requirements for reliable estimation of N balance for a given climate-soil domain (Chapter 4). Lastly, a smaller producer database (that contain more robust data on biophysical and management practices in each field (total of 311 field-years) was used to identify manageable factors that can potentially improve yield and/or reduce N balance

(Chapter 5). Major findings were summarized and dicussed in a broader context, highlighting future research priorities (Chapter 6).

The specific objectives of this study were:

- to identify major factors influencing GNC and develop a predictive model for GNC estimation at field-level (Chapter 2);
- to evaluate the current spatio-temporal variation in on-farm N balance (Chapters 3, 4);
- to develop a framework to diagnose on-farm yield and N balance (Chapter 3);
- to identify the number of years and fields per year that are needed for reliable N balance estimation and assess the persistence in N balance in individual fields over time (Chapter 4);
- to identify major soil and agronomic management factors influencing variation in N balance in producer fields (Chapter 5).

REFERENCES

Baker, J.M., Griffith, T.J., 2005. Examining strategies to improve the carbon balance of corn/soybean agriculture using eddy covariance and mass balance techniques. Agric. Forest Meteorol. 128, 168–77.

Basso, B., Shuai, G., Zhang, J., Robertson, G.P., 2019. Yield stability analysis reveals sources of large-scale nitrogen loss from the US Midwest. Sci. Rep. 9, 5774. doi.org/10.1038/s41598-019-42271-1.

Blanco-Canqui, H., Lal, R., 2008. No-tillage and soil-profile carbon sequestration: An onfarm assessment. Soil Sci. Soc. Am. J. 72, 693–701.

Broadbent, F.E., Carlton, A.B., 1978. Field trials with isotopically labeled nitrogen fertilizer, in: Nielsen, D.R. (Ed.), Nitrogen in the Environment. Academic Press, San Diego, CA.

Camp, R., 1989. Benchmarking: The search for industry best practice that lead to superior performance. New York: Quality Resources.

Cassman, K.G., Gines, G.C., Dizon, M.A., Samson, M.I., Alcantara, J.M., 1996. Nitrogen-use efficiency in tropical lowland rice systems: contributions from indigenous and applied nitrogen. Field Crops Res. 47, 1–12.

Cassman, K.G., Dobermann, A., Walters, D.T., 2002. Agroecosystems, nitrogen-use efficiency, and nitrogen management. Ambio. 31, 132–140.

Connor, D.J., Loomis, R.S., Cassman, K.G., 2011. Crop Ecology. Productivity and management in agricultural systems. Cambridge Univ. Press, Cambridge, UK.

Craswell E.T., Godwin, D.C., 1984. The efficiency of nitrogen fertilizers applied to cereals grown in different climates. In: Tinker P.B., Lauchli, A. (Eds.), Advances in Plant Nutrition, Praeger Scientific, New York, New York, USA.

Del Grosso, S.J., Parton, W.J., Adler, P.R., Davis, S., Keogh, C., Marx, E., 2012. DayCent model simulations for estimating soil carbon dynamics and greenhouse gas fluxes from agricultural production systems, In: Liebig, M.A., Franzluebbers, A.J., Follet, R.F. (Eds.), Managing agricultural greenhouse gases: coordinated agricultural research through GRACEnet to address our changing climate. London, UK: Academic.

Ferguson, R.B., 2015. Groundwater quality and nitrogen use efficiency in Nebraska's Central Platte River Valley. J. Environ. Qual. 44, 449–459.

Franks, J.R., Collis, J., 2003. On-farm benchmarking: how to do it and how to do it better. Proceedings International Farm Management Congress Farming at the Edge, Perth, Australia.

French, R.J., Schultz. J.E., 1984. Water use efficiency of wheat in a Mediterranean-type environment. I. The relation between yield water use and climate. Aust. J. Agric. Res., 35, 743–764.

Gibson, K.E.B., Gibson, J., Grassini, P., 2019. Benchmarking irrigation water use in producer fields in the US central Great Plains. Environ. Res. Lett. 14, 054009.

Godwin, D.C., Singh, U., 1998. Nitrogen balance and crop response to nitrogen in upland and lowland cropping systems, In: Tsuji, G.Y., Hoogenboom, G., Thornton, P.K. (Eds.), Understanding Options for Agricultural Production. System Approaches for Sustainable Agricultural Development. Kluwer Academic Publishers, Dordrecht, Netherlands, 55–77.

Grassini, P., Hall, A.J., Mercau, J.L., 2009. Benchmarking sunflower water productivity in semiarid environments. Field Crops Res. 110, 251–262.

Grassini, P., Torrion, J.A., Cassman, K.G., Yang, H.S., Specht, J.E., 2014. Drivers of spatial and temporal variation in soybean yield and irrigation requirements in the western US cornbelt. Field Crops Res. 163:32–46. doi:10.1016/j.fcr.2014.04.005.

Grassini, P., Yang, H., Irmak, S., Thorburn, J., Burr, C., Cassman, K.G., 2011. High-yield irrigated maize in the Western U.S. Corn Belt. II. Irrigation management and crop water productivity. Field Crops Res. 120, 133–141.

Harmel, D., Qian, S., Reckhow, K., Casebolt, P., 2008. The MANAGE database: nutrient load and site characteristic updates and runoff concentration data. J. Environ. Qual. 37, 2403– 2406.

Hochman, Z., Prestwidge, D., Carberry, P.S., 2014. Crop sequences in Australia's northern grain zone are less agronomically efficient than implied by the sum of their parts. Agric. Syst. 129, 124–32.

Holland, E.A., Dentener, F.J., Braswell, B.H., Sulzman, J.M., 1999. Contemporary and pre-industrial global reactive nitrogen budgets. Biogeochemistry 46, 7–43.

Howarth, R.W., Billen, G., Swaney, D., Townsend, A., Jaworski, N., Lajtha, K., Downing, J.A., Elmgren, R., Caraco, N., Jordan, T., Berendse, F., Freney, J., Kudeyarov, V., Murdoch, P., Zhao-Liang, Z., 1996. Regional nitrogen budgets and riverine N & P fluxes for the drainages to the North Atlantic Ocean: natural and human influences. Biogeochemistry 35, 75–139.

Howarth, R.W., Swaney, D.P., Boyer, E.W., Marino, R., Jaworski, N., Goodale, C., 2006. The influence of climate on average nitrogen export from large watersheds in the Northeastern United States. Biogeochemistry 79, 163–186.

Kariyapperuma, K.A., Wagner-Riddle, C., Furon, A.C., Li, C., 2011. Assessing spring thaw nitrous oxide fluxes simulated by the DNDC model for agricultural soils. Soil Sci. Soc. Am. J. 75, 678–690.

Khanal, S., Anex, R.P., Gelder, B.K., Wolter, C., 2014. Nitrogen balance in Iowa and the implications of corn–stover harvesting. Agric. Ecosyst. Environ. 183, 21–30.

Krupnik, T. J., Six, J., Ladha, J. K., Paine, M. J., and Van Kessel, C., 2004. An assessment of fertilizer nitrogen recovery efficiency by grain crops. In: Mosier, A.R., Syers, J.K., Freney, J.R. (Eds.), Agriculture and the Nitrogen Cycle: Assessing the Impacts of Fertilizer Use on Food Production and the Environment. Paris, France, 193–207.

Lassaletta, L., Billen, G., Grizzetti, B., Anglade, J., and Garnier, J., 2014. 50 year trends in nitrogen use efficiency of world cropping systems: the relationship between yield and nitrogen input to cropland. Environ. Res. Lett. 9, 105011.

Linquist, B.A., Adviento-Borbe, M.A., Pittelkow, C.M., van Kessel, C., van Groenigen, K.J., 2012b. Fertilizer management practices and greenhouse gas emissions from rice systems: a quantitative review and analysis. Field Crops Res. 135, 10–21.

Linquist, B.A., c, K.J., Adviento-Borbe, M.A., Pittelkow, C.M., van Kessel, C., 2012a. An agronomic assessment of greenhouse gas emissions from major cereal crops. Global Change Biol. 18,194–209.

McLellan, E.L., Cassman, K.G., Eagle, A.J., Woodbury, P.B., Sela, S., Tonitto, C., Marjerison, R.D., van Es, H.M., 2018. The nitrogen balancing act: tracking the environmental performance of food production. Biosci. 68 (3), 194–203.

Passioura, J.B., 2006. Increasing crop productivity when water in scare–from breeding to field management. Agric. Water Manage. 80, 176–196.

Pittelkow, C.M., Adviento-Borbe, M.A., van Kessel, C., Hill, J.E., Linquist, B.A. 2014. Optimizing rice yields while minimizing yield-scaled global warming potential. Glob Chang Biol. 20, 1382–1393.

Rattalino Edreira, J.I. Guilpart, N., Sadras, V., Cassman, K.G., van Ittersum, M.K., Schils, R.L.M., Grassini, P., 2018. Water productivity of rainfed maize and wheat: a local to global perspective. Agr. Forest Meteorol. 259, 364–373.

Robertson, D.M., Saad, D.A., Schwarz, G.E., 2014. Spatial variability in nutrient transport by HUC8, state, and subbasin based on Mississippi/ Atchafalaya River Basin SPARROW models. J. Am. Water Resour. Assoc.50, 988–1009.

Roelsma, J., Hendriks, R.F.A., 2014. Comparative study of nitrate leaching models on a regional scale. Sci. Total Environ. 499, 481–496.

Sadras, V.O., Angus, J.F., 2006. Benchmarking water-use efficiency of rainfed wheat in dry environments. Aust. J. Agric. Res. 57, 847–856.

Sanz-Cobena, A., Lassaletta, L., Estellés, F., Del Prado, A., Guardia, G., Abalos, D., Aguilera, E., Pardo, G., Vallejo, A., Sutton, M.A., Garnier, J., Billen, G., 2014. Yield-scaled mitigation of ammonia emission from N fertilization: the Spanish case. Environ. Res. Lett. 9, 125005.

Shcherbak, I., Millar, N., Robertson, G.P., 2014. Global metaanalysis of the nonlinear response of soil nitrous oxide (N2O) emissions to fertilizer nitrogen. Proc. Natl. Acad. Sci. U.S.A. 111, 9199-9204.

Skaggs, R.W., Breve, M.A., Gilliam, J.W., 1995. Predicting effects of water table management on loss of nitrogen from poorly drained soils Eur. J. Agronomy, 4 (4), 441–451.

Tilman, D., Cassman, K.G., Matson, P.A., Naylor, R., Polasky, S., 2002. Agricultural sustainability and intensive production practices. Nature 418, 671–677.

Tilman, D., Fargione, J., Wolff, B., D'Antonio, C., Dobson, A., Howarth, R., Schindler, D., Schlesinger, W.H., Simberloff, D., Swackhamer, D., 2001. Forecasting agriculturally driven global environmental change. Science, 292, 281– 284.

Van Drecht, G., Bouwman, A.F., Knoop, J.M., Beusen, A.H.W., Meinardi, C.R., 2003. Global modeling of the fate of nitrogen from point and nonpoint sources in soils, groundwater, and surface water. Global Biogeochem. Cycles 17, 1115.

van Groenigen, J.W., Velthof, G., Oenema, O., van Groenigen, K.J., van Kessel, C., 2010. Towards an agronomic assessment of N2O emissions: A case study for arable crops. Eur J Soil Sci 61, 903–913.

Venterea, R.T., Halvorson, A.D., Kitchen, N., Liebig, M.A., Cavigelli, M.A., Grosso, S.J.D., Motavalli, P.P., Nelson, K.A., Spokas, K.A., Singh, B.P., Stewart, C.E., Ranaivoson, A., Strock, J., Collins, H., 2012. Challenges and opportunities for mitigating nitrous oxide emissions from fertilized cropping systems. Front. Ecol. Environ. 10, 562–570.

Venterea, R.T., Rolston, D. E., 2000. Mechanistic modeling of nitrite accumulation and nitrogen oxide gas emissions during nitrification. J. Environ. Qual. 29, 1741-1751.

Venterea, R.T., Maharjan, B., Dolan, M.S., 2011. Fertilizer source and tillage effects on yield scaled nitrous oxide emissions in a corn cropping system. J. Environ. Qual. 40, 1521–1530.

Verma S.B., Dobermann, A., Cassman, K.G., Walters, D.T., Knops, J.M., Arkebauer, T.J., Suyker, A.E., Burba, G.G., Amos, B., Yang, H., Ginting, D., Hubbard, K.G., Gitelson, A.A., Walter-Shea, E.A., 2005 Annual carbon dioxide exchange in irrigated and rainfed maize-based agroecosystems. Agric Forest Meteorol. 131, 77–96.

Waterfield, W., 2002. Benchmarking as a means of improving the financial wellbeing of organic dairy farms. UK Organic Research 2002: Proceedings of the COR Conference. 26-28 March 2002. Aberystwyth.

Wortmann, C.S., Tarkalson, D.D., Shapiro, C.A., Dobermann, A.R., Ferguson, R.B., Hergert, G.W., Walters, D.T., 2011. Nitrogen use efficiency of irrigated corn for three cropping systems in Nebraska. Agron. J. 103, 76–84.

Xu, Z., Christianson, L., Harmel, D., Pittelkow, C.M., 2016. Assessment of drainage nitrogen losses on a yield-scaled basis. Field Crops Res. 199, 156-166.

Zhao X., Christianson, L.E., Harmel, D., Pittelkow, C.M., 2016. Assessment of drainage nitrogen losses on a yield-scaled basis Field Crops Res. 199, 156–66.

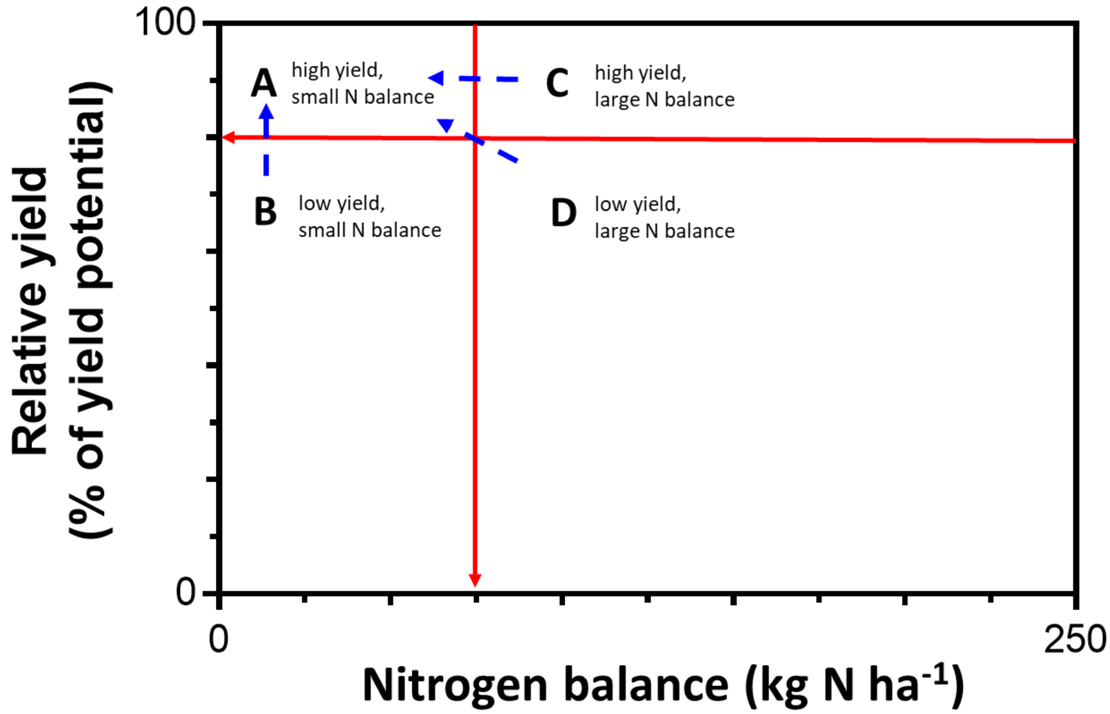

Figure 1-1. Conceptual diagram showing relative yield (RY; ratio of producer yield to simulated yield potential) *versus* nitrogen (N) balance (difference between producer N inputs (from fertilizer and applied N irrigation water] and grain N removal). Four categories are shown: (A) high RY, small N balance, (B) low RY and small N balance, (C) high RY and large N balance, and (D) low RY, and large N balance. Red solid arrows delineate categories and dashed blue arrows show possible trajectories to increase yield, reduce N balance, or both.

CHAPTER 2: ASSESSING VARIATION IN MAIZE GRAIN NITROGEN CONCENTRATION AND ITS IMPLICATIONS FOR ESTIMATING NITROGEN BALANCE IN THE US NORTH CENTRAL REGION

ABSTRACT

Accurate estimation of nitrogen (N) balance (a measure of potential N losses) in producer fields requires information on grain N concentration (GNC) to estimate grain-N removal, which is rarely measured by producers. The objectives of this study were to (i) examine the degree to which variation in GNC can affect estimation of grain-N removal, (ii) identify major factors influencing GNC, and (iii) develop a predictive model to estimate GNC, analyzing the uncertainty in predicted grain-N removal at field and regional levels. We compiled GNC data from published literature and unpublished databases using explicit criteria to only include experiments that portray the environments and dominant management practices where maize is grown in the US North Central region, which accounts for one-third of global maize production. We assessed GNC variation using regression tree analysis and evaluated the ability of the resulting model to estimate grain-N removal relative to the current approach using a fixed GNC. Across all site-year-treatment cases, GNC averaged 1.15%, ranging from 0.76 to 1.66%. At any given grain yield, GNC varied substantially and resulted in large variation in estimated grain-N removal and N balance. However, compared with GNC, yield differences explained much more variability in grain-N removal. Our regression tree model accounted for 35% of the variation in GNC, and returned physiologically meaningful associations with mean air temperature and water balance in July (*i.e.*, silking) and August (*i.e.*, grain filling), and with N fertilizer rate. The predictive model has a slight advantage over the typical approach based on a fixed GNC for estimating grain-N removal for individual site-years (root mean square error: 17 *versus* 21 kg N ha^{-1}, respectively). Estimates of grain-N removal with both approaches were more reliable when aggregated at climate-soil domain level relative to estimates for individual site-years.

Keywords: grain nitrogen concentration, grain nitrogen removal, nitrogen balance, maize

Abbreviations: ANOVA, analysis of variance; ETO, grass-based reference evapotranspiration (mm); GNC, grain nitrogen concentration (%); ME, absolute mean error; NIR, near infrared; RMSE, root mean square error; SS, sum of squares; TED, technology extrapolation domain; Tmax, maximum temperature (°C); Tmean, mean temperature (°C); Tmin, minimum temperature (°C); US, United States

2.1. INTRODUCTION

Nitrogen (N) fertilizer is an essential input to sustain high cereal yields (Cassman et al., 2002). However, mismatches between N inputs and crop N demand could result in

N losses to the environment (Erisman et al., 2013). As a result, there is growing interest in developing cost-effective indicators to evaluate the degree to which N fertilizer inputs are congruent with crop N requirements (Zhang et al., 2015). A simplified N balance, calculated as the difference between N inputs (including fertilizer, manure, symbiotic N2 fixation, deposition) and grain-N removal, can be used to assess potential for N losses in producer fields (McLellan et al., 2018 and references cited therein). However, estimating N balance depends on the calculation of grain-N removal, and while maize producers usually know the grain yield achieved on each of their fields, they rarely measure grain nitrogen concentration (GNC). Lack of GNC measurements reflects that most maize grain produced in the US is used for livestock feed, and its value derives from its energy rather than its protein content. Some maize crop models (*e.g.*, CERES-Maize; Jones and Kiniry, 1986) can simulate grain- N removal, but they require calibration and copious amounts of data inputs (*i.e.*, daily weather, soil properties, cultivar coefficients, and management practices) to be useful for predicting grain-N removal in individual fields. Additionally, previous studies have shown that these models performed relatively poor at reproducing measured GNC in field-grown maize (*e.g.*, Liu et al., 2010; Yakoub et al., 2017). Hence, at issue is how reliable the estimation of grain-N removal can be in the absence of measured GNC.

Average maize GNC has declined over time as an unintended consequence of breeders' selection for higher yields (Duvick and Cassman, 1999; Ciampitti and Vyn, 2012; DeBruin et al., 2017), and a number of published studies have aimed to understand the associated physiological drivers (Chen and Vyn, 2017 and references cited therein).

Early in the 1970s, Welch (1971) used an average GNC of 1.61% to estimate grain-N removal. Later, Boone et al. (1984) reported a mean of 1.33% based on measured data across commercial maize hybrids grown in the Midwestern US at different plant densities. A review paper by Ciampitti and Vyn (2012) reported the same mean GNC of 1.33% for maize hybrids released between 1940 to 1990, with mean GNC decreasing to 1.20% for hybrids released between 1991 and 2011. The GNC values reported here are all expressed at a standard 15.5% moisture content. Besides the long-term decline in GNC, prior studies on maize have reported substantial variation in GNC due to climate and management practices (Viets and Domingo, 1948; Zuber et al., 1954; Genter et al., 1956; Lang et al., 1956; Boone et al., 1984; Feil et al., 1990; Liang et al., 1996). In the absence of measured GNC data, the typical approach is to assume a fixed GNC from the literature. For example, the International Plant Nutrition Institute (IPNI) recommended using an average GNC of 1.2% for estimating grain-N removal in absence of measured data (http://www.ipni.net/article/IPNI-3296). However, the degree to which variation in GNC would affect the estimation of grain-N removal and N balance in individual field has not been explicitly evaluated.

There are many studies aiming to model sources of variation in GNC for winter cereals such as wheat and barley (Correll et al., 1994; Smith and Gooding, 1999; Hansen et al., 2002; Zhao et al., 2005). For instance, Correll et al. (1994) developed a predictive model based on seasonal air temperature and precipitation to explain variation in GNC for wheat and barley in South Australia. Later, Smith and Gooding (1999) reported a model showing that cultivar and N fertilizer rate were also important factors influencing

GNC in wheat. Although both environmental and management factors have been reported to influence GNC in maize, no attempt has been made to synthesize and analyze existing GNC data to generate a predictive model for maize GNC. Such a model would be useful for estimating grain-N removal and N balance in producer fields in the absence of directly measured GNC data.

In the present study, we collected existing maize GNC data from experiments conducted across the US North Central region (Figure 2-1), which is an area that accounts for *ca.* 33% of global maize production. Only data that portray the range of dominant on-farm management practices and hybrids were used for the analysis. The specific objectives were to (i) examine the degree to which variation in GNC can affect estimation of grain-N removal in maize, (ii) identify major factors influencing GNC and model these sources of variation, and (iii) evaluate an approach to estimate GNC as an alternative to a fixed GNC, analyzing the uncertainty in predicted grain-N removal at field as opposed to regional level.

2.2. MATERIALS AND METHODS

2.2.1. Database description and criteria

Published articles and online databases were screened to compile experimental data on GNC from field-grown maize across the US North Central region. Major climate, soil, and management features of maize based agroecosystems in the US North Central region are described elsewhere (Grassini et al., 2014). The search was restricted to experiments conducted during the 1999-2016 period to represent recent hybrids and management practices. Our database included observations from nine states: Illinois (IL), Indiana (IN), Iowa (IA), Kansas (KS), Minnesota (MN), Nebraska (NE), Ohio (OH), South Dakota (SD), and Wisconsin (WI) (Figure 2-1; Table 2-1). Only data from replicated experiments that meet two criteria were included: (i) field grown grain maize crops managed with current crop and soil management practices in the region, and (ii) reported data on grain yield, GNC, N fertilizer rate, and water regime (irrigated or rainfed). We thus excluded experiments sown for silage or hybrid seed production, with experimental hybrids, with outdated practices (*e.g.*, moldboard plow), or with unrealistic treatments (*e.g.*, N omission plots). Likewise, we excluded experiments in which maize was grown after alfalfa because only a very small fraction of US maize follows alfalfa and potential soil N supply following this perennial legume crop can be large and difficult to calculate. Hence, only experiments sown after maize and soybean were included because majority (>85%) of maize across the US Corn Belt region is grown continuously or in a maize-soybean rotation (Farmaha et al., 2016). Experiments receiving manure were also excluded given the difficulties to quantify N inputs from the manure. A total of 1307 site-year-treatment cases met our criteria, which were used for the subsequent analyses. The database included rainfed and irrigated crops (43 and 57% of total cases, respectively).

Since GNC and grain yield were reported across studies either at oven-dry or standard moisture content, all grain yield and GNC data were standardized to 15.5% moisture content for analysis. Reported oven-dry moisture content was assumed to be zero. GNC was measured using combustion and near infrared (NIR) in 70% and 30% of total observations, respectively. Although we did not have side-by-side data to rigorously compare GNC measured with different methods (NIR *versus* combustion), we did not find strong evidence that this would bias the analysis because average GNC (± standard deviation) differed little among experiments using NIR (1.19 ± 0.16%) *versus* combustion (1.13 ± 0.16%) to determine GNC. Additionally, results from the statistical analyses using the database with NIR- *versus* combustion-measured GNC were almost identical; hence, we showed the results using the pooled database (see Section 2.2.2). For half of the sites, geographic coordinates were available; county or nearby city were reported for the remaining sites. Other variables were available for a reasonable number of experiments (> 40%), including plant density, previous crop, artificial drainage, tillage method, N fertilizer source, N split application (yes/no), and N application timing (spring only or fall and spring). Analytical methods that can handle missing values, such as the regression tree analysis followed in this study, allowed inclusion of the full suite of data (see Section 2.2.2).

Daily maximum (Tmax) and minimum (Tmin) air temperature and precipitation were retrieved for each field from DAYMET (https:// daymet.ornl.gov/) while incident solar radiation was retrieved from the Prediction of Worldwide Energy Resources (NASA POWER, https:// power.larc.nasa.gov/) based on the coordinates or approximate site reported for each experiment. Both DAYMET and NASA POWER provide gridded weather data (resolution: 1 km^2 and 12,000 km^2, respectively). The DAYMET weather has shown good agreement with measured data for average temperature and total precipitation when summed over several months or an entire growing season (Mourtzinis et al., 2017), while NASA POWER incident solar radiation has shown strong agreement with measured records in agricultural areas with flat terrain, as in the US North Central region (van Wart et al., 2013). Informed by physiological principles (Cantarero et al., 1999; Cicchino et al., 2010; Lobell et al., 2013), key weather variables influencing crop growth and grain yield were investigated in relation to their influence on GNC. For July, which roughly coincides with silking, and for August, corresponding to grain filling in the target region, we calculated mean air temperature (*Tmean*), number of days with Tmax ≥ 32 °C, number of days with Tmin ≥ 22 °C, mean incident solar radiation, and total water balance, calculated as the difference between total precipitation and reference grass-based evapotranspiration (ETo; Allen et al., 1998). Thresholds of 22 °C (Tmin) and 32 °C (Tmax) were chosen for stressful high air temperatures for maize (Herrero and Johnson, 1980; Prasad et al., 2006a; Cicchino et al., 2010; Lobell et al., 2013). Unfortunately, dates of silking and physiological maturity were not recorded in most experiments; hence it was not possible to derive means of weather variables for specific crop phases rather than on a calendar basis. For irrigated crops, water balance was assumed to be zero as irrigation ensures adequate water supply during the entire crop season. Because coordinates were not available for *ca.* half of the experiments, and given the large spatial variability in soil properties, we did not attempt to retrieve site-specific soil parameters.

Experiments were assigned to technology extrapolation domains (TEDs; Rattalino Edreira et al., 2018). Each TED corresponds to a climate-soil domain, within which crop growth and nutrient cycling are expected to be similar. In those cases in which field coordinates were not available, experiments were assigned to the prevalent TED in the area around/within the near town/county where the study was conducted. Experiments used for the analysis were located within TEDs that account for 58% of the total US maize harvested area (Figure 2-1). Because of data imbalance among states, with higher number of experiments in NE and MN, the regression tree was repeated 20 times using resampling of 50 observations in these two states, to obtain a balanced experimental design. The test indicated that using either a balanced *versus* unbalanced number of observations or different subsets of randomly selected fields had little impact on the results. Hence, in the present study, we reported only the results derived from the regression trees using the entire database.

2.2.2. Data analysis

Nitrogen removed with harvested grain was estimated based on reported grain yield and GNC. To evaluate sensitivity of grain-N removal to variation in GNC at a given yield level, we plotted grain-N removal *versus* grain yield and fitted boundary functions using quantile regression for the 5th and 95th percentiles (Koenker and Basset, 1978) *via* the “quantreg” package (Koenker, 2017) in R (Figure 2-2). Additionally, analysis of variance (ANOVA) was performed to determine the percentage of total variance in grain-N removal explained by grain yield and GNC.

Whereas GNC varies with hybrid (Genter et al., 1956; Boone et al., 1984; Uribelarrea et al., 2004), the large number of hybrids available in the market and their fast turn over precluded adding hybrid as an explanatory factor for prediction purposes. Here we used ANOVA to discern the degree to which hybrid explains variation in GNC relative to other factors, using a subset of data that contained 12 hybrids grown consistently across 3 sites and 2 years in IL. All hybrids were grown under rainfed conditions, with N fertilizer rate of 252 kg N ha^{-1}, and plant density of 7.9 plant m^{-2}. Relative maturity ranged between 109-114 d among hybrids and GNC was measured using near infrared. Likewise, previous studies have attributed differences in GNC to a ‘dilution effect’, suggesting a trade-off between GNC and grain yield (*e.g.*, Gupta et al., 1975; Dudley et al., 1977; Boone et al., 1984; Simmonds, 1995). To assess the degree to which GNC could be explained by grain yield, linear regression models between GNC and grain yield were fitted separately for the entire database, each study, and each study-site-year.

Regression tree analysis was used to quantify the influence of weather and management variables on GNC using the “rpart” package in R (Hothorn et al., 2006). Regression tree analysis is a non-parametric method which recursively partitions the data into successively smaller groups with binary splits based on a single continuous predictor variable (Breiman et al., 1984; Verbyla, 1987; Clark and Pregibon, 1992; Prasad et al., 2006b). Regression tree analysis produces a tree-diagram output, with branches determined by splitting rules and a series of terminal nodes that contain the mean response (*i.e.*, GNC) and the number of observations that fall within each terminal node. The procedure initially grew maximal trees and then used a cross-validation technique (*i.e.*, maxdepth) to prune the over-fitted tree to an optimal size (Therneau and Atkinson, 1997). A "caret" package in R was used to split the dataset into training (80%) and testing (20%) datasets. The training dataset was used to run the regression tree analysis, while the testing dataset was utilized to estimate the mean square error (MSE) between observed and predicted GNC (Table 2-1). The regression tree analysis handled missing values in the explanatory factors (*na.rpart* function), excluding cases only if the response variable (*i.e.*, GNC) or all explanatory factors were missing. When missing values were encountered in considering a split, they were ignored and predictions are calculated from the non-missing values of that factor (Venables and Ripley, 2002). For the regression tree analysis, we excluded some variables due to high collinearity. For example, high correlation (Pearson $r = 0.87$, $P < 0.001$) was found between number of days in July with Tmax ≥ 32 °C and July *Tmean*, so we only included the latter variable (Table 2-2). Likewise, incident solar radiation in July was correlated with water balance (Pearson $r = 0.31$; $P < 0.001$) and *Tmean* (Pearson $r = 0.44$, $P < 0.001$). Additionally, source of N applied was highly associated with geographical site (ammonium nitrate was only used in MN, while urea and urea ammonium nitrate were the dominant sources in other experiments); hence, we did not include it in the analysis. Initially, previous crop (*i.e.*, maize and soybean) was included as an explanatory factor and showed to influence GNC. However, in the regression tree, previous crop only differentiated between maize or soybean *versus* no previous crop reported, hence, it was excluded as an explanatory factor. After accounting for these issues, 10 variables remained as potential explanatory factors for variation in GNC (Tables 2-3 and 2-4). This same set of explanatory factors was used to generate a regression tree for grain yield to help differentiate drivers for GNC *versus* grain yield variation (Figure 2-5).

Relationships between GNC and weather and agronomic factors that were identified as the most important at explaining GNC variation by the regression tree were further explored using linear regression. These factors included July *Tmean* and N fertilizer rate. Mean GNC and standard error were calculated for different intervals of July *Tmean* and N fertilizer rate. Duncan's multiple range test was used to determine significant differences (α =0.05) between means.

We compared the grain-N removal prediction ability of the regression tree GNC estimates with a fixed 1.2% GNC value (as recommended by IPNI in absence of measured GNC) at two spatial levels: field and climate-soil domain (*i.e.*, TED). Agreement between observed and predicted grain-N removal was evaluated using the root mean square error (RMSE) and absolute mean error (ME). Regression analysis was used to explore biases in the relationship between predicted and observed grain-N removal. Frequency distributions were used to estimate the percentage of fields with differences in observed *versus* predicted grain-N removal $\geq |20|$ kg N ha^{-1}. At the TED scale, grain-N removal was estimated by averaging the values across all fields located within the same TED (Figure 2-1). The objective of this evaluation was two-fold: (i) to discern any advantage of estimating GNC using a predictive model instead of using a fixed GNC value and (ii) to analyze the uncertainty in predicted grain-N removal at field as opposed to regional level.

2.3. RESULTS

2.3.1. Variation in grain nitrogen concentration

The database included variation in GNC, weather, and management practices that is typical of conditions across producer fields in the US North Central region (Tables 2-3 and 2-4). The GNC ranged from 0.76 to 1.66%, averaging 1.15% across all observations. Average GNC derived here was slightly, though statistically significant (*t*-test; $P < 0.001$), lower than the 1.2% reference reported by IPNI. On average, grain-N removal increased at a rate of 11.5 kg N per Mg of grain yield (Figure 2-2), although there was substantial variation in grain-N removal at a given grain yield level due to variation in GNC. Slopes of the quantile regression in Figure 2-2 indicated that GNC can vary from 0.89% to 1.41% for a given grain yield. Hence, using the recent (2013−2017) US average grain yield of 10.6 Mg ha^{-1} (https://www.nass.usda.gov), grain-N removal can vary from 94 to 150 kg N ha^{-1}, corresponding to a difference of 56 kg N ha^{-1} in the associated N balance. On the other hand, the proportion of variation in grain-N removal explained by grain yield was *ca.* three times larger than the variance accounted for by GNC (73 *versus* 25%) (Figure 2-2, inset).

2.3.2. Environment *versus* hybrid influence on grain nitrogen concentration

At issue is the degree to which GNC is influenced by hybrid. An ANOVA, using a subset with a uniform set of hybrids grown across multiple site-years in IL, showed that hybrid influenced GNC more than it affected grain yield (% of sum of squares [%SS]=32 *versus* 6%, respectively). The portion of variation explained by year, site, and their interaction (*i.e.*, environmental effects) on GNC was higher, but of same order of magnitude, compared with the variation explained by hybrid alone (%SS=49 *versus* 32). Site effect on GNC was 4-fold larger than year effect, which may reflect the importance of site-specific average weather and/or soil properties (Table 2-5).

2.3.3. Relationship between grain yield and grain nitrogen concentration

If variation in GNC is associated with a 'N dilution' effect, one would *a priori* expect a strong negative relationship between GNC and grain yield. In contrast with this expectation, we found a statistically significant, though weak, positive relationship between GNC and grain yield when the entire dataset was used ($p<0.001$; $r^2=0.02$) (Figure 2-3a). The linear regression analysis using the entire database may have been biased by differences in the environmental and/or management background across site-years. To account for this potential confounding effect, we fitted separate regressions to the data compiled from each study (Figure 2-3b) and from each study-site-year (Figure 2-3c), which indicated that there was a statistically significant negative relationship (*p*

<0.001) in only 11 and 3% of the cases, respectively. We concluded that, for our dataset, observed variation in GNC cannot be attributed to ‘N dilution’ effect due to yield. Hence, our subsequent analysis did not consider grain yield as an explanatory factor for variation in GNC.

2.3.4. Environmental factors influencing variation in grain nitrogen concentration

The regression tree explained 35% of variation in maize GNC using five variables, including July and August *Tmean*, July and August total water balance, and N fertilizer rate (Figure 2-4). July *Tmean* was the most important variable associated with GNC, with crops exposed under warm conditions during July (*Tmean* ≥ 22.5 °C) exhibiting higher GNC in relation with their counterparts with lower *Tmean* (1.17 *versus* 1.09%). The influence of high air temperature during July on GNC was amplified in fields that were also exposed to unfavorable water balance (*i.e.*, water shortage) and high air temperature in August. In contrast, N fertilizer rate was the most important factor influencing GNC in fields exposed to lower July *Tmean* (< 22.5 °C). In these fields, highest GNC was observed with large N fertilizer input and unfavorable water balance, while fields with lowest GNC were associated with small N fertilizer inputs (Figure 2-4). Fields with lowest GNC corresponded to those exposed to the same conditions as fields with highest GNC, but with lower *Tmean* during August (< 21.6 °C). Finally, the explanatory power of the regression tree for GNC was about one-half of that for grain yield (R^2 = 0.35 *versus* 0.65; Figures 2-4, 2-5) and different in relation to the driving variables.

We further investigated the relationships between GNC and two variables identified in the regression tree: July *Tmean* and N fertilizer rate (Figure 2-6). GNC increased with increasing July *Tmean* and N fertilizer rates (Figure 2-6a, b). Across the entire range of N fertilizer rates, GNC was higher in warmer environments; however, this difference was larger for small and moderate N fertilizer rates (Figure 2-6c). At high N rates (300-400 kg N ha^{-1}), there was no significant difference in GNC between fields exposed to high *versus* low July *Tmean*.

2.3.5. Comparison of grain-N removal with fixed and modelled GNC

We evaluated two methods (regression tree's estimates *versus* fixed 1.2% GNC value) on their performance to reproduce the observed grain-N removal (Figure 2-7). Predicted grain-N removal based on reported grain yield and GNC estimated from the regression tree had a slightly better fit to observed values compared with the approach based on a fixed value, with RMSE representing 12% *versus* 15% of the mean observed grain-N removal, respectively (Figure 2-7a, b). Consistent with this finding, the percentage of site-years with large differences ($\geq |20|$ kg N ha^{-1}) between predicted and observed grain-N removal was smaller using regression tree *versus* fixed GNC values (25 *versus* 36% of total fields) (Figure 2-7a, b, insets). However, both approaches underestimated grain-N removal in the upper range of observed values (> 200 kg N ha^{-1}), which was consistent with the statistically significant quadratic term revealed by our regression analysis ($P < 0.001$). Agreement between predicted and observed values at the TED level was improved compared to agreement of field-level data (average RMSE% = 9 *versus* 13%), with very little difference in accuracy between estimates based on the fixed GNC *versus* regression-tree (RMSE%: 10 *versus* 9% of observed mean) (Figure 2-7c, d).

2.4. DISCUSSION

The influence of environmental and management factors on maize GNC were assessed using data collected from multiple sites and years across the US North Central region to include field experiments that are representative of dominant management practices in producer fields. Average maize GNC calculated for the entire database was 1.15%, which was slightly lower than the commonly used GNC of 1.2%, and corresponds with a continuing decline in GNC over time (Welch, 1971; Boone et al., 1984; Duvick and Cassman, 1999; Ciampitti and Vyn, 2012). Overall, the regression tree explained 35% of variation in GNC across the US North Central region, with air temperature and water balance during July and August and N fertilizer rate identified as the most important factors explaining variation in GNC. We recognize that part of the unexplained variation could be attributed to hybrid, which could account for *ca.* one third of GNC variation as indicated by our analysis using a subset of site-years where the same set of hybrids were grown. Nonetheless, accounting for hybrid effect for predictive purpose is very difficult given the large number of hybrids available in the market and their rapid turnover. Soil factors may also account for part of the unaccounted variation in GNC. Our ANOVA indicated a much larger influence of site rather than year on GNC, which could reflect differences in soil properties, although it is difficult to separate this effect from weather variation across sites. This finding highlights the importance of collecting *in situ* key soil and topography data (*e.g.*, available-water holding capacity, soil texture, landscape position, *etc*.) or, at least, reporting of exact experiment coordinates so that these attributes can be retrieved from existing databases such as SSURGO (www.websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx). Unfortunately, soil parameters and/or field coordinates were not collected and/or missing for most of the observations in our database, so we could not include these factors in our evaluation.

Results from the regression tree analysis are consistent with current understanding of factors influencing GNC. In general, stressful weather conditions during July and August, such as high air temperature and unfavorable water balance (*i.e.*, water shortage), and high N fertilizer rates led towards high GNC, which is consistent with previous studies (Genter et al., 1956; Mayer et al., 2016). High temperature and unfavorable water balance during the kernel setting phase reduces kernel number (Hall et al., 1981; Otegui et al., 1995; Rattalino Edreira et al., 2011). Our study also suggested that unfavorable (favorable) weather conditions during August seem to amplify (ameliorate) the effect of stressful conditions during July. In relation to N supply, our analysis revealed an interactive effect of air temperature and N fertilizer rate on GNC, with largest differences in GNC between fields exposed to contrasting temperature in low N fertilizer rate conditions, which are consistent with published results for wheat (Altenbach et al., 2003).

Previous studies have reported that maize GNC tends to increase with decreasing grain yield as a result of ‘N dilution’ effect (Zuber et al., 1954; Simmonds, 1995; Uribelarrea et al., 2004). However, in the current study, GNC and yield were related weakly and inconsistently. Further, the fitted regression tree for grain yield was substantially different from the one for GNC (Figures 2-4, 2-5). A possible explanation for the discrepancy between our study and previous reports is that our database did not include extreme conditions such as severe drought, N omission plots or very high or low plant densities as in previous studies (Zuber et al., 1954; Lang et al., 1956) because these conditions are not common in producer fields. Instead, our objective was to understand GNC variation within the range of environment and management practices typically found in producer fields. Another explanation is that most studies used for our analysis included treatments with varying N fertilizer amounts which caused, in most cases, a simultaneous increase in grain yield and GNC with increasing N fertilizer input. In contrast, previous studies reporting a trade-off between GNC and grain yields for maize were based on experiments in which yield differences were a consequence of using different hybrids and/or plant densities across treatments, without changing N fertilizer amounts (*e.g.*, Gupta et al., 1975; Dudley et al., 1977; Boone et al., 1984; Simmonds, 1995). In other words, the trade-off between grain yield and GNC is not apparent when variation in yield is due to differences in N fertilizer input. In agreement with this hypothesis, a number of studies (Zuber et al., 1954; Chen and Vyn, 2017; DeBruin et al.,

2017) reported decreasing GNC with increasing yield due to improved hybrids and/or higher plant density, but the same authors reported that *both* GNC and grain yield increased with increasing N fertilizer rate.

The predictive model developed for estimating GNC is more accurate, relative to the approach using a fixed GNC value, at estimating grain-N removal and N balance for individual site-years. Hence, the predictive model can help obtain more accurate estimates of grain-N removal and N balance in producer maize fields, in absence of GNC data, although this advantage needs to be weighed against the extra data needed (weather, N fertilizer) to use the model. The predictive model underestimated grain-N removal in the upper range of observed values (> 200 kg N ha^{-1}). An implication of this finding is that grain-N removal may be underestimated in high-yield environments that favor large N uptake. Indeed, 96% of the observations with grain-N removal > 200 kg N ha^{-1} corresponded to irrigated maize in NE - a production environment where producers routinely attain yields that correspond to 80−90% of their yield potential as determined by climate and current genetics (Grassini et al., 2011). Predictions of grain-N removal using both approaches were more accurate at climate-soil domain level compared with estimates for individual site-year cases. This suggests that comparisons for these parameters (*i.e.*, grain-N removal and N balance) among climate-soil domains using aggregated values are more reliable compared with assessments for individual fields. In addition, result from this study indicates that using the fixed GNC value of 1.2% would work reasonably well for estimating grain-N removal at climate-soil domain level.

Hence, in absence of measured GNC data, the N balance approach would still provide reasonable estimates of potential N losses for major climate-soil domains where maize is grown in the US North Central region. In contrast, estimates for individual fields will be subjected to greater uncertainty and, ultimately, GNC should be measured for accurate quantification of N balance. New technologies, such as combines equipped with NIR to map protein at the same level of yield maps, may allow direct measurement of N-grain removal at field and intra-field scales in the future (Montes et al., 2006; https://grdc.com.au/resources-and-publications/grdc-update-papers/tab-content/grdc-updatepapers/ 2017/07/on-the-go-protein-sensors-using-real-time-protein-data-formore-profitable-marketing-aggregations-and-nitrogen-decisions). The methodology described in this paper for understanding sources of variation in GNC estimation could potentially be applied to other regions or crops depending upon availability of data on GNC and ancillary variables.

REFERENCES

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop Evapotranspiration: Guidelines for computing crop water requirements, FAO Irrigation and Drainage Paper 56. FAO, Rome, Italy.

Altenbach, S.B., DuPont, F.M., Kothari, K.M., Chan, R., Johnson, E.L., Lieu, D. 2003. Temperature, water and fertilizer influence the timing of key events during grain development in a US spring wheat. J. Cereal Sci. 37, 9–20.

Boone L.V., Vasilas, B.L., Welch, L.F. 1984. The nitrogen content of corn grain as affected by hybrid, population, and location. Commun Sol Sci Plant Anal. 15, 639–650.

Breiman, L., Friedman, J., Olshen, R., Stone, C. 1984. Classification and regression trees. Wadsworth, Belmont, CA.

Burzaco, J., Smith, D.R., Vyn, T.J. 2013. Nitrous oxide emissions in Midwest U.S. maize production vary widely with band-injected N fertilizer rates, timing and nitrapyrin presence. Environ. Res. Lett. 8, 1–11.

Cantarero, M.G., Cirilo, A.G., Andrade, F.H. 1999. Night temperature at silking affects set in maize. Crop Sci. 39, 703–710.

Cassman, K.G., Dobermann, A., Walters, D.T. 2002. Agroecosystems, nitrogen-use efficiency, and nitrogen management. Ambio. 31, 132–140.

Chen K., Vyn, T.J., 2017. Post-silking factor consequences for N efficiency changes over 38 years of commercial maize hybrids. Frontiers Plant Sci. 8, 1-18.

Ciampitti, I.A., Vyn, T.J. 2012. Physiological perspectives of changes over time in maize yield dependency on nitrogen uptake and associated nitrogen efficiencies: A review. Field Crops Res. 133, 48–67.

Cicchino, M., Rattalino Edreira, J.I., Uribelarrea, M., Otegui, M.E. 2010. Heat stress in field-grown maize: response of physiological determinants of grain yield. Crop Sci. 50, 1438–1448.

Clark, L.A., Pregibon, D. 1992. Tree-based models. In: Chambers, J.M., Hastie, T.J. (Eds.), Statistical models in S. Pacific Grove (CA), Wadsworth, pp. 377–419.

Correll, R., Butler, J., Spouncer, L., Wrigley, C. 1994. The relationship between grain-protein content of wheat and barley and temperatures during grain filling. Aust J Plant Physiol. 21, 869–873.

DeBruin, J.L., Schussler, J.R., Mo, H., Cooper, M. 2017. Grain yield and nitrogen accumulation in maize hybrids released during 1934 to 2013 in the US Midwest. Crop Sci. 57, 1–16.

Dobermann, A., Wortmann, C.S., Ferguson, R.B., Hergert, G.W., Shapiro, C.A., Tarkalson, D.D., Walters, D.T. 2011. Nitrogen response and economics for irrigated corn in Nebraska. Agron J. 103, 67–75.

Dudley, J.W., Lambert, R.J., de la Roche, I.A. 1977. Genetic analysis of crosses among corn strains divergently selected for percent oil and protein. Crop Sci. 17, 111-117.

Duvick, D.N., Cassman, K.G. 1999. Post-green revolution trends in yield potential of temperate maize in the north-central United States. Crop Sci. 39, 1622–30.

Erisman, J.W., Galloway, J.N., Seitzinger, S., Bleeker, A., Dise, N.B., Petrescu, A.M.R., Leach, A.M., de Vries, W. 2013. Consequences of human modification of the global nitrogen cycle. Philos Trans Royal Soc Lond B Biol Sci. 368, 1621.

Farmaha, B.S., Eskridge, K.M., Cassman, K.G., Specht, J.E., Yang, H., Grassini, P. 2016. Rotation impact on on-farm yield and input-use efficiency in high-yield irrigated maize–soybean systems. Agron. J. 108, 2313–2321.

Feil, B., Thiraporn, R., Geisler, G., Stamp, P. 1990. Genotype variation in grain nutrient concentration in tropical maize grown during a rainy and a dry season. Agronomie 10, 717–725.

Genter, C.F., Eheart, J.F., Linkous, W.N. 1956. Effect of location, hybrid, fertilizer, and rate of planting on the oil and protein content of corn grain. Agron J. 48, 63–67.

Grassini, P., Thornburn, J., Burr, C., Cassman, K.G. 2011. High-yield irrigated maize in the Western U.S. Corn Belt: I. On-farm yield, yield potential, and impact of agronomic practices. Field Crops Res. 120, 144-152.

Grassini, P., Specht, J., Tollenaar, T., Ciampitti, I., Cassman, K.G. 2014. High-yield maize-soybean cropping systems in the U.S. Corn Belt. In: Crop Physiology-Applications for genetic improvement and agronomy (2nd edition), Sadras, V.O., Calderini, D.F. (Eds). Elsevier, The Netherlands.

Gupta, D., Kovacs, I., Gaspar, L. 1975. Protein quality traits and their relationships with yield and yield components of opaque-2 and analogous normal hybrids and inbred lines. Theor Appl Genet. 45, 341-348.

Hall, A.J., Lemcoff, J.H., Trapani, N. 1981. Water stress before and during flowering in maize and its effects on yield, its components, and their determinants. Maydica 26, 19–38.

Hansen, P.M., Jørgensen, J.R., Thomsen, A. 2002. Predicting grain yield and protein content in winter wheat and spring barley using repeated canopy reflectance measurements and partial least squares regression. J. Agric. Sci. 139, 307–318.

Hothorn, T., Hornik, K., van de Wiel, M. A., Zeileis, A. 2006. A lego system for conditional inference. Am Stat. 60, 257–263.

Jones, C.A., Kiniry, J.R. 1986. CERES-Maize: A simulation model of maize growth and development, College Station, TX, U.S.A., Texas A&M University Press, pp. 194.

Kim, K.I., Clay, D.E., Carlson, C.G., Clay, S.A., Trooien, T. 2008. Do synergistic relationships between nitrogen and water influence the ability of corn to use nitrogen derived from fertilizer and soil? Agron. J. 100, 551–556.

Koenker, R., Basset, G. 1978. Regression quantiles. Econometrica. 46, 33–50.

Koenker, R. 2017. Quantreg: quantile regression. R package version 5.36, 2017 http://CRAN.R-project.org/package=quantreg.

Lang, A.L., Pendleton, J.W., Dungan, G.H. 1956. Influence of population and nitrogen levels on yield and protein and oil contents of nine hybrids. Agron. J. 48, 284–289.

Liang, B.C., MacKenzie, A.F., Zhang, T.Q. 1996. Grain yields and grain nitrogen concentration of corn as influenced by fertilizer nitrogen rate. J Agron Crop Sci. 177, 217–223.

Licht, M.A. 2015. Influence of corn seeding rate, soil attributes, and topographic characteristics on grain yield, yield components, and grain composition. *Graduate Theses and Dissertations*. 14949. https://lib.dr.iastate.edu/etd/14949.

Liu, H.L., Yang, J.Y., Drury, C.F., Reynolds, W.D., Tan, C.S., Bai, Y.L., He, P., Jin, J., Hoogenboom, G. 2010. Using the DSSAT-CERES-Maize model to simulate crop yield and nitrogen cycling in fields under long-term continuous maize production. Nutr Cycl Agroecosyst. 89, 313–328.

Lobell, D.B., Hammer, G.L. McLean, G., Messina C., Roberts, M.J., Schlenker, W. 2013. The critical role of extreme heat for maize production in the United States. Nat. Clim. Change 3, 497–501.

Mayer, L.I., Rossini, M.A., Maddonni, G.A. 2016. Heat stress during grain filling modifies kernel protein composition in field-grown maize. Crop Sci. 56, 1890–1903.

McLellan, E.L., Cassman, K.G., Eagle, A.J., Woodbury, P.B., Sela, S., Tonitto, C., Marjerison, R.D., van Es, H.S. 2018. The nitrogen balancing act: Tracking the environmental performance of food production. BioSci. 68, 194-203.

Maharjan, B., Rosen, C.J., Lamb, J.A., Venterea, R.T. 2016. Corn response to nitrogen management under fully-irrigated vs. water-stressed conditions. Agron. J. 108, 2089-2098.

Mastrodomenico, A.T., Haegele, J.W, Seebauer, J.R., Below, F.E. 2018. Yield stability differs in commercial maize hybrids in response to changes in plant density, nitrogen fertility, and environment. Crop Sci. 58, 230-241.

Montes, J., Utz, H., Schipprack, W., Kusterer, B., Muminovic, J., Paul, C., Melchinger, A. 2006. Near-Infrared spectroscopy on combine harvesters to measure maize grain dry matter content and quality parameters. Plant Breed. 125, 591–595.

Mourtzinis, S., Rattalino Edreira, J.I., Conley, S.P., Grassini, P. 2017. From grid to field: Assessing quality of gridded weather data for agricultural applications. Eur. J. Agron. 82, 163–172.

Murrell, T.S., Coulter, J.A., Nosov, V., Sawyer, J., Barker, D., Biryukova, O., Vetsch, J. 2017. Opportunities for ecological intensification approaches when yield gaps are narrow. Better Crops Plant Food. 101, 13-16.

Otegui, M.E., Andrade, F.H., Suero, E.E. 1995. Growth, water use, and kernel abortion of maize subjected to drought at silking. Field Crops Res. 40, 87–94.

Prasad, A.M., Iverson, L.R., Liaw, A. 2006. Newer classification and regression tree techniques: bagging and random forests for ecological prediction. Ecosystems. 9, 181–99.

Rattalino Edreira, J.I., Budakli Carpici, E., Sammarro, D., Otegui, M.E. 2011. Heat stress effects around flowering on kernel set of temperate and tropical maize hybrids. Field Crops Res. 123, 62–73.

Rattalino Edreira, J.I. Guilpart, N., Sadras, V., Cassman, K.G., van Ittersum, M.K., Schils, R.L.M., Grassini, P., 2018. Water productivity of rainfed maize and wheat: a local to global perspective. Agr. Forest Meteorol. 259, 364–373.

Smith, G.P., Gooding, M.J. 1999. Models of wheat grain quality considering climate, cultivar and nitrogen effects. Agric For Meteorol. 94, 159–170.

Simmonds, N.W. 1995. The relation between yield and protein in cereal grain. J. Sci. Food Agric. 67, 309-315.

Sindelar, A.J., Coulter, J.A., Lamb, J.A., Vetsch, J.A. 2013. Agronomic responses of continuous corn to stover, tillage, and nitrogen management. Agron J. 105, 1498–1506.

Sindelar, A.J., Coulter, J.A., Lamb, J.A., Vetsch, J.A. 2015. Nitrogen, stover, and tillage management affect nitrogen use efficiency in continuous corn. Agron J. 107, 843–850.

Therneau, T.M., Atkinson, E.J. 1997. An introduction to recursive partitioning using the RPART routine. Technical Report 61, Mayo Clinic, Section of Statistics.

Uribelarrea, M., Below, F.E., Moose, S.P. 2004. Grain composition and productivity of maize hybrids derived from the Illinois protein strains in response to variable nitrogen supply. Crop Sci. 44, 1593–1600.

Van Wart, J., Grassini, P., Cassman, K.G. 2013. Impact of derived global weather data on simulated crop yields. Glob. Change Biol. 19, 3822-3834.

Venables, W.N., Ripley, B.D. 2002. Modern Applied Statistics with S, fourth edition. New York: Springer-Verlag.

Verbyla, D.L. 1987. Classification trees: a new discrimination tool. Can J For Res. 17, 1150–1152.

Viets, F. G. Jr., Domingo, C.E. 1948. Yields and nitrogen content of corn hybrids as affected by nitrogen supply. Soil So Am Proc. 73, 303–306.

Welch, L.F. 1971. More nutrients are added to soil than are hauled away in crops. Illinois Research 14, No. 1, pp. 3–4.

Wortmann, C.S., Dobermann, A.R., Ferguson, R.B., Hergert, G.W., Shapiro, C.A., Tarkalson, D.D., Walters, D.T. 2009. High-yielding corn response to applied phosphorus, potassium and sulfur in Nebraska. Agron J. 101, 546–555.

Yakoub, A., Lloveras, J., Biau, A., Lindquist, J.L., Lizaso, J.I. 2017. Testing and improving the maize models in DSSAT: development, growth, yield, and N uptake. Field Crops Res. 2012, 95-106.

Zhang, X., Davidson, E.A., Mauzerall, D.L., Searchinger, T.D., Dumas, P., Shen, Y. 2015. Managing nitrogen for sustainable development. Nature 528, 51–59.

Zhao, C.J., Liu, L.Y., Wang, J.H., Huangm, W.J., Song, X.Y., Li, C.J. 2005. Predicting grain protein content of winter wheat using remote sensing data based on nitrogen status and water stress. Int J Appl Earth Obs Geoinf. 7, 1–9.

Zuber, M.S., Smith, G.E., Gehrke, C.W. 1954. Crude protein of corn grain and stover as influenced by different hybrids, plant population and N levels. Agron J. 46, 257–6

Table 2-1. Sources of data used for the analysis of variation in grain nitrogen concentration for maize in the US North Central region.

State	Citations/Link	Total number of observations†	Number of observations in training dataset
Illinois	unpublished data	30	25
	Mastrodomenico et al. (2018)	16	13
Indiana	unpublished data	16	14
	Burzaco et al. (2013)	16	13
Iowa	Licht (2015)	30	27
Kansas	unpublished data	14	11
Minnesota	Sindelar et al. (2013); Sindelar et al. (2015); Murrell et al. (2017)	442	346
	Maharjan et al. (2016)	44	34
Nebraska	Dobermann et al. (2011); Wortmann et al. (2009)	500	406
Ohio	unpublished data	8	5
South Dakota	Kim et al. (2008)	18	16
Wisconsin	unpublished data	85	66
Illinois	http://vt.cropsci.illinois.edu/corn.html	59	48
Ohio	https://u.osu.edu/perf/archive	29	23
Total		1307	1047

† Number of observations = combinations of year x site x treatment.

Table 2-2. Correlation matrix of continuous variables.

Variable	Acronym	fert	gy	gnc	wd_jul	wd_aug	rf_jul	rf_aug	sr_jul	sr_aug	tmax≥32_jul	tmax≥32_aug	tmin≥22_jul	tmin≥22_aug	tmean_jul	tmean_aug	density
N fertilizer rate (kg N/ha)	fert	1	0.365	0.263	0.255	0.252	-0.025	-0.086	0.118	0.055	0.139	0.164	-0.041	-0.035	0.077	0.116	0.000
Grain yield, (@15.5% ,Mg/ha)	gy	<.0001	1	0.127	0.521	0.492	0.059	-0.050	0.156	0.114	0.138	0.182	-0.087	-0.028	0.054	0.193	0.083
Grain N concentration (@15.5%)	gnc	<.0001	<.0001	1	0.029	0.021	-0.162	-0.124	0.090	0.263	0.325	0.324	0.349	0.196	0.399	0.331	-0.152
July total water balance (mm)	wd_jul	<.0001	<.0001	0.3009	1	0.874	0.082	-0.092	0.314	0.131	0.321	0.347	-0.008	0.081	0.206	0.302	-0.137
August total water balance (mm)	wd_aug	<.0001	<.0001	0.4485	<.0001	1	-0.181	0.126	0.262	0.087	0.308	0.354	-0.082	-0.018	0.082	0.250	-0.138
July total rainfall (mm)	rf_jul	0.3779	0.0343	<.0001	0.0032	<.0001	1	0.077	-0.228	-0.229	-0.510	-0.417	-0.260	-0.074	-0.285	-0.215	0.079
August total rainfall (mm)	rf_aug	0.002	0.0728	<.0001	0.001	<.0001	0.0058	1	-0.209	-0.571	-0.163	-0.310	-0.050	-0.121	-0.183	-0.072	0.061
July average solar radiation ($MJm^{-2}d^{-1}$)	sr_jul	<.0001	<.0001	0.0012	<.0001	<.0001	<.0001	<.0001	1	0.346	0.599	0.469	0.006	-0.272	0.437	0.265	-0.030
August average solar radiation ($MJm^{-2}d^{-1}$)	sr_aug	0.0477	<.0001	<.0001	<.0001	0.0018	<.0001	<.0001	<.0001	1	0.459	0.592	0.145	0.101	0.421	0.375	-0.034
Number of days with tmax≥32ºC in July	tmax≥32_jul	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	1	0.731	0.580	0.233	0.874	0.561	-0.140
Number of days with tmax≥32ºC in August	tmax≥32_aug	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	1	0.325	0.378	0.625	0.780	-0.106
Number of days with tmin≥22ºC in July	tmin≥22_jul	0.1383	0.0018	<.0001	0.782	0.0033	<.0001	0.0746	0.8229	<.0001	<.0001	<.0001	1	0.594	0.755	0.420	0.045
Number of days with tmin≥22ºC in August	tmin≥22_aug	0.2075	0.3232	<.0001	0.0034	0.5294	0.0077	<.0001	<.0001	0.0003	<.0001	<.0001	<.0001	1	0.376	0.485	0.007
July mean air temperature (ºC)	tmean_jul	0.0056	0.0524	<.0001	<.0001	0.0033	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	1	0.640	-0.089
August mean air temperature (ºC)	tmean_aug	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0097	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	1	-0.082
Plant density at harvest (plants m^{-2})	density	0.9919	0.0059	<.0001	<.0001	<.0001	0.0086	0.0437	0.3293	0.2602	<.0001	0.0005	0.1343	0.8117	0.0033	0.0065	1

Table 2-3. Summary statistics for maize grain nitrogen concentration and continuous variables (N fertilizer rate, weather variables, and plant density) collected from maize experiments across the US North Central region. The 25th (P25) and 75th (P75) percentiles of the distributions are also shown.

Variables	*n*	Minimum	P25	Median	Mean	P75	Maximum
Grain N concentration (g kg^{-1})	1307	0.76	1.03	1.14	1.15	1.26	1.66
Continuous variables							
N fertilizer rate (kg N ha^{-1})	1307	45	134	196	186	224	381
Total water balance (mm)	1300						
July		-314	-227	-125	-120	0	0
August		-325	-220	-122	-115	0	25
Mean air temperature (ºC)	1300						
July		18.9	21.9	23.8	23.6	25.7	27.9
August		17.8	20.9	21.6	22.1	23.7	28.2
Plant density at harvest (m^{-2})	1096	4.4	7.4	8.0	7.9	8.2	11.9

Table 2-4. Summary statistics for categorical factors used in the analysis.

Categorical variables	% observations
N application time (*n = 589*)	
spring only	89
fall and spring	11
N split application (*n =1307*)	
yes	25
no	75
Tile drainage (*n = 1030*)	
yes	30
no	70
Tillage method (*n = 715*)	
conventional [†]	81
no-till	19

[†] Conventional tillage includes chisel plow, disk, field cultivator, strip till, and vertical till.

Table 2-5. Analysis of variance (ANOVA) for the effects of year, site, hybrid, and their interactions on maize grain nitrogen concentration (GNC) and grain yield, in a factorial combination of 6 site-years by 12 commercial hybrids.

Variables	d.f.	F-value [a]		% SS (%) [b]	
		GNC (%)	Grain yield	GNC (%)	Grain yield
Year (Y)	1	40^{***}	88^{***}	7	23
Site (S)	2	95^{***}	64^{***}	32	34
Hybrid (H)	11	17^{***}	2^{*}	32	6
Y x S	2	30^{***}	33^{***}	10	17
Y x H	11	3^{***}	1	5	4
S x H	22	2^{**}	1	8	8
Y x S x H	22	2	1	6	8

[a] *F*-test significant at $^{*}P<0.05$, $^{**}P<0.01$, and $^{***}P<0.001$.
[b] Proportion (in %) of total sum of squares (SS) excluding the error.

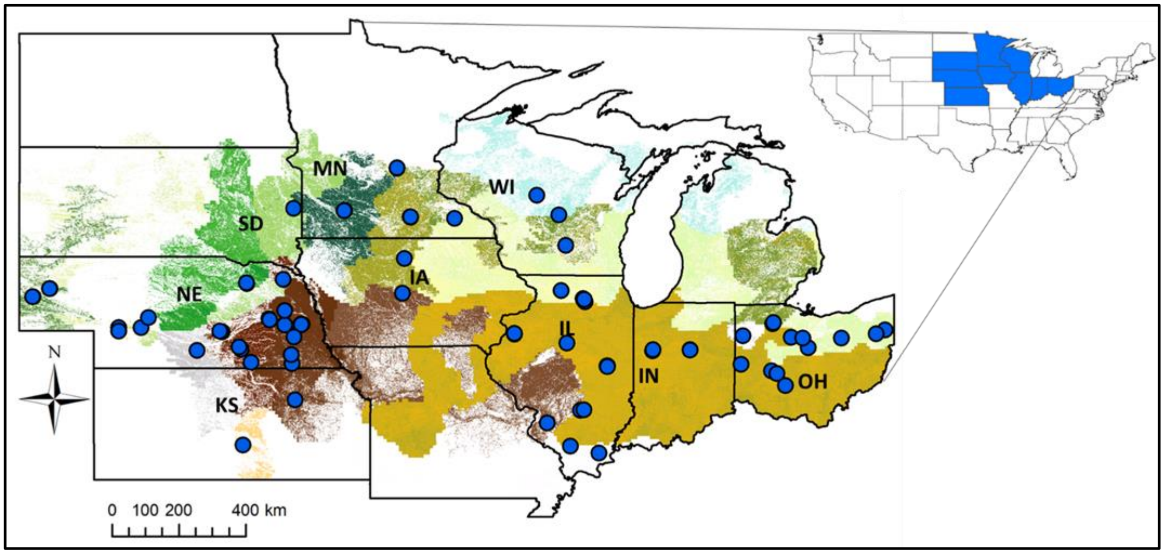

Figure 2-1. Map of US North Central region showing the sites of the experiments used in the analysis (circles). Each color represents a climate-soil combination (Technology Extrapolation Domain [TED], Rattalino Edreira et al., 2018). Experiments were located in TEDs that account for 58% of total US maize harvested area. Acronyms are: Illinois (IL), Indiana (IN), Iowa (IA), Kansas (KS), Minnesota (MN), Nebraska (NE), Ohio (OH), South Dakota (SD), and Wisconsin (WI).

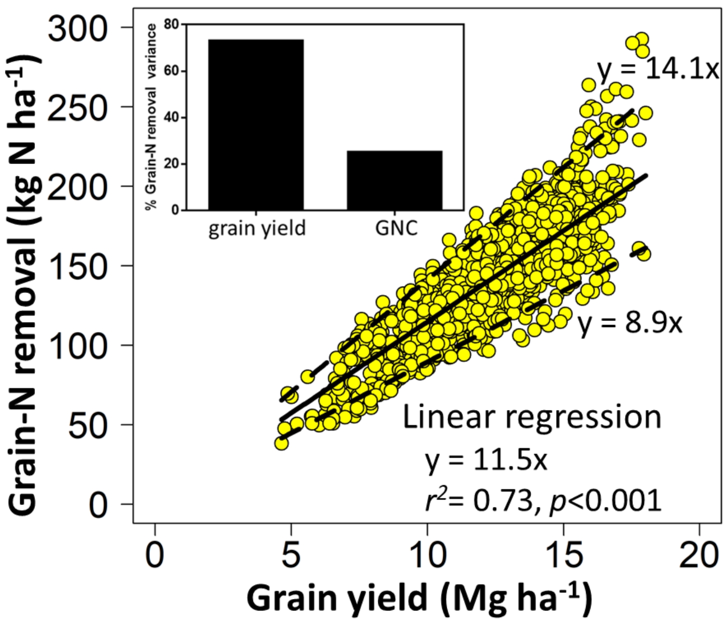

Figure 2-2. Relationship between grain-nitrogen (N) removal and grain yield based on data collected from field-grown maize across the US North Central region. Slopes of the linear regression (solid line) and boundary functions fitted for the 5th and 95th percentiles are shown (dashed lines). Fitted regressions were forced through the origin. Grain yields were reported at 15.5% moisture content. Inset shows proportion of grain-N removal variation explained by grain yield and grain N concentration (GNC).

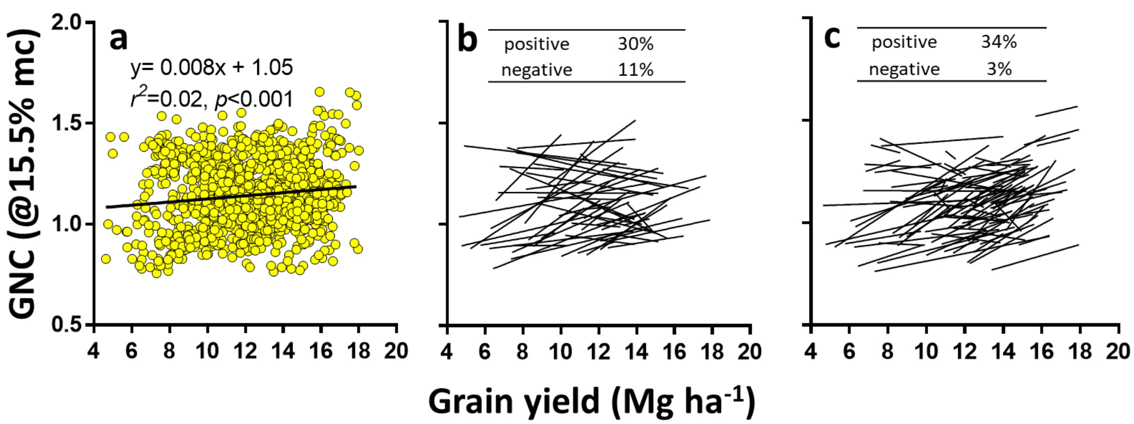

Figure 2-3. Relationships between grain nitrogen concentration (GNC) and grain yield for the entire dataset (a), each study (b), and each study-site-year (c). Data points were removed and only the fitted linear regressions are shown in (b) and (c) and percentage of cases with statistically significant positive and negative relationships are shown ($p <$ 0.001).

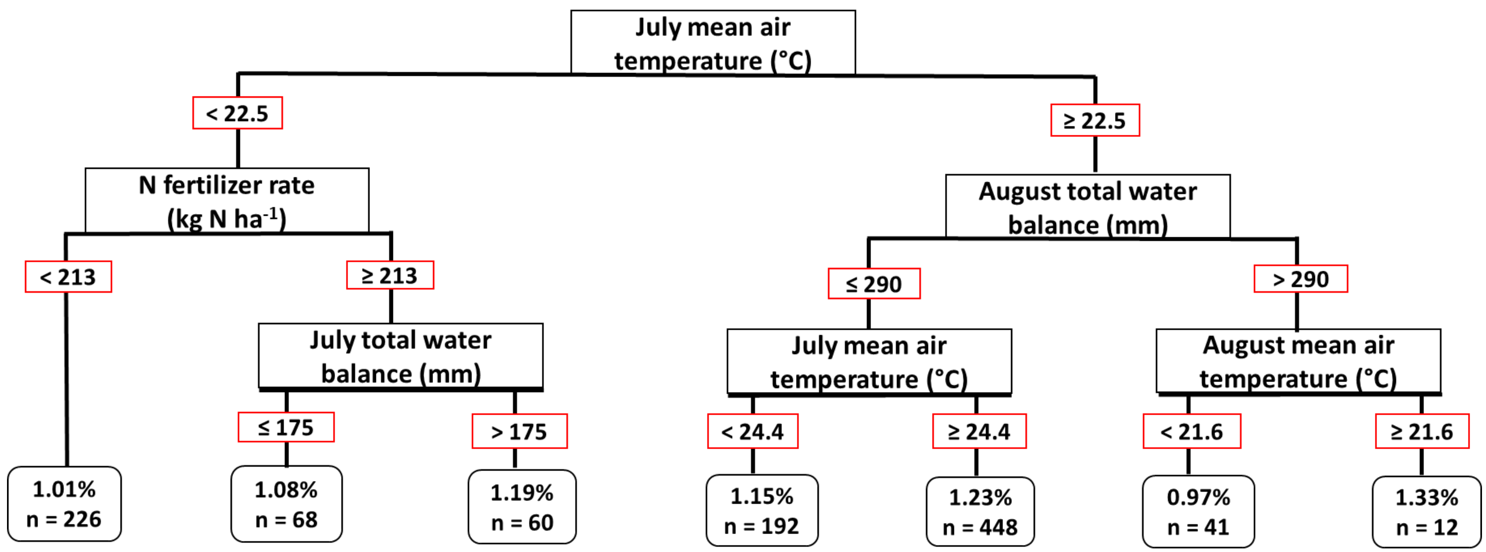

Figure 2-4. Regression tree model showing sources of variation in grain nitrogen concentration (GNC) due to weather and management factors (overall R^2=0.35; MSE=0.02%). Boxes are splitting nodes (SN), with bottom boxes representing terminal nodes (TN). Values within each TN indicate average GNC at a 15.5% moisture content basis and the number of observations (n) in each terminal node.

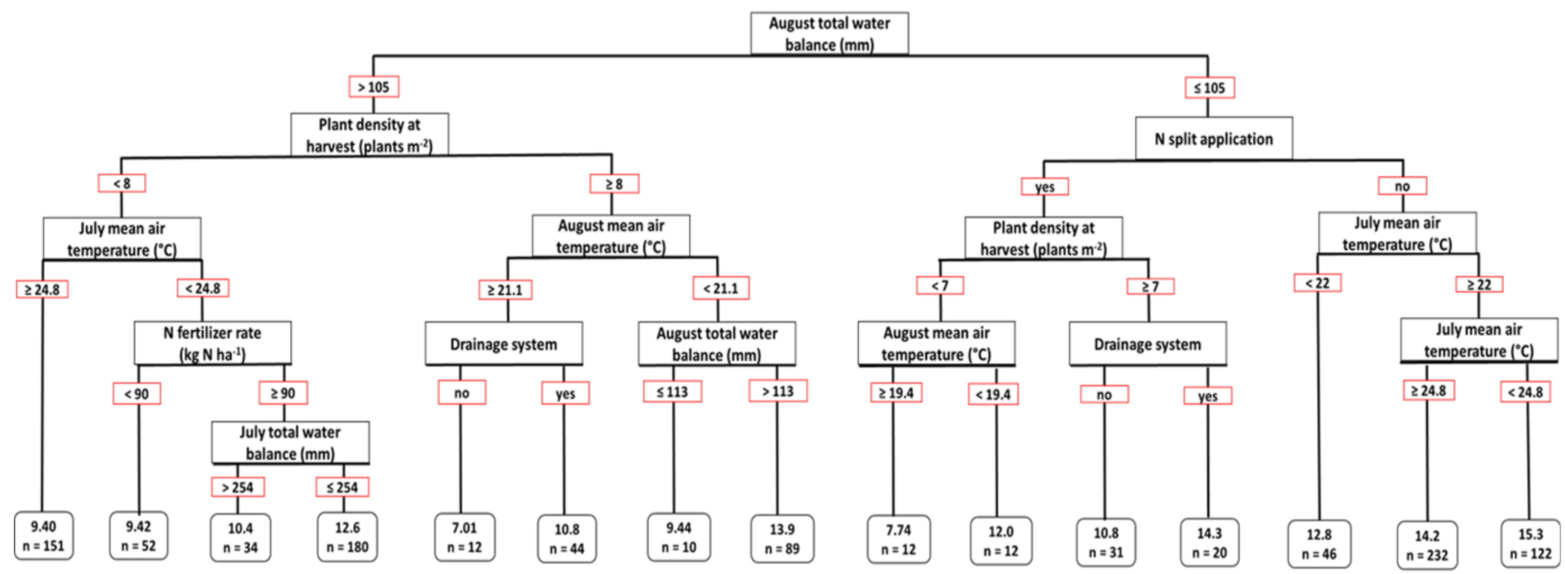

Figure 2-5. Regression tree model showing sources of variation in grain yield due to weather and management factors (overall $R^2 = 0.65$). Boxes are splitting nodes (SN), with bottom boxes representing terminal nodes (TN). Values within each TN indicate average grain yield (Mg ha^{-1}) at a 15.5% moisture content basis and the number of observations (n) in each terminal node.

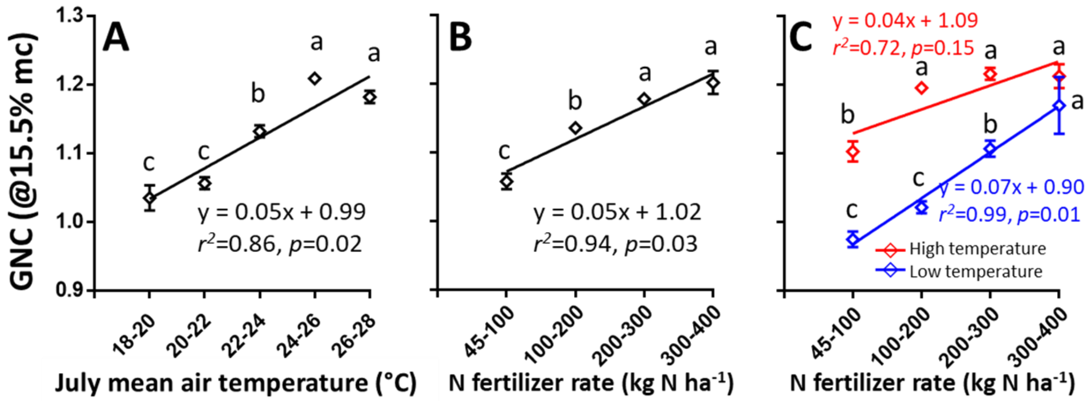

Figure 2-6. Relationships between average grain nitrogen concentration (GNC, 15.5% moisture content basis) and July mean air temperature (A) and N fertilizer rate (B). Relationship between GNC and N fertilizer rate, for fields with contrasting July mean air temperature (greater or lower than 22.5 ºC based on Figure 2-4), is shown in (C). Fitted linear regressions and their parameters are shown. Each data point represents average GNC for fields that fall within each July mean air temperature and/or N fertilizer rate interval. Vertical bars indicate the standard error of the mean. Different letters indicate statistically significant differences (Duncan's test; alpha=0.05).

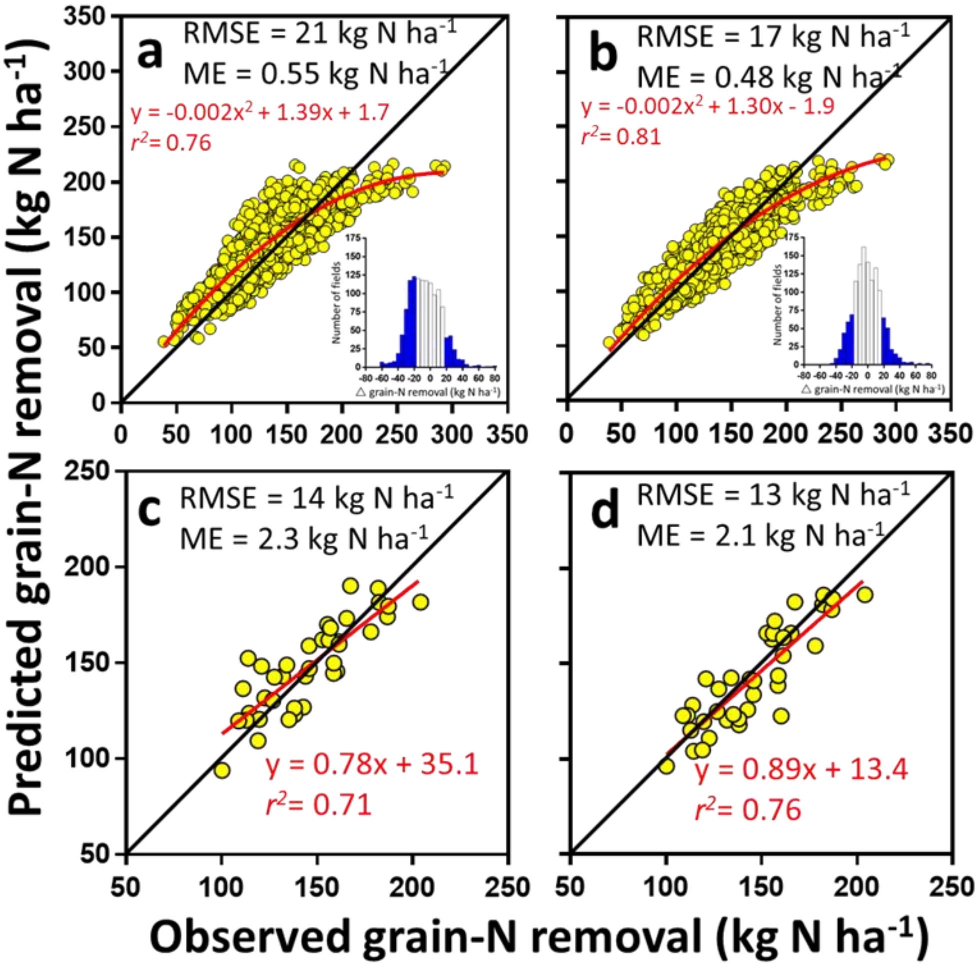

Figure 2-7. Predicted *versus* observed grain-N removal in maize for each site-year-treatment case (a, b) and for climate-soil domains (c, d). Predicted grain-N removal was calculated based on a fixed (1.2 %) grain nitrogen concentration (a, c) or based on concentration estimated from the regression tree model (b, d). Root mean square error (RMSE) and mean error (ME) are indicated and y=x (black) and quadratic or linear regression (red) lines are shown. Insets show frequency distributions for the difference between observed and predicted grain-N removal; fields with differences ≥ |20| kg N ha^{-1} are shown in blue.

CHAPTER 3: BENCHMARKING IMPACT OF NITROGEN INPUTS ON GRAIN YIELD AND ENVIRONMENTAL PERFORMANCE OF PRODUCER FIELDS IN THE WESTERN US CORN BELT

ABSTRACT

Benchmarking crop yields against nitrogen (N) input levels can help provide opportunities to improve N fertilizer efficiency and reduce N losses on maize in the US Corn Belt by identifying fields most likely to benefit from improved N management practices. Here, we evaluated a large producer database that includes field-level data on yield and applied N inputs from 9,280 irrigated and rainfed fields over a 7-year period (2009-2015) in Nebraska (USA). A spatial framework, based on technology extrapolation domains (TEDs), was used to cluster each field into spatial units with similar climate and soil type that represents 1.3 million ha of US farm land sown annually with maize. Three metrics were employed to evaluate agronomic and environmental performance: partial factor productivity for N inputs (PFP_N, ratio between yield and N inputs), N balance (difference between N inputs and grain N removal), and yield-scaled N balance (ratio between N balance and yield). Nitrogen inputs included N from fertilizer and N contained in applied irrigation water. Fields receiving manure were not included in this evaluation because they represent a relatively small proportion of US maize production area. Average yield and N inputs were 40 and 44% higher in irrigated *versus* rainfed fields. The N balance was more than 2-fold greater in irrigated *versus* rainfed fields (82 *versus*

37 kg N ha^{-1}). Of the total number of field-years, 58% (irrigated) and 14% (rainfed) had N balance ≥ 75 kg N ha^{-1}, which was considered a threshold to identify fields with potentially large N losses. Very large (> 150 kg N ha^{-1}) or negative N balance estimates were not apparent when analysis was based on field averages using a minimum of three years data instead of individual field-years. Nitrogen balance was smaller for maize crops following soybean compared to continuous maize. Despite the larger N balance (on an area basis), irrigated fields exhibited smaller yield-scaled N balance relative to rainfed fields. The approach proposed here can readily be adopted to benchmark current use of N fertilizer for other cereal-based crop systems, inform policy, and identify opportunities for improvement in N management.

Keywords: maize; yield; nitrogen; nitrogen balance; fertilizer; rotation

3.1. INTRODUCTION

Nitrogen (N) is an essential nutrient to support crop growth and a key pillar for global food security (Cassman et al., 2002; Tilman et al., 2002; Mueller et al., 2012). Sources of N that contribute to crop N supply include synthetic fertilizer, manure, biological N fixation, mineralization of soil organic matter, dry and wet atmospheric deposition, nitrate-N in shallow water tables, and, in the case of irrigated agriculture, N contained in applied irrigation water (Skaggs et al., 1995; Connor et al., 2011). Synthetic N fertilizer accounts for *ca.* half of total N input to global cropland, and increasing N fertilizer use since the middle of the 20^{th} century has been a major contributor to rapid increases in cereal crop yields (Cassman et al., 2002, Tilman et al., 2002; Foley et al., 2011). Globally, nitrogen inputs exceeding crop N requirements (*i.e.,* N surplus) are straining the capacity of the earth to meet humanity's need for clean water, clean air, and abundant, healthy food (Matson et al., 1998; Erisman et al., 2013; Steffen et al. 2015). For agriculture, the N fertilizer lost via denitrification, leaching, volatilization, and run-off is an empty investment. In contrast, N fertilizer inputs consistently below crop N requirements (*i.e.,* N deficit) can lead to soil N mining and reduced soil quality (Sanchez, 2002; Sanchez and Swaminathan, 2005). The challenge is to find an effective balance between N inputs and crop N requirements, to achieve high crop productivity while preserving soil quality and reducing environmental footprint (Zhang et al., 2012; Lassaletta et al., 2014).

Benchmarking N input use in individual fields against a large number of cohort fields may help identify fields with greatest opportunities to improve productivity and reduce overall environmental impact. However, we are not aware of previous studies that used actual field-level data to benchmark the efficacy of N inputs to produce grain and avoid N losses to the environment. Instead, studies addressing both productivity and environmental performance of agro-ecosystems in relation to N inputs can roughly be grouped in two categories. The first category includes the large number of studies conducted in experimental plots or field trials in which researchers selectively applied different N input levels or management practices and carefully measured yield and N losses (*e.g.,* Harmel et al., 2008; Venterea et al., 2012). The second category includes *in-silico* modeling studies at regional and global levels (*e.g.,* Van Drecht et al., 2003;

Howarth et al., 2006). In between these two extremes, we found few studies that explicitly aimed to benchmark on-farm yield and N input use (*e.g.*, Khanal et al., 2014; Lassaletta et al., 2014; Basso et al., 2019). However, most of these studies have relied on N fertilizer use data reported at a high level of spatial aggregation (*e.g.,* country, state). The major reason for scarcity of such studies is lack of field-level data on yield and N inputs. For example, for the Corn Belt, a large region in the north-central USA that produces *ca.* one third of global maize production, data on N fertilizer rates applied to maize are available only at the state level at 5-year intervals (USDA-ERS, https://data.ers.usda.gov/reports.aspx?ID=17883). Due to the lack of more detailed data, some studies have attempted to generate predictions of N fertilizer for small regions or even individual fields following tortuous methods (*e.g.,* fertilizer sales records, university-based N recommendations), but such predictions have not been validated on their ability to reproduce actual N fertilizer rates in producer fields (Khanal et al., 2014; Basso et al., 2019).

Accurate assessments of both the current situation and opportunities for improvement require cost-effective approaches for evaluating on-farm yield and environmental footprint in relation to N inputs to identify those fields with poor N use efficiency. To be feasible, such an approach would need to rely on a small number of parameters that are readily available from producers. To that end, we evaluated three metrics related to agronomic and environmental performance (hereby called 'N-metrics'): partial factor productivity for N inputs from fertilizer and irrigation water (PFP_N), N balance, and yield-scaled N balance. The PFP_N – the ratio between grain yield and the amount of applied N inputs (Cassman et al., 1996) – represents an N fertilizer efficiency metric and only requires data on yield and N inputs. However, while PFP_N provides an indication of N fertilizer efficiency for grain production, it tells little about potential environmental impact and long-term sustainability of the resource base. It may also give a biased assessment of agronomic performance of the cropping system. For example, high PFP_N values can result from a combination of low yields and *nil* N inputs; if this situation continues over time, it would invariably lead into soil N mining, loss of soil quality, and, at scale, a deficient cereal supply. Another metric is the partial N balance (hereafter simply referred to as 'N balance'), which is defined as the difference between N inputs and grain N removal (Treacy et al., 2008; Oenema et al., 2012; McLellan et al., 2018). As in the previous example, a persistent negative N balance over time would invariably lead to soil N mining. In contrast, a large N balance is a strong indicator of potentially large N losses. For example, in the case of maize, N losses increase exponentially when N balance exceeds 75 kg N ha^{-1} (Zhao et al., 2016; McLellan et al., 2018). An example of the application of the N balance approach is the framework for assessing N use or management developed by the European Union Nitrogen Expert Panel that considers (i) minimum amount of N input required for production; (ii) maximum N surplus that is environmentally acceptable; and (iii) minimum and maximum N use efficiency, defining a "safe operating space", which shows the most desirable range for N output and N input (EU-NEP, 2015). Other examples of application of the N balance approach include whole-farm level assessments, including dairy farms (Schroder et al., 2003; Spears et al., 2003; Cela et al., 2014). Finally, the N balance can also be expressed per unit of yield (hereafter referred to as 'yield-scaled N balance') to recognize the different land requirements associated with low- and high-yield cropping systems to meet a given production goal (Schroder et al., 2003; Grassini and Cassman, 2012). Estimating N balance and other N-metrics in producer fields can help understand potential N losses in current agro-ecosystems, on a per-area and per-output basis. Greatest opportunities for improving agronomic and environmental performance associated with N input use would most likely be found in fields with large N balance and low PFP_N.

To establish a baseline and determine the variability among maize fields in both production and environmental outcomes related to N input use, we developed an approach using producer-reported data, a combination of N-metrics (PFP_N, N balance, and yield-scaled N balance), and a spatial framework to cluster fields into near-similar climate-soil domains. We used Nebraska, (NE), USA as a study case—a state that produces 43 million MT of maize annually in *ca.* 4 million ha (USDA-NASS, 2014-2018). The assessment was based on a large database including field-level data on yield and N fertilizer rates collected from irrigated and rainfed maize over multiple years (total of 9,280 field-year observations). Specific objectives were to (i) determine current PFP_N, N balance, and yield-scaled N balance for irrigated and rainfed maize; (ii) evaluate the sensitivity of these N-metrics as a result of different levels of spatial and temporal aggregation (field averages, year averages, and individual field-year observations); and (iii) assess the influence of water regime and crop sequence on yield, N inputs, and N-metrics as a first step towards understanding how management practices affect these N performance metrics.

3.2. MATERIALS AND METHODS

3.2.1. Study region, on-farm database, and field grouping based on climate and soil

The United States accounts for 28% of global maize production (FAOSTAT, 2013-2017). About 90% of maize in the USA is produced in the north-central region, commonly referred to as the "Corn Belt", where maize is grown as monoculture or in a 2-y rotation with soybean (Grassini et al., 2014). Nebraska ranks third among USA maize producing states, with irrigated area accounting for *ca.* 58% and 65% of total NE maize cropland and production, respectively (USDA-NASS, 2014-2018). Nebraska is divided into 23 Natural Resources Districts (NRDs; www.nrdnet.org), with each NRD serving as a government entity authorized to establish regulations to conserve water and soil resource quality and quantity (Exner et al., 2010; Ferguson, 2015). Some of the NRDs require producers with fields located within their boundaries to report field-level data on yield and applied inputs every year. In the present study, we used data reported from maize fields located in four NRDs: Little Blue, Lower Platte North, Tri-Basin, and Upper Big Blue (Figure 3-1). Producer-reported data included field location (township, range, and section), maize yield (at standard moisture content of 155 g H_2O kg^{-1} grain), N fertilizer rate, irrigation amount, some management practices (previous crop, irrigation system type, and manure application), and nitrate-N (NO_3^--N) concentration contained in applied irrigation water. The database included irrigated and rainfed fields sown with maize during seven crop seasons (2009-2015) with contrasting weather conditions. For example, 2012 exhibited warmer and dry conditions, with seasonal temperature and total rainfall averaging 22°C and 202 mm, respectively, across the study area. In contrast, 2014 was cooler and wet, with seasonal temperature and total rainfall averaging 20°C and 544 mm, respectively. Water table depth was consistently below the rooting depth across the region where the reporting fields were located.

Field boundaries were mapped using Google Earth® based on the field location as provided by the NRDs. Associated data were screened for erroneous and incomplete entries, using quality control measures that set acceptable ranges for yield, N inputs, and applied irrigation. For example, fields that reported maize yields >20 Mg ha^{-1} and/or N fertilizer amounts >350 kg N ha^{-1} were excluded from the database (*ca.* 0.1% of total observations). Fields receiving manure application were excluded because (i) on average, only 5% of maize fields in NE receive manure (USDA-ERS, 2005), and (ii) it is difficult to estimate the release and amount of N from applied manure (van Kessel and Reeves, 2002). Only pivot-irrigated fields were considered for our study as surface (flood) irrigation accounts for a small fraction of irrigated maize area in NE (*ca.* 14%) and its area has steadily declined over time (USDA-ERS, 2010). Because the majority (>85%) of maize across the US Corn Belt region is grown continuously or in a maize-soybean rotation (Farmaha et al., 2016), fields sown with maize after wheat, alfalfa, or other crops besides maize and soybean were excluded from the analysis. Our study only includes fields sown with maize for grain; other maize fields sown for seed production or silage were excluded. The group of reporting fields remained the same during the 2009-2015 time period in the four NRDs.

A robust comparison of producer fields in terms of yield, N inputs, and N-metrics requires grouping fields based on those factors with greatest influence on yield potential, yield stability and, indirectly, on nutrient cycling and other variables influencing crop responses to N inputs. In the present study, maize fields were grouped into technology extrapolation domains (TEDs; Rattalino Edreira et al., 2018). Briefly, a TED corresponds to a unique combination of annual growing-degree days (GDD), aridity index (ratio between precipitation and reference ET), temperature seasonality (as quantified with standard deviation for monthly temperature), and plant available water holding capacity (PAWHC). Within a defined region, such as the US Corn Belt, the TED framework categorizes soils into cohort groups, within which climate and soils are of sufficient similarity that crop responses to management practices (including N fertilizer) are expected to be similar. Detailed description of the TED spatial framework is available at http://www.yieldgap.org/web/guest/cz-ted. For our analysis, we grouped fields into two TEDs (TED 1 and 2) which, together, account for *ca.* 1.3 million ha land in the US sown with maize every year. Both TEDs have high temperature seasonality and same GDD range (*i.e.*, 3792 – 4829 °Cd). In contrast, TED 1 had higher PAWHC (>300 *versus* 250-300 mm) and higher water limitation (*i.e.*, lower aridity index) compared to TED 2. The TED 1 only included irrigated fields, while TED 2 included both irrigated (I) and rainfed fields (R), which were disaggregated for the analysis. Hence, fields were grouped into three TED-water regime (TED-WR) combinations: TED 1I, TED 2I, TED 2R. After applying quality control measures and grouping the fields into the three TED-WRs, the database contained a total of 9,280 field-year observations; of these, 91 and 9% corresponded to irrigated and rainfed fields, respectively. On average, there were 511, 691 and 124 fields per year in TEDs 1I, 2I, and 2R, respectively.

3.2.2. On-farm data quality assessment

Previous studies have shown that NRD producer-reported data aligned well with data collected by other independent sources (Grassini et al., 2014). In this study, we further evaluated the quality of the NRD data by comparing average annual N fertilizer and yield derived from the NRD database for each TED-WR against independent estimates derived from producer survey data (Grassini et al., 2015; Gibson et al., 2019) and official statistics (USDA-NASS, http://quickstats.nass.usda.gov/; USDA-ERS, https://data.ers.usda.gov/). Survey data included two crop seasons (2010 and 2011) and a total of 55 fields located within the same NRDs in the three TED-WRs (1I, 2I, and 2R). Data were disaggregated by water regime for the comparison. For consistency, we used the 2010-2011 time period for all yield and fertilizer paired comparisons. Unfortunately, USDA ERS data on N fertilizer amount for irrigated and rainfed maize were aggregated at state level and only available for 2010; hence, the comparison against our database average N rate could not be made at the same level of spatial aggregation.

3.2.3. Retrieval of weather and soil data and simulation of yield potential for each TED-water regime in each year

Weather and soil data were retrieved to assess differences among selected TED-WR combinations. Averages of weather variables retrieved for each TED-year during the crop season (emergence to physiological maturity) were calculated for the 2009-2015 time period per TED. Average dates of emergence and physiological maturity in each year were simulated using Hybrid-Maize model (Yang et al., 2004, 2017) based on average sowing date and hybrid maturity data available for each TED-WR (Morell et al., 2016; Gibson et al., 2019) and measured daily weather data from three or four meteorological stations located within each TED (Figure 3-1). Weather variables included incident solar radiation, minimum and maximum temperature (T_{min} and T_{max}, respectively), precipitation, and Penman-Monteith grass-referenced evapotranspiration (ET_o; Allen et al., 1998). Soil variables including percentage of soil organic matter, PAWHC, and topographic wetness index (TWI) for each field were retrieved from Soil Survey Geographic database (SSURGO, https://websoilsurvey.nrcs.usda.gov). PAWHC represents the amount of water (mm) that the soil can hold between field capacity and wilting point within the rootable depth. TWI indicates the likelihood of surface runoff (run-on) from (to) an area based on slope and surrounding area, with bottom and upland areas having highest and lowest values, respectively (Sørensen et al., 2006).

Yield potential (Yp) is defined as the yield attained by an adapted crop cultivar when grown with non-limiting nutrient and water supplies and with pests and diseases effectively controlled (Evans, 1993; van Ittersum et al., 2013). Water-limited yield potential (Yw) is influenced by the same factors that define Yp but also determined by precipitation amount and distribution and soil properties that influence water availability such as PAWHC and field slope. In our study, we estimated Yp and Yw for three purposes. First, the ratio between Yw and Yp provides an objective estimate of the degree of water limitation, which is useful to discern the degree of water limitation in rainfed *versus* irrigated fields in TED 2. Second, comparison of average producer yield against simulated Yp (irrigated fields) or Yw (rainfed fields) provides an estimate of the yield gap (difference between producer yield and Yp or Yw), which is useful to understand yield performance in relation to the N balance for a given field-year. For example, a large yield gap and a large N balance suggests an opportunity to produce more yield with the same or even smaller N balance. Third, expressing producer yield as a percentage of the Yp (or Yw) for a given TED-WR-year (hereafter referred to as 'relative yield') allows a fair comparison of producer yields and N balance across years with contrasting weather conditions, which is critical in the case of rainfed fields that depends on the erratic fluctuation in precipitation amount and distribution across years.

We used Hybrid-Maize model (Yang et al., 2006, 2017) to estimate Yp (irrigated) and Yw (rainfed) for each TED-WR-year combination. Hybrid-Maize model has been widely evaluated for its ability to estimate yield potential in well-managed crops that grew without nutrient limitations and kept free of biotic stresses (Yang et al., 2004; Grassini et al., 2009a). Because the goal was to estimate the maximum possible yield that results from the best possible management in each TED-WR, we selected the combination of sowing date, hybrid maturity, and plant density that give the highest yield in each TED-WR based on previous survey data (Farmaha et al., 2016; Gibson et al., 2019). Data inputs and model parameters used to simulate Yp or Yw are shown in Tables 3-1 and 3-2. Producer yield exceeded simulated Yp (or Yw) in 4% of the total field-year observations, likely due to inaccuracies in weather, soil, or producer yield data. For the purposes of this analysis, relative yield was set at one when producer yield exceeded Yp (or Yw).

3.2.4. Calculation of partial factor productivity for nitrogen (N) inputs, N balance, and yield-scaled N balance

The N inputs include N from synthetic fertilizer, applied irrigation water (in the case of pivot-irrigated fields), manure, atmospheric dry and wet deposition, inorganic soil N at sowing, and soil organic matter (SOM) mineralization during the crop season. Quantification of all N input sources for a large population of producer fields would require expensive and laborious measurements. Hence, we focused on those N inputs that account for the largest fraction of total N inputs and that are readily available from producer fields. In our study, we excluded fields receiving manure application as this is not a common practice in NE. In the case of atmospheric N deposition, NE is situated far from industrial areas and overall annual N deposition has been estimated to be very small (<10 kg N ha^{-1}; NADP, USDA-REEIS, https://reeis.usda.gov/web/crisprojectpages/1007486-the-national-atmospheric-deposition-program-nadp.html). We assumed N released from SOM mineralization (which includes the inorganic soil N at sowing) to be similar to soil N immobilization, which is a reasonable assumption for soils in which SOM is near steady state as it is the case in the US Corn Belt (Baker and Griffis, 2005; Verma et al., 2005; Blanco-Canqui and Lal, 2008). In contrast, the amount of N contained in applied irrigation water (hereafter referred to as "N irrigation") cannot be neglected for irrigated fields (Grassini et al., 2014; Ferguson, 2015). Hence, we considered N from both fertilizer and applied irrigation water for our calculation of PFP_N, N balance, and yield-scaled N balance.

Nitrogen added *via* irrigation was calculated from reported irrigation amount and NO_3^--N concentration in groundwater. For field-years with no data to estimate N irrigation (because irrigation amount and/or NO_3^--N concentration were not available), we used the average N irrigation calculated for other fields located within the same TED-WR-year. Because irrigation amounts were not reported for TED2I, we estimated an irrigation amount consistent across all fields within a TED-year, using the relationship between seasonal water deficit and on-farm irrigation amount for silt loam soils reported by Gibson et al. (2018) for the same region. While the NO_3^--N concentration used was the average value estimated across fields in TED2. We note that N irrigation accounts for a relatively small portion of the N inputs (*ca.* 11%), so the estimation of N irrigation for TED 2I is unlikely to bias results.

Partial factor productivity for N inputs (PFP_N) was calculated as the ratio between yield and N inputs. The N balance was calculated as the difference between N inputs and grain N removal. Maize grain N removal was estimated based on producer yield, assuming a grain nitrogen concentration of 11.5 g kg^{-1} grain (at standard moisture content of 155 g H_2O kg^{-1} grain) as derived from a recent review study for the US Corn Belt (Tenorio et al., 2019). We note that the goal is not to achieve zero N balance because that would lead to mining of soil organic matter for its mineralized N. Instead, here we used a threshold of 75 kg N ha^{-1} to identify fields with large N balance and, hence, potentially large N losses (Zhao et al., 2016; McLellan et al., 2018). Using data from individual field-year may give a biased assessment of producer performance in relation with using N inputs to produce grain. For example, a severe drought (*e.g.,* year 2012) would reduce yield and lead to a relatively large N balance in rainfed fields. Likewise, a severe soil mining can be (wrongly) inferred from a field that (purposely) received little N fertilizer in a specific year because of large residual soil N from previous crop as measured using soil nitrate tests. To evaluate the degree to which our estimates of N balance may be biased due the aformentioned factors, we calculated the N balance at three different levels of aggregation: (i) individual field-years, (ii) individual fields with N balance averaged across years, and (iii) individual years with N balance averaged across fields. In the case of (ii), we included only those fields with at least three years of data. Finally, the yield-scaled N balance was calculated as the ratio between N balance and producer yield.

Frequency distributions were used to assess variation in yield, N inputs, and N-metrics. Deviation from normality was tested using D’Agostino-Pearson normality test. In addition, a three-way analysis of variance (ANOVA) was used to quantify the influence of TED-WR, year, previous crop, and their interactions at explaining observed variation on yield, N inputs, N balance, PFP_N, and yield-scaled N balance. Proportion of sum of squares (%SS) attributable to each term was computed after excluding the error. Mean contrasts were used to assess the overall effect of water regime and crop sequence on the different parameters. Tukey's test was used to determine statistically significant differences among averages (α= 0.05). Yield *versus* N balance plots were assessed to determine the frequency of fields with small or large N balance and low or high yield. The analysis was also performed using relative yield (as % of Yp or Yw) to account for weather variation across years, TEDs, and WR. Fields were subsequently grouped in four categories: (A) high relative yield, N balance <75 kg N ha^{-1}; (B) low relative yield, N balance <75 kg N ha^{-1}; (C) high relative yield, N balance ≥75 kg N ha^{-1}; (D) low relative yield, N balance ≥75 kg N ha^{-1}. Following Lobell et al. (2009) and van Ittersum et al. (2013), we used 80% and 70% of Yp and Yw as thresholds to distinguish high *versus* low yields in irrigated and rainfed fields, respectively. These values represent reasonable yield goals, with the smaller yield goal in the case of rainfed crops aiming to account for the higher production risk associated with erratic rainfall across years.

3.3. RESULTS

3.3.1. On-farm yield, N inputs, and N-metrics across climate x soil x water regime domains

Averages of meteorological variables were similar between the three TED-WRs, except for ET_o, which tended to be higher in TED 1 *versus* TED 2 (Table 3-3). Irrigated fields exhibited higher PAWHC and TWI, and lower soil organic matter in TED 1 compared with TED 2. Within TED 2, irrigated fields had higher soil organic matter and TWI compared with rainfed fields, explained by the fact that pivot-irrigated fields are usually located in the best soils and give higher yields, which means increased mass of returned crop residues. Weather and soil parameters exhibited relatively small year-to-year and field-to-field variation, respectively, as indicated by their respective coefficients of variation (CVs ≤16%); although total precipitation was an important exception, exhibiting large variation across years in both TEDs (CVs = 30-35%) (Table 3-3).

Averages for NRD yield and N fertilizer were in reasonable agreement with estimates derived from independent survey data, collected from fields located in same NRD, with differences among databases within ±4% of NRD averages (Table 3-4). Similarly, there was good agreement between NRD and NASS maize yields (differences <4%). In contrast, average statewide N fertilizer data reported through official statistics was 7-10% (irrigated) and 5% (rainfed) lower than average N fertilizer rate as reported to the NRDs. Inclusion of other regions of NE with lower maize yields and, probably, lower fertilizer N amounts in the calculation of the statewide average (for the official statistics) may explain these differences. Indeed, our study area has slightly higher average irrigated and rainfed maize yields (13.4 and 9.3 Mg ha^{-1}) compared with the state averages (12.7 and 9.0 Mg ha^{-1}; USDA-NASS, 2013-2017).

Average producer yield represented *ca.* 81% of simulated Yp for irrigated fields and *ca.* 70% of Yw for rainfed crops (Table 3-5). The Yw for rainfed maize in TED 2 was *ca.* 30% lower and three times more variable compared with the simulated Yp for irrigated maize in the same TED. Average yield and inter-annual CV for irrigated maize is similar to those reported for favorable rainfed maize production environments in the central and eastern portions of the US Corn Belt, including Iowa, Illinois, and Indiana (Grassini et al., 2014).

Frequency distributions for irrigated and rainfed producer field yields were negatively skewed, with the majority of the fields closer to highest yields (Figures 3-2 a, c). TED-WR had the greatest influence on yield and N inputs, accounting for 70-90% of SS excluding the error, with the rest of the modelled variation mostly explained by year, TED-WR x year interaction, and, in the case of N inputs, also by previous crop (Table 3-6). This result was expected as the TED-WR stratification aimed to account for differences in climate, soil, and water supply between regions and water regimes. Average producer yield was *ca.* 40% lower (and 5x more variable) in rainfed *versus* irrigated fields (Table 3-6). Consistent with the yield difference, average N input was 44% higher in irrigated *versus* rainfed fields (Figures 3-2 b, d). In contrast to crop yield, the degree of inter-annual variation for N inputs was identical for both water regimes (CV = 6%). Distribution of field-level N inputs was normally distributed in irrigated fields but positively skewed in rainfed fields, indicating that a relatively smaller number of fields received much larger N inputs than the rest of the fields. In irrigated fields, N fertilizer exhibited a negatively skewed distribution (skewness = -0.19). Average N irrigation represented 11% of the N input in irrigated fields, exhibiting larger inter-annual variation compared with N fertilizer (CV = 41 *versus* 4%) as a result of variation in irrigation amounts across years in response to water demand as affected by weather (Figure 3-2b, inset).

Frequency distribution for N balance and PFP_N showed contrasting patterns between water regimes: the N balance was negatively and positively skewed in irrigated and rainfed fields, respectively (Figures 3-3 a, d) while PFP_N exhibited the inverse trend (Figures 3-3 b, e). However, yield-scaled N balance was positively skewed in both water regimes, indicating that a relatively smaller number of fields in irrigated (1%) and rainfed (9%) exhibited very large yield-scaled N balance (> 15 kg N Mg^{-1} grain).

The TED-WR term of our ANOVA explained *ca.* half of the modelled variation in N balance; the rest of the variation was accounted for by year, TED-WR x year, and previous crop (Table 3-6). In contrast, TED-WR explained a small portion of modelled variation in PFP_N and yield-scaled N balance (<10%), with most variation accounted for by year, TED-WR x year, and, in the case of PFP_N, by previous crop as well. The large portion of unaccounted variation in N balance, PFP_N, and yield-scaled N balance (75, 75, and 63% of total SS, respectively) suggests that magnitude of field-to-field variation was as important as variation due to TED-WR, year, previous crops, and their interactions.

3.3.2. Benchmarking yield and N balance in producer fields

Similar to the observed pattern in average yield, the average N balance, calculated using all field-year observations, decreased in the following order: TED 1I (86 kg N ha^{-1}), 2I (77 kg N ha^{-1}) and 2R (37 kg N ha^{-1}) (Figures 3-4 a, b, c). About 61, 54, and 14% of the field-years in TED 1I, 2I, and 2R, respectively, exhibited N balance ≥ 75 kg N ha^{-1}. Results were similar when field averages (*i.e.*, averages for each field based on at least 3 years of data) were used for the analysis instead of individual field-year observations (Figures 3-4 d, e, f), except that the range of N balance narrowed considerably. For example, cases with very large N balance (> 150 kg N ha^{-1}) or negative N balance were not apparent when the analysis was based on field averages instead of field-years.

Average annual N balance did not vary substantially among years in the case of irrigated maize (CV = 15%) (Figures 3-4 g, h). In contrast, rainfed maize exhibited a large year-to-year variation (CV = 51%), with larger (smaller) N balance corresponded to years with lower (higher) yield (Figure 3-4i). For instance, highest N balance in TED 2R (rainfed) occurred in 2012, which corresponded to a drought year with very low yield. The year-to-year variation in N balance in irrigated fields was mostly due to variation in N irrigation (CV = 34-56%), but not in N fertilizer (CV = 3-5%).

Analysis of yield variation across field-years, for a given N balance level, is confounded by year-to-year variation in weather. Expressing producer yields as percentage of Yp (irrigated fields) or Yw (rainfed fields) using field averages allows an objective assessment of available room for improving yield at a given N balance level through better agronomic practices. About 41 and 52% of the irrigated and rainfed fields fell into the low relative yield categories (*i.e.*, below 80% and 70% of Yp and Yw, respectively, categories B and D in Figure 3-5), indicating room to further increase yields within the observed range of N balance (Figure 3-5). Of particular concern are those fields exhibiting large N balance *and* low relative yield (category D), representing 29 and

3% of total irrigated and rainfed fields, respectively. Attaining high yields with a smaller N balance (category A) is a realistic goal: 24% and 47% of irrigated and rainfed fields, respectively, exhibited N balance < 75 kg N ha^{-1} *and* attained or even exceeded their respective yield goals.

3.3.3. Yield, N inputs and N-metrics as influenced by TED, water regime, and previous crop

Average N input rates were 44% larger in irrigated *versus* rainfed fields, but higher yields in irrigated fields meant that PFP_N was remarkably similar between water regimes (Table 3-6, Figure 3-3). And while N balance was 51% larger in irrigated *versus* rainfed fields, yield-scaled N balance was smaller in irrigated fields. For a given TED-WR, yield and N inputs were 2% lower and 10% larger, respectively, in maize after maize *versus* maize after soybean (Table 3-6, Figure 3-6). As a result, PFP_N and N balance was higher and lower, respectively, in maize after soybean compared to maize after maize. Consistent with these results, frequency of fields with N balance ≥ 75 kg N ha^{-1} was lower in soybean-maize than in maize-maize: 40% *versus* 71% (irrigated fields) and 11% *versus* 18% (rainfed fields).

3.4. DISCUSSION

Benchmarking crop yields against external input use provides insight about opportunities to increase producer profit while using the same or less amount of input. There are many examples using this approach in the literature. For example, in a classic study, French and Schultz (1984) developed a boundary function for the relationship between yield and seasonal water supply for wheat in Australia; these authors documented large variation in yield across a wide range of water supply, which was attributable to management. This framework has been subsequently used in a multitude of studies to assess crop water productivity and identify opportunities for improvement (Sadras and Angus, 2006; Passioura, 2006; Grassini et al., 2009b, 2011). As far as we know, Hochman et al. (2014) is the only study that used a similar approach to benchmark crop yields in relation with N inputs. These authors presented an input-yield production frontier that benchmarked the efficiency of applied N fertilizer in terms of crop production; however, the approach had a (data-intensive) modeling component to estimate crop N requirement and did not explicitly focus on assessing potential N losses or estimating the N balance. In contrast, our study provides a cost-effective approach to benchmark yields in relation to N balance of individual producer fields using several readily-available parameters.

At issue is the degree to which the observed variation in N balance across producer fields is attributable to variation in agronomic management. Our study showed that field-to-field variation in N balance was much larger than the portion of variance accounted for by year, TED-WR, crop sequence, and their interactions (*ca.* 75 *versus* 25%, respectively; Table 3-6). Similarly, although fields were grouped into TED-WRs, and N balance was averaged across years, there was still large variation in N balance at any given yield level and *vice versa*. For instance, at a yield level of *ca*. 13 Mg ha^{-1}, the N balance in irrigated fields varied from *ca*. 30 to 150 kg N ha^{-1} **(**Figure 3-4**)**. Altogether, these findings suggest that management practices likely have a large influence on on-farm N balance, though part of the variation can also be attributed to spatial and temporal variation in climate and soil within each TED-WR combinations. It is still uncertain, however, how much of that variation is manageable through cost-effective agronomic technologies. In this regard, a key challenge to improved N fertilizer efficiency is that producers apply fertilizer without knowing the magnitude of total crop N demand, which is largely determined by Yp (or Yw in the case of rainfed fields) of the crop season ahead. If the season is unfavorable, the amount of N fertilizer they apply may be too large compared with crop N requirements that year. In contrast, if the year has Yp (or Yw) well above average, the applied N fertilizer may be insufficient to meet crop N requirements. Uncertainty in yield and N demand is most important in rainfed fields because Yw fluctuates dramatically from year to year (inter-annual CV = 31%) as a result of contrasting in-season precipitation amounts and temporal distribution, while N fertilizer remains fairly constant (inter-annual CV = 6%) as rainfed producers did not try to adjust N fertilizer rates in response to the large annual yield variation. Not surprisingly, our study shows that N balance is smaller and more variable in rainfed *versus* irrigated fields as a result of its higher climatic risk (Figure 3-4). We note that NE is a harsh environment for rainfed maize production; in contrast, irrigated maize yield (and its stability) in NE will be comparable to those of rainfed maize production in the most favorable environments in the eastern and central portions of the US Corn Belt (Grassini et al., 2014). Hence, results from this study for irrigated maize in NE are likely to be comparable to those for maize grown in favorable rainfed environments in the US Corn Belt.

While it may be difficult for producers to optimize N balance based on in-season weather, there may be other options that can help reduce the N balance regardless of the year-specific weather, and with little (if *nil*) yield penalty. The present study has identified some of those factors. For example, irrigated maize in rotation with soybean exhibited substantially smaller N balance with a slightly higher yield **(**Figure 3-6**)**. In connection to this finding, we note that future studies addressing the N balance in agro-ecosystems should aim to include the entire crop sequence into the analysis rather than individual crops. This is critical in the case of maize-soybean rotation considering the typical negative N balance during the soybean cycle as documented by a number of studies (Connor et al., 2011; Santachiara et al., 2017; Ciampitti and Salvagiotti, 2018). While the goal of having N balance < 75 kg N ha^{-1} seems realistic for continuous maize systems, this threshold may need to be re-examined in the case of maize-soybean sequences where an apparent large N balance during the maize cycle may actually be needed if the goal is to keep the N balance for the entire crop sequence above a level at which there is sufficient N to maintain soil organic matter at steady state.

Our proposed framework to categorize fields into low/small N balance and yield gap is useful to inform meaningful agronomic interventions and orient policy (Figure 3-5). Firstly, our findings demonstrated that the goal of achieving high yields without a large N balance is not an oxymoron as 25% of the fields in our study cases achieved these two goals simultaneously **(**category A in Figure 3-5**)**. Secondly, the framework can help avoid the "one-size-fits-all" solutions promoted by some environmental advocacy groups that propose restricting the amount of N fertilizer that can be applied across all fields regardless of crop yields and N demand. This approach would punish producers who are already producing high yields while achieving small positive N balance. Instead, agronomic and extension efforts should focus on those fields with large positive N balance and large yield gaps **(**category D in Figure 3-5**)**, which roughly represent 30% of the irrigated fields in our study and likely contribute disproportionately more to the overall N footprint compared with the other fields. Similar findings have been reported for irrigated wheat in Mexico (Ahrens et al., 2010). Finally, the framework is useful for individual producer and crop consultants to diagnose their current N fertilizer management, serving as a starting point to identify inefficiencies and possible solutions. For example, if the current yield gap is small, it may be wise for producers to look for opportunities to reduce N input use without reducing crop yields, which would lead to greater input-use efficiency and extra producer revenue as it has been documented in the case of irrigation water management in NE (Irmak et al., 2012; Gibson et al., 2019).

Our assessment makes two key contributions relative to estimation of N balance. First, our study showed that calculation of N balance for individual fields should rely on more than one year to avoid the confounding effect of weather and episodic adjustments in N fertilizer rates to account for large residual soil N from previous crop or other factors. For example, the analysis based on all field-year observations would have pointed out to an important number of fields with apparent soil mining (*i.e.*, negative N balance) or very large N balance; this pattern was not apparent when the analysis was based on average N balance using three or more years (Figure 3-5). Second, our assessment clearly indicated that using a suite of N-metrics is more robust compared with the use of single indicators. For instance, results in this study showed that (low-input) rainfed systems exhibited lower N balance with almost same PFP_N compared to (high-input) irrigated systems. However, in a broader scale, to reach the same total grain production target, the low-input system would need *ca.* 40% more cropland, which would lead to an overall N balance (on a regional basis) that is similar or even higher compared with the high-input irrigated systems. In other words, as reported by previous studies (*e.g.*, Grassini and Cassman, 2012), when the N balance was scaled by yield (*i.e.*, yield-scaled N balance), the apparent advantage of low-input *versus* high-input systems vanished. So, while N balance at a field-level would be the proper indicator to evaluate environmental footprint in relation to crop-system performance, yield-scaled N balance is a more relevant metric for regional and global assessments that account for possible changes in land use.

REFERENCES

Ahrens, T.D, Lobell, D.B., Ortiz-Monasterio, J.I., Li, Y., Matson, P.A., 2010. Narrowing the agronomic yield gap with improved nitrogen use efficiency: a modeling approach. Ecol. Appl. 20, 91–100.

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements, FAO Irrigation and Drainage. FAO, Rome, Italy, pp. 56.

Baker, J.M., Griffith, T.J., 2005. Examining strategies to improve the carbon balance of corn/soybean agriculture using eddy covariance and mass balance techniques. Agric. Forest Meteorol. 128, 168–77.

Basso, B., Shuai, G., Zhang, J., Robertson, G.P., 2019. Yield stability analysis reveals sources of large-scale nitrogen loss from the US Midwest. Sci. Rep. 9, 5774.

Blanco-Canqui, H., Lal, R., 2008. No-tillage and soil-profile carbon sequestration: An on-farm assessment. Soil Sci. Soc. Am. J. 72, 693–701.

Cassman, K.G., Gines, G.C., Dizon, M.A., Samson, M.I., Alcantara, J.M., 1996. Nitrogen-use efficiency in tropical lowland rice systems: contributions from indigenous and applied nitrogen. Field Crops Res. 47, 1–12.

Cassman, K.G., Dobermann, A., Walters, D.T., 2002. Agroecosystems, nitrogen-use efficiency, and nitrogen management. Ambio 31, 132–140.

Cela, S., Ketterings, Q.M., Czymmek, K., Soberon, M., Rasmussen, C., 2014. Characterization of nitrogen, phosphorus, and potassium mass balances of dairy farms in New York State. J. Dairy Sci. 97, 7614–7632.

Ciampitti, I.A., Salvagiotti, F., 2018. New insights into soybean biological nitrogen fixation. Agron. J. 110, 1185–1196.

Connor, D.J., Loomis, R.S., Cassman, K.G., 2011. Crop Ecology. Productivity and management in agricultural systems. Cambridge Univ. Press, Cambridge, UK.

Erisman, J.W., Galloway, J.N., Seitzinger, S., Bleeker, A., Dise, N.B., Petrescu, A.M.R., Leach, A.M., de Vries. W., 2013. Consequences of human modification of the global nitrogen cycle. Phil. Trans. R. Soc. B. 368, 20130116.

Evans, L.T., 1993. Crop Evolution, Adaptation, and Yield (Cambridge, UK: Cambridge University Press).

Exner, M.E., Perea-Estrada, H., Spalding, R.F., 2010. Long-term response of groundwater nitrate concentrations to management regulations in Nebraska's Central Platte Valley. Sci. World J. 10, 286–297.

Farmaha, B.S., Eskridge, K.M., Cassman, K.G., Specht, J.E., Yang, H., Grassini, P. 2016. Rotation impact on on-farm yield and input-use efficiency in high-yield irrigated maize–soybean systems. Agron. J. 108, 2313–2321.

Ferguson, R.B., 2015. Groundwater quality and nitrogen use efficiency in Nebraska's Central Platte River Valley. J. Environ. Qual. 44, 449–459.

Foley, J.A., Ramankutty, N., Braunman, K.A., Cassidy, E.S., Gerber, J.S., Johnston, M., Mueller, N.D., O'Connell, C., Ray, D.K., West, P.C., Balzer, C., Bennett, E.M.. Carpenter, S.R., Hill, J., Monfreda, C., Polasky, S., Rockström, J., Sheehan, J., Siebert, S., Tilman, G.D., Zaks, D.P.M., 2011. Solutions for a cultivated planet. Nature 478, 337–342.

French, R.J., Schultz. J.E., 1984. Water use efficiency of wheat in a Mediterranean-type environment. I. The relation between yield water use and climate. Aust. J. Agric. Res., 35, 743–764.

Gibson, K.E.B., Gibson, J., Grassini, P., 2019. Benchmarking irrigation water use in producer fields in the US central Great Plains. Environ. Res. Lett. 14, 054009.

Gibson, K.E.B., Yang, H.S., Franz, T., Eisenhauer, D., Gates, J.B., Nasta, P., Farmaha, B.S., Grassini, P., 2018. Assessing explanatory factors for variation in on-farm irrigation in US maize-soybean systems. Agric. Water Manage. 197, 34–40.

Grassini, P., Cassman, K.G., 2012. High-yield maize with large net energy yield and small global warming intensity. Proc. Natl. Acad. Sci. U.S.A. (PNAS) 109, 1074–9.

Grassini, P., Hall, A.J., Mercau, J.L., 2009b. Benchmarking sunflower water productivity in semiarid environments. Field Crops Res. 110, 251–262.

Grassini, P., Torrion, J.A., Cassman, K.G., Yang, H.S., Specht, J.E., 2014. Drivers of spatial and temporal variation in soybean yield and irrigation requirements in the western US Corn Belt. Field Crops Res. 163:32–46.

Grassini, P., Torrion, J.A., Yang, H.S., Rees, J., Andersen, D., Cassman, K.G., Specht, J.E., 2015. Soybean yield gaps and water productivity in the western U.S. Corn Belt. Field Crops Res. 179, 150–63.

Grassini, P., Yang, H., Irmak, S., Thorburn, J., Burr, C., Cassman, K.G., 2011. High-yield irrigated maize in the Western U.S. Corn Belt. II. Irrigation management and crop water productivity. Field Crops Res. 120, 133–141.

Grassini, P., Yang, H.S., Cassman, K.G., 2009a. Limits to maize productivity in the Western Corn-Belt: a simulation analysis for fully irrigated and rainfed conditions. Agric. For. Meteorol. 149, 1254–1265.

Harmel, D., Qian, S., Reckhow, K., Casebolt, P., 2008. The MANAGE database: nutrient load and site characteristic updates and runoff concentration data. J. Environ. Qual. 37, 2403– 2406.

Hochman, Z., Prestwidge, D., Carberry, P.S., 2014. Crop sequences in Australia's northern grain zone are less agronomically efficient than implied by the sum of their parts. Agric. Syst. 129, 124–32.

Howarth, R.W., Swaney, D.P., Boyer, E.W., Marino, R., Jaworski, N., Goodale, C., 2006. The influence of climate on average nitrogen export from large watersheds in the Northeastern United States. Biogeochem. 79, 163–186.

Irmak S, Burgert, M.J., Yang, H.S., Cassman, K.G., Walters, D.T., Rathje, W.R., Payero, J.O., Grassini, P., Kuzila, M.S., Brunkhorst, K.J., Van DeWalle, B., Rees, J.M., Kranz, W.L., Eisenhauer, D.E., Shapir,o C.A., Zoubek, G.L., Teichmeier, G.J., 2012. Large scale on-farm implementation of soil moisture-based irrigation management strategies for increasing maize water productivity. Trans. ASABE. 55, 881–894.

Khanal, S., Anex, R.P., Gelder, B.K., Wolter, C., 2014. Nitrogen balance in Iowa and the implications of corn–stover harvesting. Agric. Ecosyst. Environ. 183, 21–30.

Lassaletta, L., Billen, G., Grizzetti, B., Anglade, J., and Garnier, J., 2014. 50 year trends in nitrogen use efficiency of world cropping systems: the relationship between yield and nitrogen input to cropland. Environ. Res. Lett. 9, 105011.

Lobell, D.B., Cassman, K.G., Field, C B., 2009. Crop yield gaps: their importance, magnitudes, and causes. Annu. Rev. Environ. Resour. 34, 179–204.

Matson, P. A., Naylor, R., Ortiz-Monasterio, I., 1998. Integration of environmental, agronomic, and economic aspects of fertilizer management. Science 280, 112–115.

McLellan, E.L., Cassman, K.G., Eagle, A.J., Woodbury, P.B., Sela, S., Tonitto, C., Marjerison, R.D., van Es, H.M., 2018. The nitrogen balancing act: tracking the environmental performance of food production. BioSci. 68, 194–203.

Morell, F.J., Yang, H.S.S., Cassman, K.G., Van Wart, J., Elmore, R.W., Licht, M., Coulter, J.A., Ciampitti, I.A., Pittelkow, C.M., Btouder, S.M., Thomison, P., Lauer, J., Graham, C., Massey, R., Grassini, P., 2016. Can crop simulation models be used to predict local to regional maize yields and total production in the US Corn Belt? Field Crops Res. 192, 1–12.

Mueller, N.D., Gerber, J.S., Johnston, M., Ray, D.K., Ramankutty, N., Foley, J.A., 2012. Closing yield gaps through nutrient and water management. Nature 490, 254–257.

Oenema, J., van Ittersum, M., van Keulen, H., 2012. Improving nitrogen management on grassland on commercial pilot dairy farms in the Netherlands. Agric. Ecosyst. Environ. 162, 116–126.

Passioura, J.B., 2006. Increasing crop productivity when water in scare–from breeding to field management. Agric. Water Manage. 80, 176–196.

Rattalino Edreira, J.I. Guilpart, N., Sadras, V., Cassman, K.G., van Ittersum, M.K., Schils, R.L.M., Grassini, P., 2018. Water productivity of rainfed maize and wheat: a local to global perspective. Agr. Forest Meteorol. 259, 364–373.

Sadras, V.O., Angus, J.F., 2006. Benchmarking water-use efficiency of rainfed wheat in dry environments. Aust. J. Agric. Res. 57, 847–856.

Sanchez, P. A., Swaminathan, M., 2005. Hunger in Africa: the link between unhealthy people and unhealthy soils. Lancet 365, 442–444.

Sanchez, P.A., 2002. Soil fertility and hunger in Africa. Science 295, 2019–20.

Santachiara, G., Borrás, L., Salvagiotti, F., Gerde, J.A., Rotundo, J.L., 2017. Relative importance of biological nitrogen fixation and mineral uptake in high yielding soybean cultivars. Plant Soil 418, 191–203.

Schröder, J.J., Aarts, H.F.M., ten Berge, H.F.M., van Keulen, H., Neeteso, J.J., 2003. An evaluation of whole-farm nitrogen balances and related indices for efficient nitrogen use. Eur. J. Agron. 20, 33–44.

Skaggs, R.W., Breve, M.A., Gilliam, J.W., 1995. Predicting effects of water table management on loss of nitrogen from poorly drained soils Eur. J. Agron. 4, 441–451.

Sørensen, R., Zinko, U., Seibert, J., 2006. On the calculation of the topographic wetness index: Evaluation of different methods based on field observations. Hydrol. Earth Syst. Sci. 10, 101–112.

Spears, R.A., Kohn, R.A., Young, A.J., 2003. Whole-farm nitrogen balance on Western dairy farms. J. Dairy Sci. 86, 4178–4186.

Steffen, W., Richardson, K., Rockström, J., Cornell, S.E., Fetzer, I., Bennett, E.M., Biggs, R., Carpenter, S.R., de Vries, W., de Wit, C.A., Folke, C., Gerten, D., Heinke, J., Mace, G.M., Persson, L.M., Ramanathan, V., Reyers, B., Sörlin, S., 2015. Planetary boundaries: Guiding human development on a changing planet. Science 347, 1259855.

Tenorio, F.A.M., Eagle, A.J., McLellan, E.L., Cassman, K.G., Howard, R., Below, F.E., Clay, D.E., J Coulter, J.A., Geyerg, A.B., Joos, D.K., Lauer, J.G., Licht, M.A., Lindsey, A.J., Maharjan, B., Pittelkow, C.M., Thomison, P.R., Wortmann, C.S., Sadras, V.O.,

Grassini, P., 2019. Assessing variation in maize grain nitrogen concentration and its implications for estimating nitrogen balance in the US North Central region. Field Crops Res. 240, 185–193.

Tilman, D., Cassman, K.G., Matson, P.A., Naylor, R., Polasky, S., 2002. Agricultural sustainability and intensive production practices. Nature 418, 671–677.

Treacy, M., Humphreys, J., Mc Namara, K., Browne, R., Watson, C.J., 2008. Farm-gate nitrogen balances on intensive dairy farms in the south west of Ireland. Irish J. Agr. Food Res. 47, 105–117.

van Drecht, G., Bouwman, A.F., Knoop, J.M., Beusen, A.H.W., Meinardi, C.R., 2003. Global modeling of the fate of nitrogen from point and nonpoint sources in soils, groundwater, and surface water. Global Biogeochem. Cycles 17, 1115.

van Ittersum. M.K., Cassman, K.G., Grassini, P., Wolf, J., Tittonell, P., Hochman, Z., 2013. Field 349 Crops Research Yield gap analysis with local to global relevance — A review Field Crops Res. 350 143 4–17.

van Kessel, J.S., Reeves, J.B., 2002. Nitrogen mineralization potential of dairy manures and its relationship to composition. Biol. Fert. Soils 36, 118– 123.

Venterea, R.T., Halvorson, A.D., Kitchen, N., Liebig, M.A., Cavigelli, M.A., Grosso, S.J.D., Motavalli, P.P., Nelson, K.A., Spokas, K.A., Singh, B.P., Stewart, C.E., Ranaivoson, A., Strock, J., Collins, H., 2012. Challenges and opportunities for mitigating nitrous oxide emissions from fertilized cropping systems. Front. Ecol. Environ. 10, 562–570.

Verma S.B., Dobermann, A., Cassman, K.G., Walters, D.T., Knops, J.M., Arkebauer, T.J., Suyker, A.E., Burba, G.G., Amos, B., Yang, H., Ginting, D., Hubbard, K.G., Gitelson, A.A., Walter-Shea, E.A., 2005. Annual carbon dioxide exchange in irrigated and rainfed maize-based agroecosystems. Agric. Forest Meteorol. 131, 77–96.

Yang, H., Dobermann, A., Cassman, K.G., Walters, D.T., 2006. Features, applications, and limitations of the hybrid-maize simulation model. Agron. J. 98, 737–748.

Yang, H., Grassini, P., Cassman, K.G., Aiken, R.M., Coyne, P.I., 2017. Improvements to the Hybrid-Maize model for simulating maize yields in harsh rainfed environments. Field Crops Res. 204, 180–190.

Yang, H.S., Dobermann, A., Lindquist, J.L., Walters, D.T., Arkebauer, T.J., Cassman, K.G., 2004. Hybrid-maize: a maize simulation model that combines two crop modeling approaches. Field Crops Res. 87, 131–154.

Zhang, X., Davidson, E., Mauzerall, D., Searchinger, T., Dumas, P., 2012. Managing nitrogen for sustainable development. Nature 528, 51–59.

Zhao X., Christianson, L.E., Harmel, D., Pittelkow, C.M., 2016. Assessment of drainage nitrogen losses on a yield-scaled basis Field Crops Res. 199, 156–66.

Table 3-1. Meteorological stations and inputs used to simulate yield potential or water-limited yield potential in each technology extrapolation domain-water regime (TED-WR).

TED-WR	Meteorological stations	Sowing date	Hybrid relative maturity (days)	Plant density (plants m^{-2})
1I	Axtell, Holdrege, Ragan, Smithfield	April 23	115	8.7
2I	Harvard, Guiderock, York	April 23	115	8.7
2R	Duncan, Harvard, York	April 25	115	7.0

Table 3-2. Soil and field input used to simulate water-limited yield potential in rainfed maize fields located in TED 2R.

Variable	Value
Rooting depth (cm)	150
Topsoil texture	silt loam
Subsoil texture	silt loam
Bulk density (g cm^{-3})	1.3
Available soil water (at sowing)	100% PAWHC
Soil surface residues coverage (%)	50
Field slope (%)	≤ 2
Soil drainage	Good

Table 3-3. Averages for weather and soil variables for each technology extrapolation domain x water regime (TED-WR) combination. Averages for weather variables during the 2009-2015 period were computed based on seasonal (emergence-to-physiological maturity) values, while averages for soil variables were computed based on the values retrieved for each individual field. Parenthetic values indicate inter-annual and field-to-field coefficient of variation (in %) for weather and soil

TED	Water regime	Solar radiation (MJ $m^{-2}d^{-1}$)	Tmin (ºC)	Tmax (ºC)	Total ETo (mm)	Total rainfall (mm)	Soil organic matter (%)	PAWHC (mm)	TWI
1	Irrigated	20.9 (7)^{a}	13.0 (6)^{a}	27.0 (6)^{a}	720 (5)^{a}	371 (35)^{a}	1.9 (10)^{c}	313 (3)^{a}	10.3 (4)^{a}
2	Irrigated	20.9 (6)^{a}	14.1 (7)^{a}	27.6 (5)^{a}	673 (5)^{b}	393 (31)^{a}	2.5 (13)^{a}	285 (3)^{b}	10.1 (6)^{b}
	Rainfed						2.4 (16)^{b}	287 (3)^{b}	9.9 (6)^{c}

Tmin: minimum temperature; Tmax: maximum temperature; ET_o: grass-based reference evapotranspiration; PAWHC: plant available water holding capacity; TWI: topographic wetness index.

Table 3-4. Comparison for yield and N fertilizer among the Natural Resource District (NRD) database (this study), independent survey producer data (Grassini et al., 2015; Gibson et al., 2019), and official statistics (National Agricultural Statistics Service [USDA-NASS]; Economic Research Service [USDA-ERS]) for each technology extrapolation domain x water regime (TED-WR) combination. Values are 2010-2011 averages, except for average N fertilizer reported by ERS, which corresponds to an average statewide value reported for year 2010.

TED-WR	Yield (Mg ha^{-1})		
	NRD	Survey	NASS/ERS
1I	12.6	12.6	12.4
2I	12.5	13.0	12.0
2R	8.9	8.8	9.0
	N fertilizer rate (kg N ha^{-1})		
1I	210	218	189
2I	204	197	
2R	138	144	131

Table 3-5. Average producer yield, yield potential (Yp; irrigated crops) or water-limited yield potential (Yw; rainfed crops), and relative yield (ratio between producer yield and Yp or Yw) for each technology extrapolation domain x water regime (TED-WR) combination. Parenthetic values indicate the inter-annual coefficient of variation (in %).

TED-WR	Producer yield (Mg ha^{-1})	Yp or Yw (Mg ha^{-1})	Relative yield
1I	13.9 (8)^{a}	17.1 (7)^{a}	0.81 (11)^{a}
2I	13.3 (4)^{b}	16.6 (10)^{b}	0.80 (9)^{b}
2R	8.2 (28)^{c}	11.8 (31)^{c}	0.69 (13)^{c}

Different letters indicate statistically significant differences among TED-WRs ($p<0.05$, Tukey's test).

Table 3-6. Analysis of variance for the effect of technology extrapolation domain x water regime combination (TED-WR), year, previous crop, and their interactions on yield, nitrogen (N) inputs, N balance, partial factor productivity for N inputs (PFP_N), and yield-scaled N balance. Mean difference of each parameter for soybean-maize *versus* continuous maize and irrigated *versus* rainfed fields in TED2 are shown.

Source of variation	d.f.	Percentage of modelled sum of squares (%SS)†				
		Yield ‡ ($Mg\ ha^{-1}$)	N inputs ‡ ($kg\ N\ ha^{-1}$)	N balance ‡ ($kg\ N\ ha^{-1}$)	PFP_N ‡ ($kg\ grain\ kg^{-1}\ N$)	Yield-scaled N balance‡ ($kg\ N\ Mg^{-1}$ grain)
TED-WR	2	72^{***}	87^{***}	45^{***}	5^{***}	7^{***}
Year	6	14^{***}	3^{***}	15^{***}	37^{***}	40^{***}
Previous crop	1	$<1^{***}$	5^{***}	20^{***}	18^{***}	5^{***}
TED-WR x year	12	13^{***}	4^{***}	17^{***}	36^{***}	42^{***}
TED-WR x previous crop	2	$<1^{***}$	$<1^{***}$	1^{***}	<1	$<1^{**}$
Year x previous crop	6	$<1^{***}$	<1	$<1^{*}$	1^{***}	2^{***}
TED-WR x year x previous crop	12	$<1^{***}$	$<1^{*}$	1^{***}	2^{***}	3^{***}
Mean estimate difference						
Previous crop (soybean *vs* maize)		0.2^{***}	-20^{***}	-23^{***}	7^{***}	-2^{***}
Water regime (irrigated *vs* rainfed in TED 2)		5^{***}	92^{***}	33^{***}	-2^{***}	-3^{***}

† Proportion (in %) of total sum of squares (SS) after excluding error.

‡ *F*-test significant at $P < 0.05^{*}$, $< 0.01^{**}$, and $<0.001^{***}$.

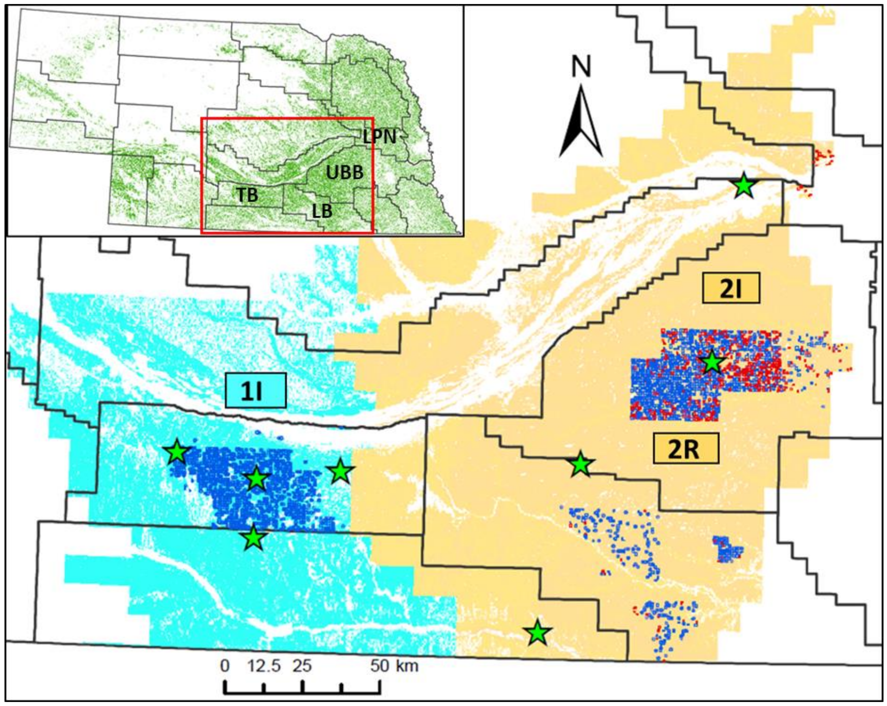

Figure 3-1. Location of irrigated (blue dots; n= 8,413 field-years) and rainfed maize fields (red dots; n= 867 field-years). Fields were grouped into two 'technology extrapolation domains' (TED 1 & 2) based on climate and soil similarity and fields in TED2 were further grouped based upon water regime (irrigated [2I] and rainfed [2R]), resulting in three TED-water regime combinations (TED 1I, 2I and 2R). Note that all fields in TED1 were irrigated. Stars indicate location of the meteorological stations. Inset shows maize harvested area (in green; USDA-NASS, 2017) and location of area of interest within Nebraska (NE). Lines show borders of NE Natural Resources Districts (NRDs). Producer data from four NRDs were used for the present study: Little Blue (LB), Lower Platte North (LPN), Tri Basin (TB), and Upper Big Blue (UBB).

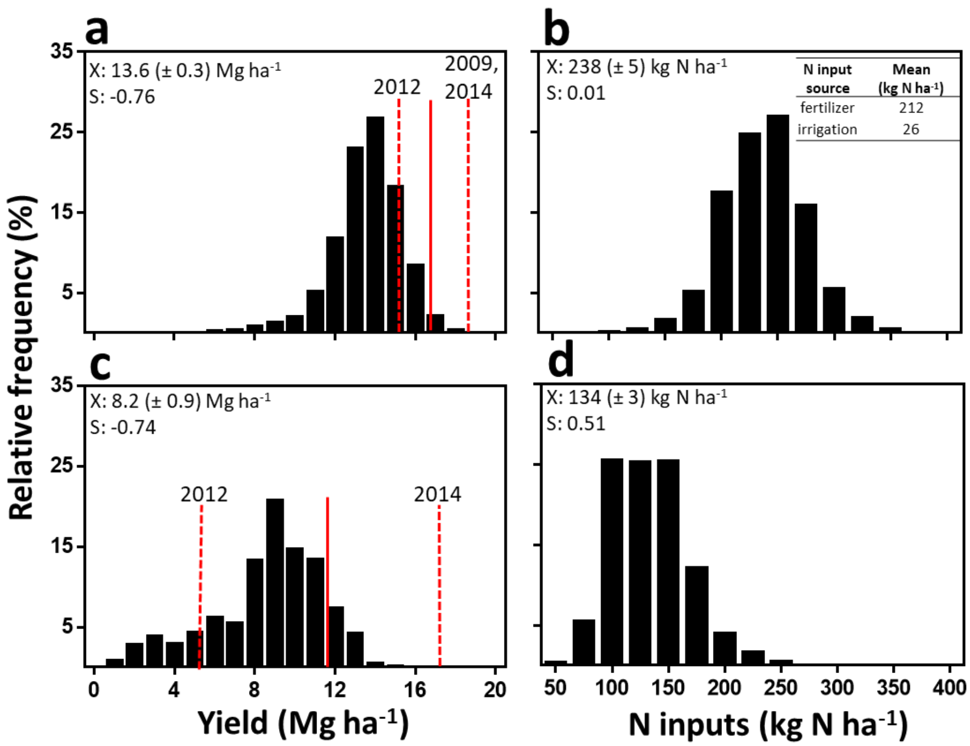

Figure 3-2. Frequency distributions for producer yield (left) and N inputs (right) in irrigated (a, b; and rainfed fields (c, d). Number of field-years were 8,413 (irrigated) and 867 (rainfed). Average (solid line), maximum and minimum (dashed lines) annual simulated yield potential (irrigated) or water-limited yield potential (rainfed) are shown. Inset in panel b shows averages for N fertilizer and N irrigation. Average (X ± standard error) and skewness (S) are shown. Irrigated data from technology extrapolation domains (TEDs) 1 and 2 were pooled as frequency distributions for yield and N inputs were almost identical.

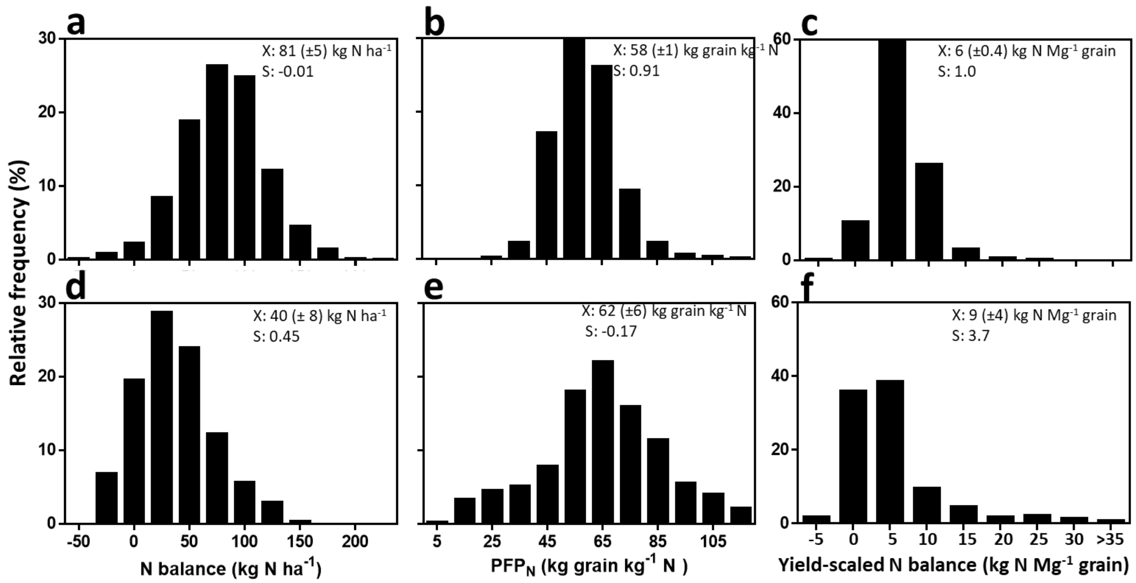

Figure 3-3. Frequency distributions for nitrogen (N) balance (left), partial factor productivity for N inputs (PFP_N, center), and yield-scaled N balance (right) in irrigated (a, b, c) and rainfed fields (d, e, f). Number of field-years were 8,413 (irrigated) and 867 (rainfed). Average (X ± standard error) and skewness (S) are shown. Irrigated data from technology extrapolation domains (TEDs) 1 and 2 were pooled as frequency distributions for yield and N inputs were almost identical.

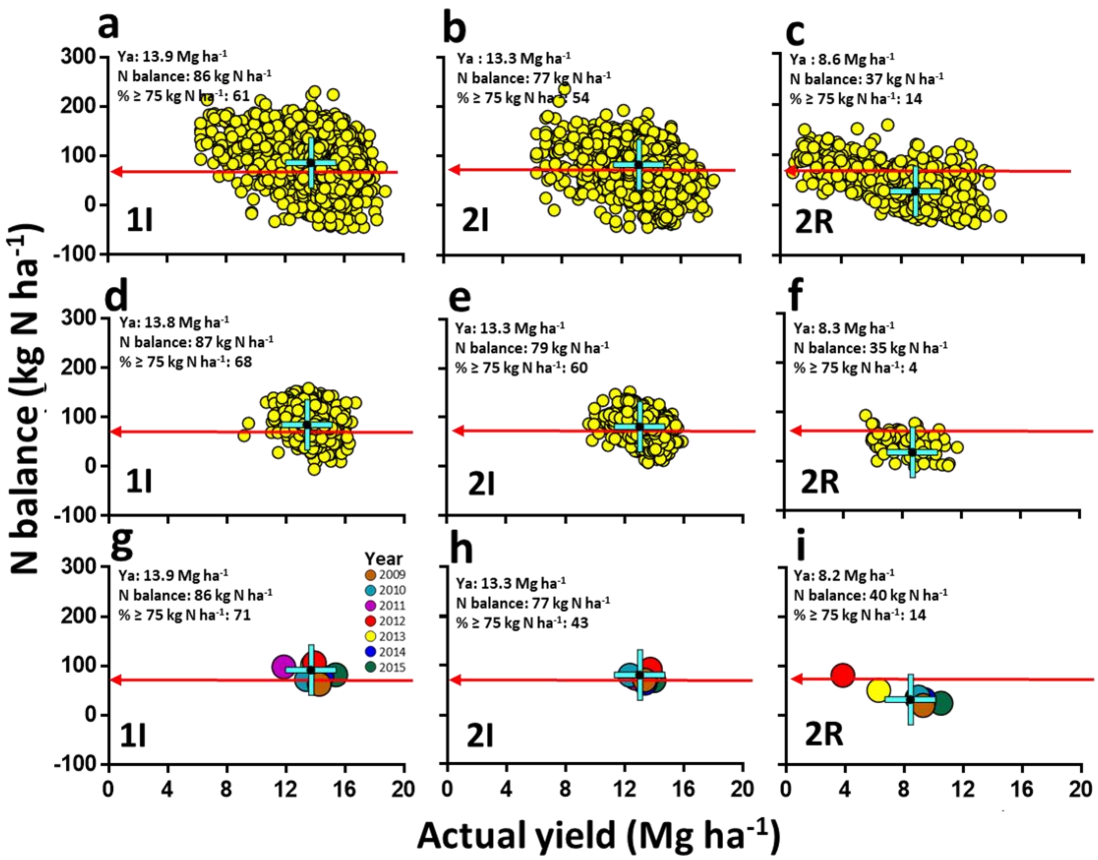

Figure 3-4. Nitrogen (N) balance and producer maize yield in irrigated fields in TED 1 (1I; left) and TED 2 (2I; center) and rainfed fields in TED 2 (2R; right). Each datapoint represents a field-year observation (a, b, c), field averages based on 3 years of data or more (d, e, f), and annual averages based on all fields in a given year (g, h, i). Horizontal arrows indicate N balance = 75 kg N ha^{-1}, which was used as a threshold to identify fields with large N balance. Average yield (Ya) and N balance are shown (and indicated with blue crosses). Percentage of field-years (a, b, c), field averages (d, e, f), and years (g, h, i) with N balance ≥ 75 kg N ha^{-1} is also shown.

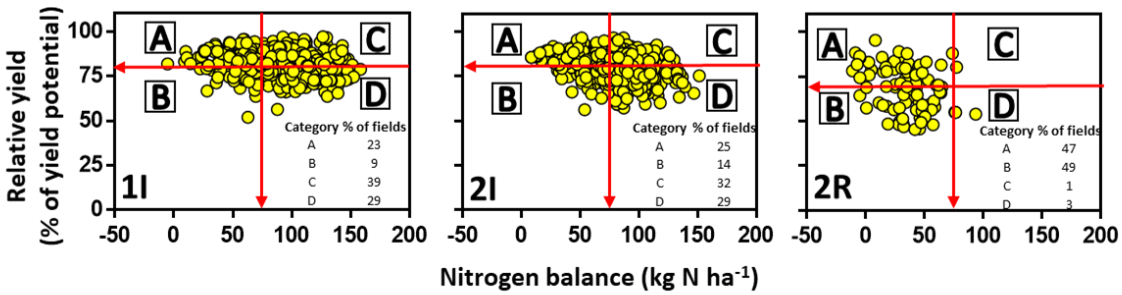

Figure 3-5. Relative yield and nitrogen (N) balance in irrigated fields in TED 1 (1I; left) and TED 2 (2I; center) and rainfed fields in TED 2 (2R; right). Relative yield was calculated based on producer yield expressed as percentage of yield potential (Yp; irrigated) or water-limited yield potential (Yw; rainfed). Each datapoint represents a field average based on at least 3 years of data. Vertical line indicates N balance = 75 kg N ha^{-1}, which was used as a threshold to identify fields with small and large N balance. Horizontal lines indicate 80% and 70% of Yp and Yw, which are reasonable yield goals for irrigated and rainfed fields, respectively. Frequency of fields in each of four (yield x N balance categories) combinations are shown.

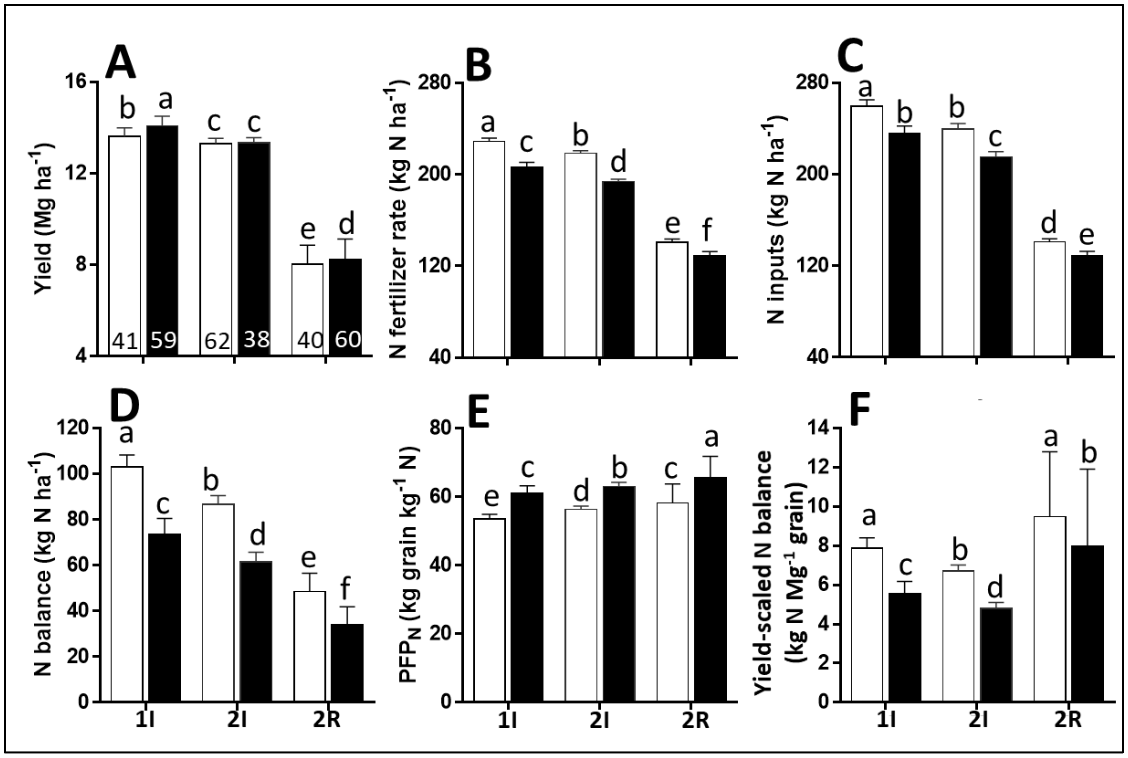

Figure 3-6. Average producer yield, nitrogen (N) fertilizer rate, N inputs, N balance, partial factor productivity for N inputs (PFP_N), and yield-scaled N balance in the three technology extrapolation domain-water regime (TED-WR) combinations: irrigated TED 1(1I), irrigated TED 2 (2I), and rainfed TED 2 (2R). Separate averages are shown for fields sown with maize after maize (empty bars) or after soybean (solid bars). Averages were calculated based on annual averages, with vertical lines indicating the standard errors. Different letters indicate statistically significant differences among TED-WR x previous crop combinations (Tukey's test; $p < 0.05$). Percentage of fields sown with maize after maize or soybean in each TED-WR combination is shown in (A).

CHAPTER 4: DATA REQUIREMENTS FOR RELIABLE ESTIMATION OF ON-FARM MAIZE NITROGEN BALANCE

ABSTRACT

The N balance, that is, the difference between N input and grain N removal, provides an indication of potential N losses to the environment. Application of this approach requires field-level data on yield and N inputs across mutiple field-years to account for variation in climate and management. The objetive of this study was to (i) determine the minimum number of years and fields per year needed for a reliable N balance estimation for a given climate-soil domain, and (ii) assess the degree to which N balance is persistent in individual producer fields over time. We used maize in Nebraska (USA) as a case study. The database included information on yield and N inputs collected from producer fields during seven years (total of 9,280 field-years). Fields were clustered into two climate-soil domains (TED 1 and TED 2) that were representative of *ca.* 1.3 million ha sown with maize. TED1 only included irrigated (TED 1I) fields while TED2 included both irrigated and rainfed fields (TED 2I and TED 2R, respectively). We found that year-to-year variation in N balance were substantially larger in rainfed *versus* irrigated fields, which resulted into a higher number of years in the former to obtain an estimate of N balance that was within ±10% of the average N balance estimated using all years of data (6 *versus* 4 years). Irrespective of water regime, our results showed that 100 fields per year was sufficient for a robust estimation of N balance within a given climate-soil domain. There were irrigated fields that consistently exhibited large N balance (LNB) as a result of consistent high N inputs and/or low yield. Similarly, the proportion of fields with maize in rotation with soybean was consistently smaller in LNB fields compared with the other fields. Our results can guide efforts in collecting producer data for estimation of N balance and understand the causes of large N balance in producer fields.

Keywords: maize, nitrogen balance, producer data, spatial variation, temporal variation

4.1. INTRODUCTION

A partial nitrogen (N) balance in producer maize fields can be estimated as the difference between N inputs and grain N removal (Treacy et al., 2008; Oenema et al., 2012; McLellan et al., 2018). The N balance is a good indicator of potential N losses to the environment associated with agricultural production (van Groenigen et al., 2007; Venterea et al., 2011; Pittelkow et al., 2014; Zhao et al., 2016; McLellan et al., 2018). Previous studies have shown evidence of either excessive (*i.e.*, N surplus) or insufficient (*i.e.*, N deficit) N application in relation to crop N demand, which unintendedly have negative impact on the environmental and soil quality (Sanchez and Swaminathan, 2005; Zhang et al., 2015). Hence, monitoring N balance of a given field is necessary to benchmark N inputs application in relation with crop N requirements, which, in turn, can help to identify pathways for reducing environmental footprint while maintaining or increasing current yields and soil quality.

Despite the simplicity of the N balance approach, a key constraint for its estimation is the lack of field-level yield and N inputs data. While there were previous efforts in benchmarking N balance, these studies retrieved yield and/or N inputs (*e.g.*, N fertilizer) from aggregated data reported at coarser spatial levels (*e.g.*, county, state, and country) such as the National Agricultural Statistics Service (NASS, https://quickstats.nass.usda.gov/) and FAO database, http://www.fao.org/faostat/en/#data/) (Khanal et al., 2014; Lassaletta et al., 2014; Basso et al., 2019). To our knowledge, Tenorio et al. (2019b) was the only study that used field-level producer data on yield and N inputs to estimate N balance for individual field-years. Despite similarity in climate and soil among fields, this study found large variation in N balance across field-years (range: -50 to 230 kg N ha^{-1}), indicating a high spatio-temporal variation in either yield, N inputs or both. In order to retrieve a robust estimate of the N balance for a given climate-soil domain, it would be necessary to have a sufficient number of years and fields so that the resulting estimate can be taken as representative of the dominant climate, soil, and management practices. Unfortunately, there has been no explicit effort to understand the data requirements, in terms of number of years and fields, needed for robust estimation of N balance.

Variation in N balance across years in a given field can be attributed to annual variation in climatic and/or management factors which lead to changes in yield, N inputs, or both. Following Lobell et al. (2007), underlying factors affecting N balance of a given field could be grouped into consistent (*e.g.*, constant management practices, soil properties, producer's skill) or inconsistent (*e.g.*, weather, crop diseases). A similar categorization was followed by Farmaha et al. (2016) and Gibson et al. (2018) to assess the persistence in yield gaps and irrigation water surplus over time in producer fields. This analysis could also help understand the degree to which N balance is manageable within a region with similar climate and soil. On one hand, if N balance in a group of fields is consistently high or low across years, it means that a persistent factor drives the variation in N balance across producer fields (*e.g.*, producer's skill, stable N input application). On the other hand, if N balance is not persistent over time, it means that the driving variation in N balance across fields are erratic and/or difficult to manage (*e.g.*, weather-induced yield variation, pest incidence). Analyzing differences between fields exhibiting persistent large and small N balance can help understand the causes for the (lack of) persistency.

To summarize, there is a dearth of knowledge in relation with the number of years and fields needed for robust estimation of N balance and the degree of persistence in N balance in individual fields. As a first step to fullfill this knowledge gap, here we used a large database collected from irrigated and rainfed producer maize fields in Nebraska (NE, western US Corn Belt) as a study case. The database was collected over seven years (2009-2015) and includes a total of 9,280 field-year observations. Specific objectives were to (i) examine the spatio-temporal variation in yield, N inputs, and N balance; (ii) examine the degree to which variation in yield and N inputs affect N balance estimation; (iii) identify the number of years and fields per year that are needed for reliable N balance estimation; and (iv) assess the persistence in N balance in individual fields over time and identify the underlying factors.

4.2. MATERIALS AND METHODS

4.2.1. Description of producer database and field clustering

This study utilized a database collected from the Natural Resources Districts (NRD, www.nrdnet.org) in Nebraska (USA). The NRDs are local government entities with authority to collect producer data every growing season as part of their programs to protect and conserve natural resources. The NRD data included field-specific information on maize yield (at standard moisture content of 155 g H_2O kg^{-1} grain), applied N fertilizer and irrigation, management practices (*e.g.*, previous crop, irrigation system type, and manure application), and nitrate-N (NO_3^--N) concentration in applied irrigation water. We used data collected over seven years (2009-2015) from fields located within four NRDs: Little Blue, Lower Platte North, Tri-Basin, and Upper Big Blue (Figure 3-1). Quality control was performed to remove fields with missing data or outliers (*e.g.*, yield >20 Mg ha^{-1}). This study considered only pivot-irrigated maize fields in rotation with maize or soybean. A small fraction of fields (5%) with manure application was discarded. Overall, we used a total of 9,280 field-year observations. Detailed explanations on the quality control measures and criteria used for data exclusion is provided elsewhere (Tenorio et al., 2019a).

Fields were grouped based on similarity of climate and soils using the technology extrapolation domain (TEDs) framework (Rattalino Edreira et al., 2018; http://www.yieldgap.org/web/guest/czted). Briefly, TEDs delineate regions with similar growing-degree days, aridity index, temperature seasonality, and plant available water holding capacity (PAWHC). Hence, crop responses to management practices (including fertilizer) are expected to be similar within a given TED. For our analysis, we grouped fields into two TEDs (TED 1 and 2), which, in turn, include *ca.* 1.3 million ha sown with maize every year. TED 1 only included irrigated fields, while TED 2 included both irrigated and rainfed fields. Hence, field-years were grouped into three TED-water regime (TED-WR) combinations: TED 1 irrigated (1I), TED 2 irrigated (2I), and TED 2 rainfed (2R). Average cumulative GDD and precipitation between *ca.* emergence and physiological maturity were estimated using weather data from meteorological stations located within each TED-WR. Detailed description of weather and soils for the three TED-WRs can be found elsewhere (Tenorio et al., 2019a). Briefly, TED 1 and 2 had similar solar radiation, temperature, and precipitation, but grass-referenced evapotranspiration (ETo) was higher in TED 1. In contrast, soil properties varied between TEDs, with TED 1 exhibiting higher PAWHC, but lower soil organic matter content, relative to TED 2. Within TED 2, soil organic matter and TWI was higher in irrigated *versus* rainfed fields. We note that irrigated maize in NE has a small inter-annual coefficient of variation (CV) for yield, which is comparable to those reported for favorable rainfed maize production environments in the central and eastern fringes of the US Corn Belt (Grassini et al., 2015).

4.2.2. Estimation of N balance and other N-related metrics

A simple maize N balance was calculated as the difference between N inputs (*i.e.*, N from fertilizer and applied irrigation water) and grain N removal in each producer field. As explained by Tenorio et al. (2019b), quantification of all N input sources (which also include manure, atmospheric dry and wet deposition, inorganic soil N at sowing, and soil organic matter mineralization) for a large population of producer fields would require expensive and laborious measurements. The N inputs used for the calculation of N balance includes N fertilizer and groundwater N in irrigation water. The N fertilizer accounts for *ca.* half of total N input to global cropland (Cassman et al., 2002). Similarly, the amount of N contained in applied irrigation water cannot be neglected for irrigated fields (Grassini et al., 2014; Ferguson, 2015). Hence, we focused on those N inputs that account for the largest fraction of total N inputs and that are readily available from producer fields. In addition, N released from SOM mineralization (which includes the inorganic soil N at sowing) was assumed to be similar to soil N immobilization, which is a reasonable assumption for soils in which SOM is near steady state as it is the case in the US Corn Belt (Baker and Griffis, 2005; Verma et al., 2005; Blanco-Canqui and Lal, 2008). Maize grain N removal was estimated based on producer yield assuming a grain N concentration of 11.5 g kg^{-1} grain, which is reported at standard moisture content of 155 g H_2O kg^{-1} grain (Tenorio et al., 2019b). Other N use efficiency metrics were also estimated, including the partial factor productivity for N inputs (PFP_N; ratio between yield and N inputs) and yield-scaled N balance (ratio between N balance and yield), to asses N balance both in area- and grain output-basis. Detailed description of estimation of N balance and other N-related metrics is provided elsewhere (Tenorio et al., 2019a).

4.2.3. Number of years and fields per year for reliable estimation of N balance

On-farm N balance estimation requires field-level data on yield and N inputs. Hence, variation in any of these parameters (or both) would lead to changes in N balance across field-years. As a first step to evaluate sensitivity of N balance to variation in yield at a given N inputs, we plotted N balance *versus* N inputs and fitted boundary functions using quantile regression for the 5th and 95th percentiles (Koenker and Basset, 1978) using the "quantreg" package in R (Koenker, 2017). Additionally, analysis of variance (ANOVA) was performed to determine the percentage of total variance in N balance explained by yield *versus* N inputs, which was quantified using the percentage of total sum of squares (SS), after excluding the error, attributable to each variable.

We followed an approach similar to the one used by Grassini et al. (2015) to analyze the number of years and fields per year required for robust estimation of N balance for a given TED. Average N balance for each TED was estimated using different number of years (*n*, from one up to seven years) with 100 subsets of years of size *n* re-sampled from the 7-y annual averages. The range in average N balance gives an indication of the uncertainty in this parameter due to year-to-year variation in yield and/or N inputs. Likewise, the sensitivity of N balance to the number of fields per year was evaluated by assessing the range of N balance using different number of fields per year (from one up to 100 fields). We chose two years which represented the crop season exhibiting the largest (year 2014) and smallest (year 2015) field-to-field variation in yield for each TED. Number of fields per TED ranged from 146 (TED 2R in year 2014) to 785 (TED 2I in year 2014). The range of average N balance, for a given number of fields used on its calculation, represents the uncertainty on TED-level average N balance due to field-to-field variation in yield and/or N inputs. We considered average N balance to be robust when all possible average values (for a given number of years or fields per year) was within ±10% of average N balance obtained using all years of data or all fields per year in each TED. A ±10% range would be equivalent to *ca.* ±7 and ±3 kg N ha^{-1} in irrigated and rainfed fields, respectively. The same analyses for number of years and fields were performed for yield and N inputs to understand the underlying drivers for variation in N balance.

4.2.4. Assesment of nitrogen balance persistency over time

Persistency in N balance in irrigated fields across years was investigated. Unfortunately, the analysis could not be performed for rainfed fields because of insufficient number of fields in some years that would not allow a reliable assesment of persistency over time. Fields that corresponded to the upper and lower quartile of the N balance distribution were grouped into two categories: large N balance (LNB) and small N balance (SNB). The year that was used to categorize fields into LNB and SNB was referred to as "ranking year" and the remaining years as "non-ranking years". Average N balance for each group was estimated in both ranking and non-ranking years. Following Farmaha et al. (2016), difference between annual (2009-2015) average N balance of SNB and LNB field categories and annual average TED N balance (hereafter called "$NB_{difference}$") was calculated for both ranking and non-ranking years. Persistence for each field category (*i.e.,* SNB and LNB) was then estimated as the ratio between average $NB_{difference}$ across non-ranking years and $NB_{difference}$ calculated for ranking year. To avoid biases due to selection of a single ranking year, the analysis was repeated separately for two years (2010 and 2014). The overall persistence in each category (SNB and LNB) was calculated as the average from the persistence calculated using the two ranking years (2010 and 2014). A high persistence value would imply that N balance in ranking and non-ranking years persistently deviated from the average TED N balance and not just in the year in which the fields were ranked. To understand the underlying drivers for variation in N balance, persistence in yield and N inputs were also estimated for the SNB and LNB fields.

To determine some of the factors explaining fields with persistent LNB or SNB, we estimated average N balance, yield, N inputs, proportion of fields in continuous maize *versus* rotation with soybean, soil properties, and efficiencies for each field category in each TED. Ranking years were taken into account for the analysis, and for each N balance field category, data were pooled across years. Differences in means between SNB and LNB for each variable were tested for statistical significance using *t*-tests, except for percentage of maize fields in rotation with soybean, which was analyzed using Chi-square (χ^2) test.

4.3. RESULTS

4.3.1. Weather patterns across the seven crop seasons

The study period (2009–2015) portrayed well the inter-annual variation in seasonal weather and providing an interesting range of environmental conditions influencing the N balance (Figure 4-1). Across TED-years, cumulative GDD was relatively stable (CV = 7%) while in-season precipitation fluctuated (CV = 29-37%). For example, accumulated GDD in TED 1I ranged from 1685 °Cd (year 2009) to 2051 °Cd (year 2012) while precipitation ranged from 163 mm (year 2012) to 527 mm (year 2010). As a result of weather variation, average yield ranged from 11.9 to 15.4 Mg ha^{-1} (irrigated) and 3.8 to 10.5 Mg ha^{-1} (rainfed) across years **(**Figure 4-2**)**. Highest and lowest average irrigated yields were associated with season with low (2015) and high (2011) temperature, respectively, while highest and lowest rainfed yields were associated with wet (2015) and dry seasons (2012), respectively (Figure 4-1).

4.3.2. Temporal and spatial variation in yield, N inputs, and N balance

Field-to-field variation in yield, N inputs, and N balance was higher than year-to-year variation (Figure 4-2). An exception was the case of rainfed yields, which exhibited similar temporal and spatial variation. Variation in N balance, both across years and among fields, was larger relative to variation in yield and N inputs. Key differences between irrigated and rainfed fields were: (i) yield was lower and year-to-year yield variation was larger in rainfed *versus* irrigated fields (CV = 28% *versus* 4-8%), (ii) field-to-field variation in yield was also larger in rainfed *versus* irrigated fields (CV = 26% *versus* 11%), (iii) both yield and N inputs exhibited low inter-annual and field-to-field variation in irrigated fields while rainfed fields exhibited large and small year-to-year variation for yield and N inputs, respectively, and (iv) both inter-annual and field-to-field variation in N balance was larger in rainfed *versus* irrigated fields, though N balance was notably smaller in the former (Figure 4-2).

The majority (71%) of the N balance field distributions shown in Figure 4-2 were normally distributed (D'Agostino-Pearson test, $p < 0.05$). The N balance was largest in the drought year (2012) in both rainfed and irrigated fields, but the drivers were different. In irrigated fields, higher applied irrigation due to low rainfall lead to higher N input from irrigation water, without detectable changes in yield compared with other years. In the case of rainfed fields, drought resulted into much lower yields and, consequently, smaller grain N removal and larger N balance (Figure 4-2).

4.3.3. Influence of yield and N inputs on N balance in irrigated and rainfed fields

On average, if N inputs exceeds 145 kg N ha^{-1}, N balance increased by 0.9 (irrigated) and 0.6 (rainfed) kg N per kg of N inputs **(**Figure 4-3). About 57 and 14% of the irrigated and rainfed field-years, respectively, exceeded the N balance threshold of 75 kg N ha^{-1} above which potential N losses increase substantially. Considerable variation in N balance at any given level of N inputs was observable due to variation in yield. For example, N balance varied from 56 to 116 kg N ha^{-1} in irrigated fields that received N inputs of *ca.* 240 kg N ha^{-1} which, in turn, was associated with yield variation from 10.8 and 16.0 Mg ha^{-1}. A similar pattern was observable in rainfed fields. However, there was an important difference between irrigated and rainfed fields. In irrigated fields, the proportion of variation explained by N inputs was *ca.* 7x larger than the variance accounted for by yield (88% *versus* 12% of SS) **(**Figure 4-3, inset**)**. In contrast, the proportion of variation accounted for by yield was higher compared with the variation explained by N inputs in rainfed fields (54% *versus* 40% of SS). This discrepancy between irrigated and rainfed fields was due to greater field-to-field variation in N inputs *versus* yield in irrigated fields, while the opposite pattern was observed in rainfed fields (Figure 4-2).

4.3.4. Number of years and fields for robust estimation of N balance

A larger number of years was needed for a robust estimation of N balance at TED level compared with yield and N inputs (Figure 4-4). For example, in TED 1I, one to three years of data were needed to estimate average yield and N inputs, but four years were needed to estimate N balance with the same level of confidence. In the case of TED 2I, only two years were needed to estimate average N balance because the inter-annual variation in yield and N inputs was smaller compared with TED 1I (Figure 4-2). In the case of rainfed fields, the number of years required to reach reliable estimate of N balance was higher (six years) because of the high variation in yield across years as a result of the erratic rainfall amount and distribution among seasons (Figure 4-2). Only two years of data allowed a robust estimation of average N inputs but six years were needed in the case of yield (Figure 4-4). If an extreme year, like a drought year (*e.g.*, 2012) would have been excluded from the analysis, the number of years required in TED 2R would have decreased from six to five years (Figure 4-5).

At question is how many fields are needed to estimate average N balance for a given TED-year with confidence. Results for year 2014 showed that a relatively small number of fields (15-20 irrigated fields and 25-35 rainfed fields) were sufficient to reliably estimate average yield and N inputs (Figure 4-6). In contrast, at least 100 fields were needed to estimate average N balance to have the same accuracy. If one would accept an accuracy of ±20% of TED average, which is equivalent to *ca.* ±15 and ±6 kg N ha^{-1} for irrigated and rainfed maize, respectively, a more reasonable number of fields would be needed (*ca.* 35 and 60 fields for irrigated and rainfed fields, respectively). Similar results were found for year 2015, except for a lower number needed (5 to 10 for irrigated fields and 20 for rainfed fields) for robust yield estimate due to lower field-to-field variation in yield than in 2014 (Figure 4-7).

4.3.5. Persistency in N balance, yield, and N inputs

The LNB fields exhibited 31-41% (2010) and 40% (2014) higher N balance than the TED average (Table 4-1). Majority of LNB fields across years in TED 1I (80%) and TED 2I (86%) had N balance ≥ 75 kg N ha^{-1} (*i.e.*, threshold for large potential N losses)

(Figure 4-8). On average, LNB fields achieved 3-4% lower yield and received 15-17% higher N inputs relative to SNB fields, resulting into lower PFP_N and higher yield-scaled N balance (Table 4-1).

Most of the fields grouped into the SNB and LNB in ranking years (2010 and 2014) also exhibited respective smaller and larger N balance in the non-ranking years (Figure 4-8, Table 4-1). In both TEDs, higher degree of persistence in N balance were observed in LNB fields (24-50%) compared with SNB fields (16-40%), suggesting that, at least, some of the factors explaining large N balance were persitent across years. Consistent with this observation, persistency in N inputs followed the same pattern as for N balance: LNB fields exhibited a relatively larger persistency in N inputs (28-62%) compared with SNB fields (18-39%). In contrast, yield in SNB and LNB fields did not deviate from the TED average yield across years. Altogether, these results indicate that persistency in N balance in LNB fields was driven by a consistently higher N input application compared with other fields located within the same TED and that this pattern was consistent during the entire time period. In addition, frequency of maize fields rotated with soybean was higher in SNB *versus* LNB fields (Table 4-1). Differences in soil properties were relatively small and weak between SNB and LNB fields, suggesting that differences in applied N inputs were not related with differences in soil properties among fields.

4.4. DISCUSSION

Agriculture is under increasing pressure to demonstrate progress towards productivity and environmental goals using cost-effective metrics that can be calculated using information readily available in producer fields. As shown in previous study, the N balance is a useful metric for benchmarking the efficiency of N input and estimating potential N losses into the environment for individual fields and regions (Tenorio et al., 2019a). The present study makes a first step in understanding the data requirements for reliable estimation of the N balance for climate-soil domains, using maize in Nebraska as a case study. Analysis based on NE data showed that rainfed fields required six years of data for robust N balance estimation relative to four years for irrigated fields and about 100 fields per TED-year. Data requirements would be more modest by excluding years with extreme weather conditions (in the case of rainfed crops) and/or by accepting a lower level of accuracy in N balance estimation.

As indicated previously, irrigated maize in Nebraska has similar yield level and stability compared with maize in favorable rainfed environment in the US Corn Belt. Hence, a modest investment on data collection can help map the N balance for the entire region as well as other regions of the world where maize or other cereal crops are produced. For example, targeting yield and N inputs data collection from the 16 TEDs with largest maize area in USA would allow estimation of N balance for an area that account for 50% of US maize area (18 million ha), which means that collecting producer data in 1600 fields per year in four years is sufficient for robust N balance estimation for half of US maize area. Covering 75% of US maize area would require an additional 28 TEDs (*i.e.*, total of 44 TEDs), which, in turn, would require data from a total of 4400 fields. Focusing on TEDs with largest maize area may not allow to identify areas with smaller maize area but high potential for N losses (*e.g.*, sandy soils). Hence, additional TEDs can be added based on biophysical attributes that are likely to contribute to large N losses. Identifying climate-soil domains with largest N balance can help orient investments on agricultural research and development to mitigate environmental footprint where most needed.

Contribution of persistent and non-persistent factors to large N balance can help determine the degree to which the N balance can be managed by producers through agronomic practices. Indeed, our study showed that producers that exhibited largest N balance in one year are likely to also be the ones exhibiting large N balance in the other years. Considering the persistency in N balance, it would be useful to differentiate between those persistent factors that are manageable (*e.g.*, crop sequence, N inputs application) *versus* non-manageable (*e.g.*, soil type) to quantify how much N balance can possibly be improved. This study found a number of manageable factors that can be fine-tuned by producers to improve their N balance, including N input rate and crop sequence. Future research should be oriented towards identification of other practices that can help reduce N surplus (when excessive) without detrimental effects on yield.

REFERENCES

Farmaha, B.S., Lobell, D.B., Boone, K.E., Cassman, K.G., Yang, H.S., Grassini, P., 2016. Contribution of persistent factors to yield gaps in high-yield irrigated maize. Field Crop Res. 186:124–132.

Gibson, K.E.B., Yang, H.S., Franz, T., Eisenhauer, D., Gates, J.B., Nasta, P., Farmaha, B.S., Grassini, P., 2018. Assessing explanatory factors for variation in on-farm irrigation in US maize soybean systems. Agric. Water Manag. 197, 34–40.

Grassini, P., Torrion, J.A., Cassman, K.G., Yang, H.S., Specht, J.E., 2014. Drivers of spatial and temporal variation in soybean yield and irrigation requirements in the western US Corn Belt. Field Crops Res. 163:32–46.

Grassini, P., van Bussel, L.G.J., van Wart, J., Wolf, J., Claessens, L., Yang, H., Boogaard, H., de Groot, H., van Ittersum, M.K., Cassman, K.G., 2015. How good is good enough? Data requirements for reliable crop yield simulations and yield-gap analysis. Field Crops Res. 177, 49–63.

Khanal, S., Anex, R.P., Gelder, B.K., Wolter, C. 2014. Nitrogen balance in Iowa and the implications of corn–stover harvesting. Agr. Ecosyst. Environ. 183, 21–30.

Koenker, R., 2017. Quantreg: quantile regression. R package version 5.36. 2017. http://CRAN.R-project.org/package=quantreg.

Koenker, R., Basset, G., 1978. Regression quantiles. Econometrica 46, 33−50.

Lassaletta, L., Billen, G., Grizzetti, B., Anglade, J. & Garnier, J. 2014. 50 year trends in nitrogen use efficiency of world cropping systems: the relationship between yield and nitrogen input to cropland. Environ. Res. Lett. 9, 105011.

Lobell, D.B., Ortiz-Monasterio, J.I., Falcon, W.P., 2007. Yield uncertainty at the fieldscale evaluated with multi-year satellite data. Agric. Syst. 92, 76–90.

McLellan, E.L., Cassman, K.G., Eagle, A.J., Woodbury, P.B., Sela, S., Tonitto, C., Marjerison, R.D., van Es, H.M. 2018. The nitrogen balancing act: tracking the environmental performance of food production. Biosci. 68, 194–203.

Oenema J, van Ittersum M, van Keulen H., 2012. Improving nitrogen management on grassland on commercial pilot dairy farms in the Netherlands. Agr. Ecosyst. Environ. 162, 116–126.

Pittelkow, C.M., Adviento-Borbe, M.A., van Kessel, C., Hill, J.E., Linquist, B.A. 2014. Optimizing rice yields while minimizing yield-scaled global warming potential. Glob Chang Biol. 20, 1382–1393.

Rattalino Edreira, J.I. Guilpart, N., Sadras, V., Cassman, K.G., van Ittersum, M.K., Schils, R.L.M., Grassini, P., 2018. Water productivity of rainfed maize and wheat: a local to global perspective. Agr. Forest Meteorol. 259, 364–373.

Sanchez, P. A., Swaminathan, M., 2005. Hunger in Africa: the link between unhealthy peopleand unhealthy soils. Lancet. 365, 442–444.

Tenorio, F.A.M., Eagle, A.J., McLellan, E.L., Cassman , K.G., Howard, R., Below, F.E., Clay, D.E., J Coulter, J.A., Geyerg, A.B., Joos, D.K., Lauer, J.G., Licht, M.A., Lindsey, A.J., Maharjan, B., Pittelkow, C.M., Thomison, P.R., Wortmann, C.S., Sadras, V.O., Grassini, P. 2019b. Assessing variation in maize grain nitrogen concentration and its implications for estimating nitrogen balance in the US North Central region. Field Crops Res. 240, 185–193

Tenorio, F.A.M., McLellan, E.L., Eagle, A.J., Cassman , K.G., Grassini, P., 2019a. Benchmarking nitrogen input use in producer fields in the western US Corn Belt. Agr. Ecosyst. Environ. *Submitted*.

Treacy M, Humphreys J, Mc Namara K, Browne R, Watson CJ (2008) Farm-gate nitrogen balances on intensive dairy farms in the south west of Ireland. Irish J. Agr. Food Res. 47, 105–117.

van Groenigen, J.W., Velthof, G.L., Oenema, O., van Groenigen, K.J., van Kessel, C. 2010. Towards an agronomic assessment of N_2O emissions: a case study for arable crops. Eur. J. Soil Sci. 61, 903–913.

Venterea, R.T., Maharjan, B., Dolan, M.S. 2011. Fertilizer source and tillage effects on yield scaled nitrous oxide emissions in a corn cropping system. J. Environ. Qual. 40, 1521–1530.

Zhang, X., Davidson, E., Mauzerall, D., Searchinger, T., Dumas, P., 2015. Managing nitrogen for sustainable development. Nature. 528, 51–59.

Zhao X., Christianson, L.E., Harmel, D., Pittelkow, C.M. 2016. Assessment of drainage nitrogen losses on a yield-scaled basis Field Crops Res. 199, 156–66.

Table 4-1. Means of nitrogen (N) balance, yield, management, soil properties, and efficiencies for small (SNB) and large (LNB) N balance in three technology extrapolation domain (TED-water regime combinations: I – irrigated; R – rainfed, based on ranking years average (2010 and 2014). Statistical significance difference between categories are shown.

Variable	TED 1I			TED 2I		
	SNB	LNB	Difference[a]	SNB	LNB	Difference
N balance (kg N ha^{-1})	24	126	-102^{***}	31	111	-80^{***}
Yield (Mg ha^{-1})	14.6	12.9	1.7^{***}	13.5	11.9	1.6^{***}
Total N inputs (kg N ha^{-1})	192	275	-83^{***}	186	248	-62^{***}
Management and inputs						
Nitrogen (N) fertilizer (kg N ha^{-1})	172	250	-79^{***}	175	237	-62^{***}
% fields with soybean as previous crop	83	21	62^{***}	67	9	58^{***}
Soil properties						
Organic matter (%)	1.9	1.9	nil	2.5	2.5	nil
pH	6.6	6.6	nil	6.0	6.0	nil
Available water holding capacity (mm)	315	312	3^{**}	286	285	1
Topographic wetness index	10.3	10.3	nil	10.2	10.1	0.1^{**}
Efficiencies						
PFP_N (kg grain kg^{-1} N) [b]	77	47	30^{***}	73	48	25^{***}
Yield-scaled N balance (kg N Mg^{-1} grain) [c]	2	10	-8^{***}	2	10	-8^{***}

[a] Asterisks indicate significance of t-test or Chi-square (χ^2) test at p-value * <0.10, ** <0.05, and *** <0.001.
[b] Partial factor productivity for N inputs (PFP_N) was estimated as yield per unit of N input.
[c] Yield-scaled N balance was estimated as the ratio between N balance and yield.

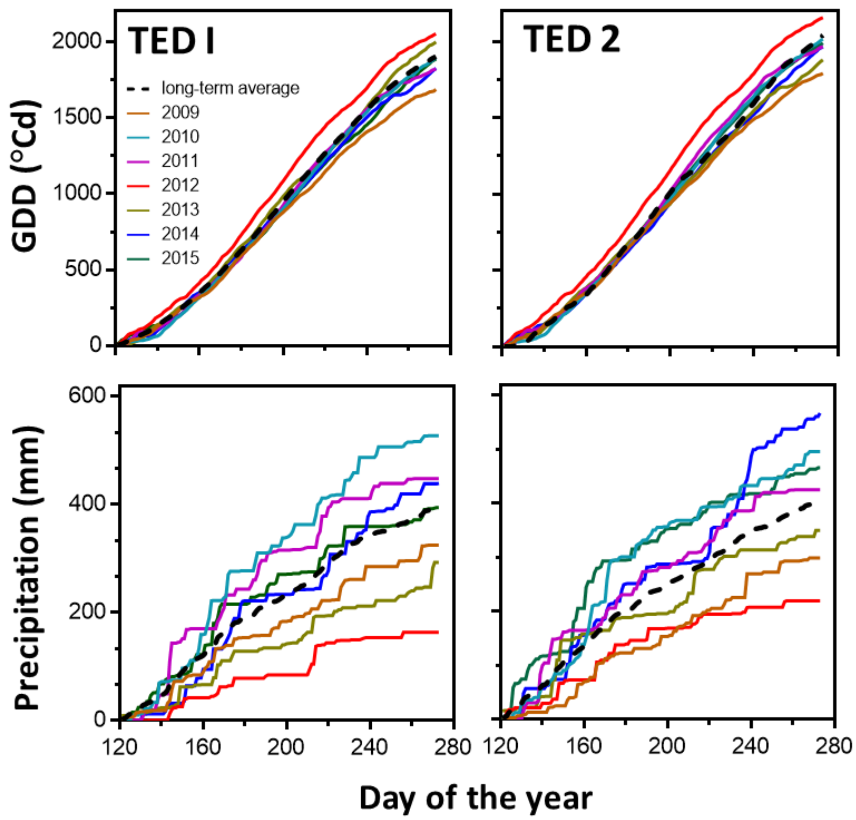

Figure 4-1. Cumulative growing-degree days (GDD, T_{base} and T_{max} = 8 °C and 30 °C, respectively) and precipitation for the period between May 1st and Sep 30th, which roughly coincides with maize emergence and physiological maturity, respectively, at each technology extrapolation domain (TED 1 and TED 2). Each colored line corresponds to a year within the (2009–2015) time interval and was averaged from representative weather stations in each TED (see Figure 3-1). Dashed line indicates the long-term historical average based on 20 years (1996-2015) of measured daily weather data.

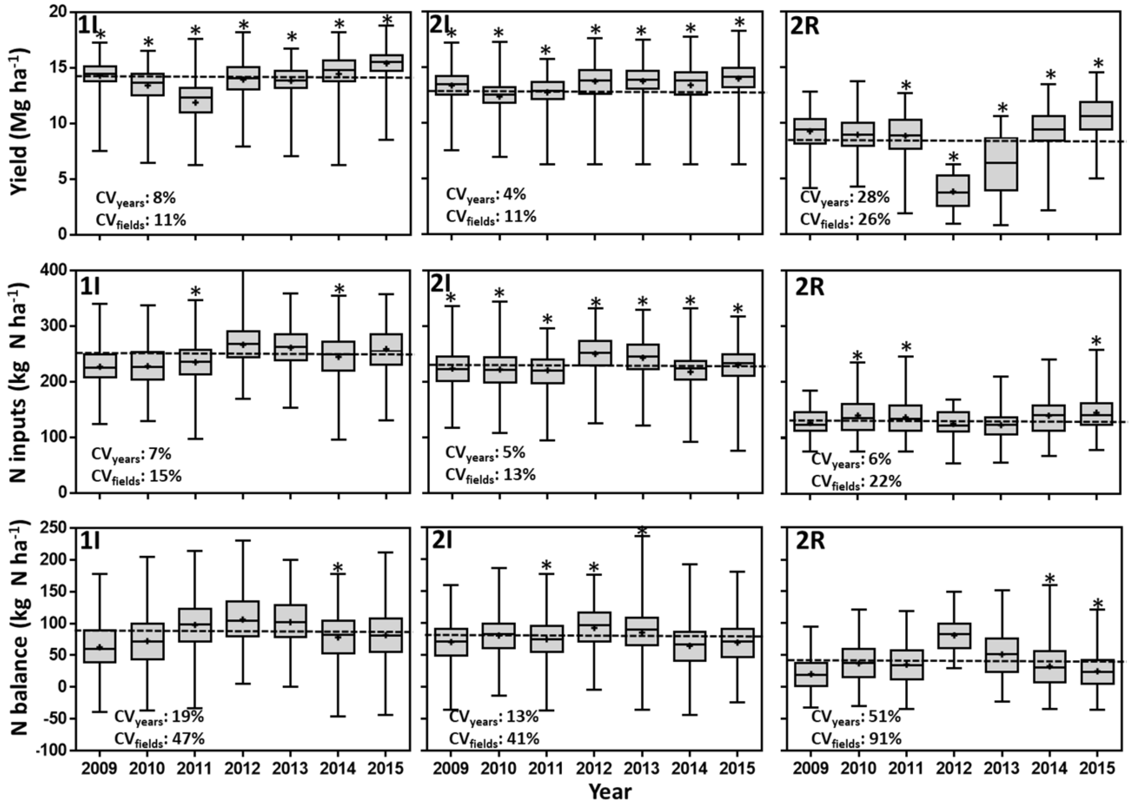

Figure 4-2. Distribution of producer yield, nitrogen (N) inputs, and N balance from 2009 to 2015 for fields across technology extrapolation domain (TEDs): TED 1 irrigated, TED 2 irrigated and TED 2 rainfed. Upper and lower boundaries of boxes indicate 75th and 25th percentile, respectively. Vertical bars indicate maximum and minimum values. Horizontal lines and crosses within boxes are the median and mean value, respectively. Horizontal dashed lines show the average N balance across years in each TED. Average year-to-year and field-to-field coefficient of variation are shown (CV_{years} and CV_{fields}; respectively; in %). Asterisks indicate when distributions deviate significantly from normality (D'Agostino-Pearson test, $p < 0.05$).

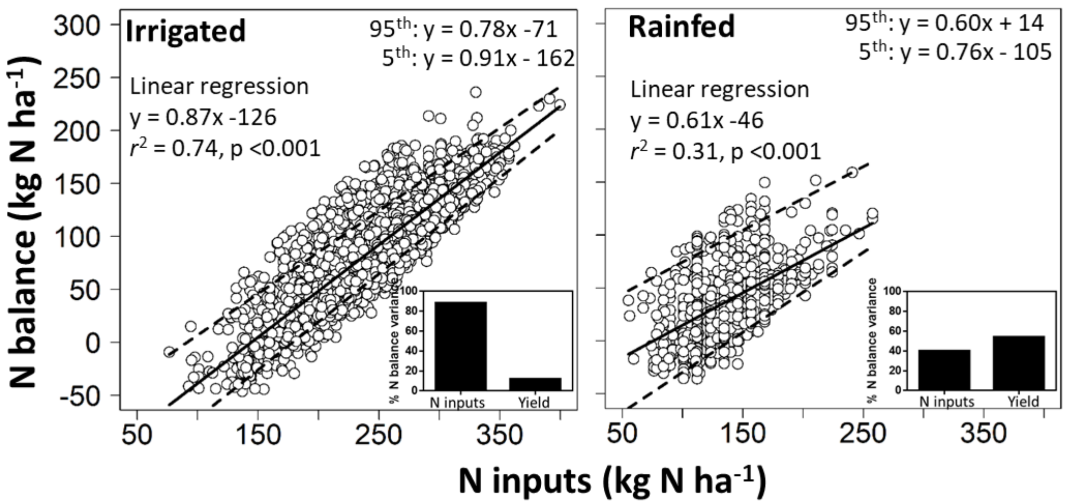

Figure 4-3. Nitrogen (N) balance and N inputs in irrigated and rainfed conditions. Each datapoint represents a field-year observation. Slopes of linear regression (solid line) and boundary functions fitted for the 5th and 95th (dashed lines) percentiles are shown. Inset shows proportion of N balance variation explained by N inputs and yield. Note that regression lines do not imply causality; instead, they are shown to illustrate how the N balance changes with increasing N inputs and the variation in N balance at any given level of N inputs.

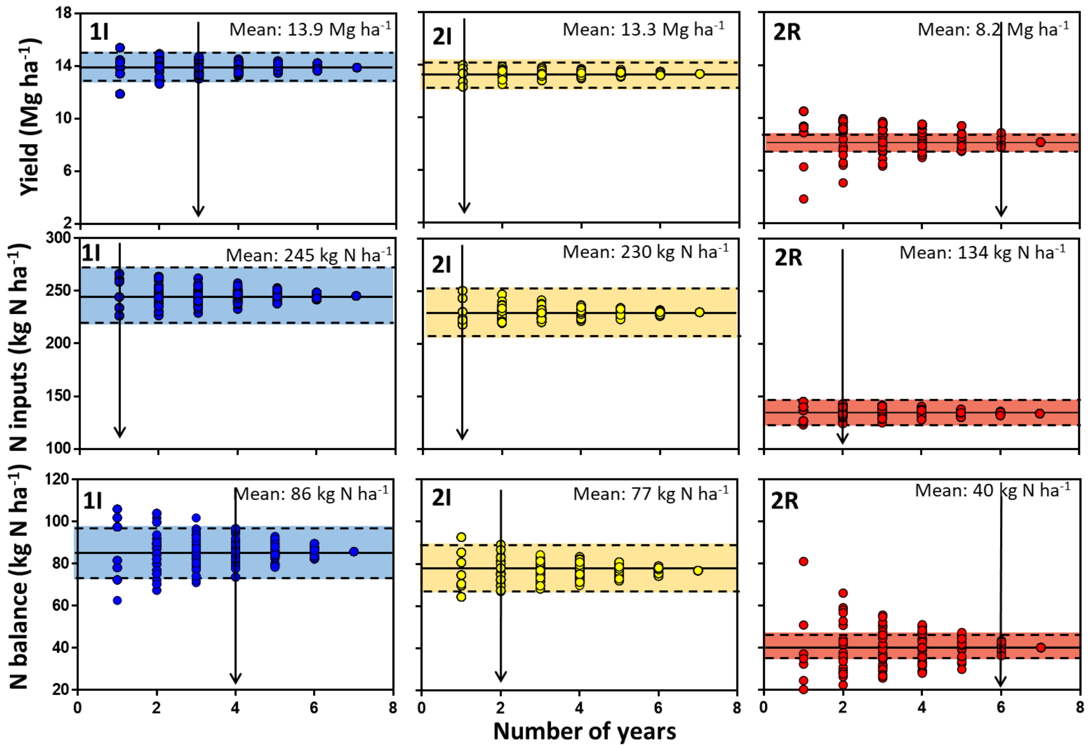

Figure 4-4. Average yield, nitrogen (N) inputs, and N balance as a function of the number of years included in the calculation for irrigated maize fields in three technology extrapolation domains (TEDs): TED 1 irrigated (TED 1I), TED 2 irrigated (TED2I), and TED 2 rainfed (TED 2R). Each data point corresponds to an average estimated using a given number of years (n_y). Averages were estimated for 100 subsets of years of size n_y, resampled from the entire 7-y database (2009-2015). Arrow shows the number of years at which all estimated averages fall within ±10% (shaded area) of the average value using all available years in each TED.

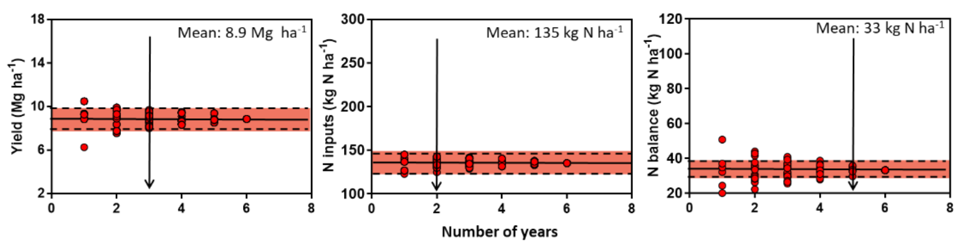

Figure 4-5. Average yield, nitrogen (N) inputs, and N balance as a function of the number of years included in the calculation for rainfed fields in TED 2. Each data point corresponds to an average estimated using a given number of years (n_y). Averages were estimated for 100 subsets of years of size n_y, resampled from the entire 6-y database

(2009-2015, excluding 2012). Arrow shows the number of years at which all estimated averages fall within ±10% (shaded area) of the average value using all available years in each TED.

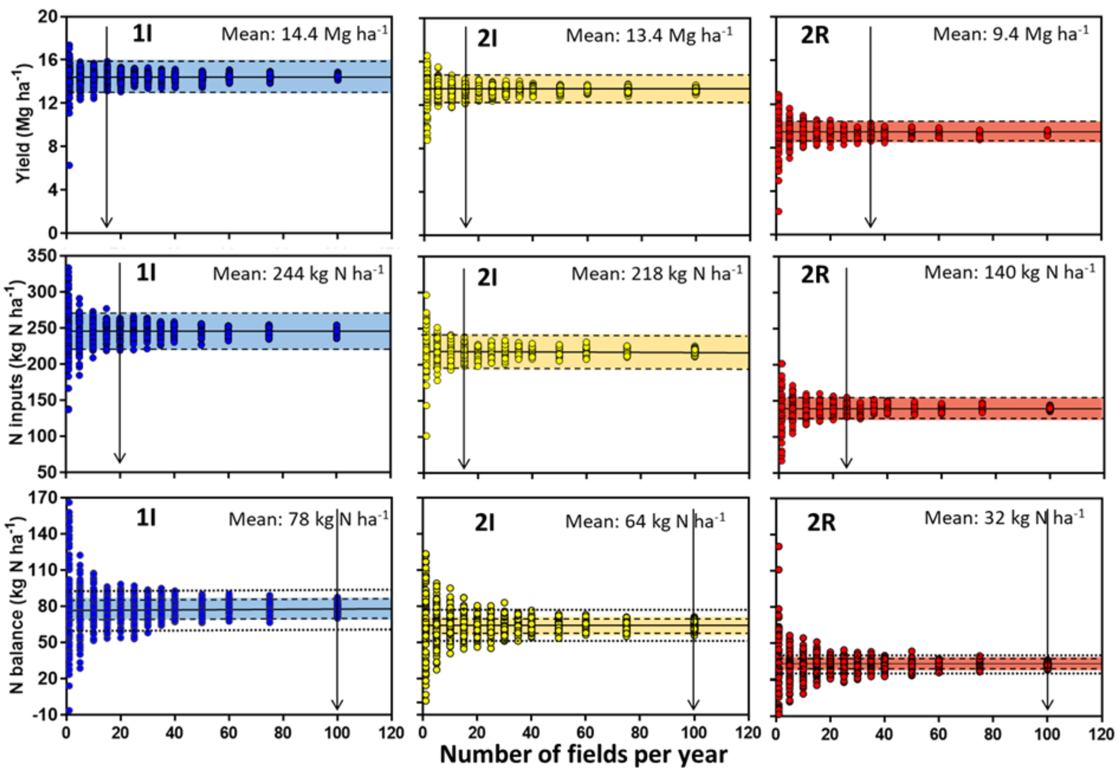

Figure 4-6. Average yield, nitrogen (N) inputs, and N balance as a function of the number of fields included in the calculation for irrigated maize fields in three technology extrapolation domains (TEDs): TED 1 irrigated (TED 1I), TED 2 irrigated (TED2I), and TED 2 rainfed (TED 2R) in year 2014. Each data point corresponds to an average estimated using a given number of fields (n_f). Averages were estimated for 100 subsets of fields of size n_f, re-sampled from the entire field distribution in 2014. Arrow shows the number of fields at which all estimated averages fall within ±10% (shaded area) of the average value using all available fields in each TED in 2014. Dotted lines indicate ±20% deviation from the average N balance value.

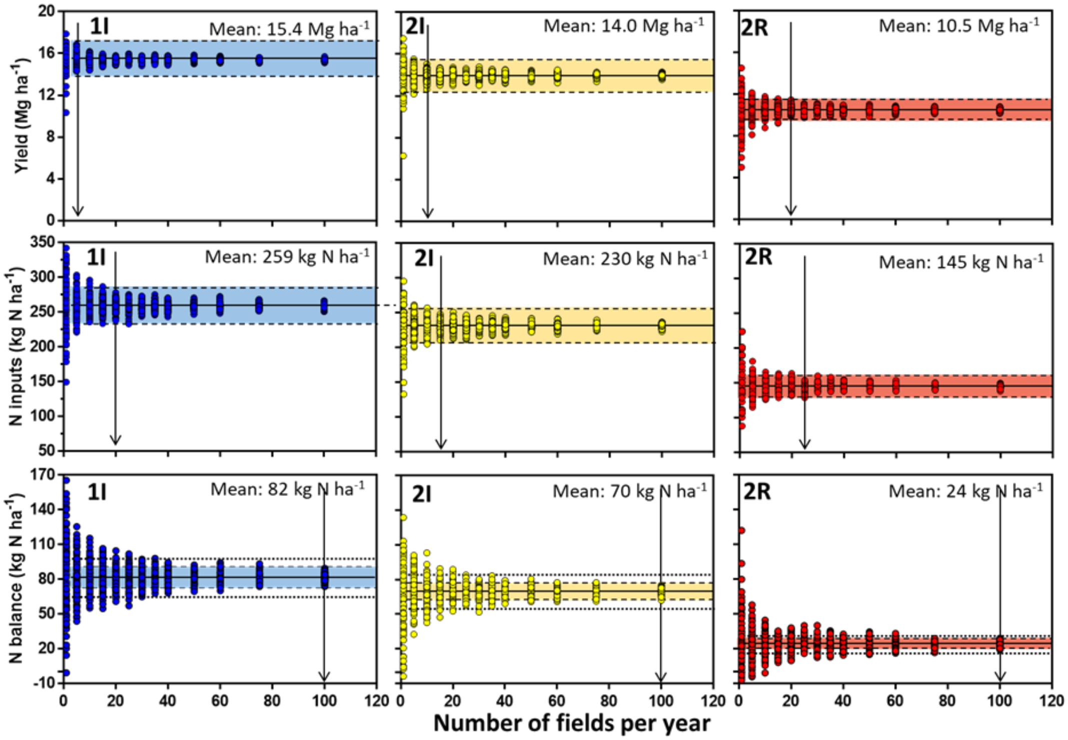

Figure 4-7. Average yield, nitrogen (N) inputs, and N balance as a function of the number of fields included in the calculation for irrigated maize fields in three technology extrapolation domains (TEDs): TED 1 irrigated (TED 1I), TED 2 irrigated (TED2I), and TED 2 rainfed (TED 2R) in year 2015. Each data point corresponds to an average estimated using a given number of fields (n_f). Averages were estimated for 100 subsets of fields of size n_f, re-sampled from the entire field distribution in 2015. Arrow shows the number of fields at which all estimated averages fall within ±10% (shaded area) of the average value using all available fields in each TED in 2015. Dotted lines indicate ±20% deviation from the average N balance value.

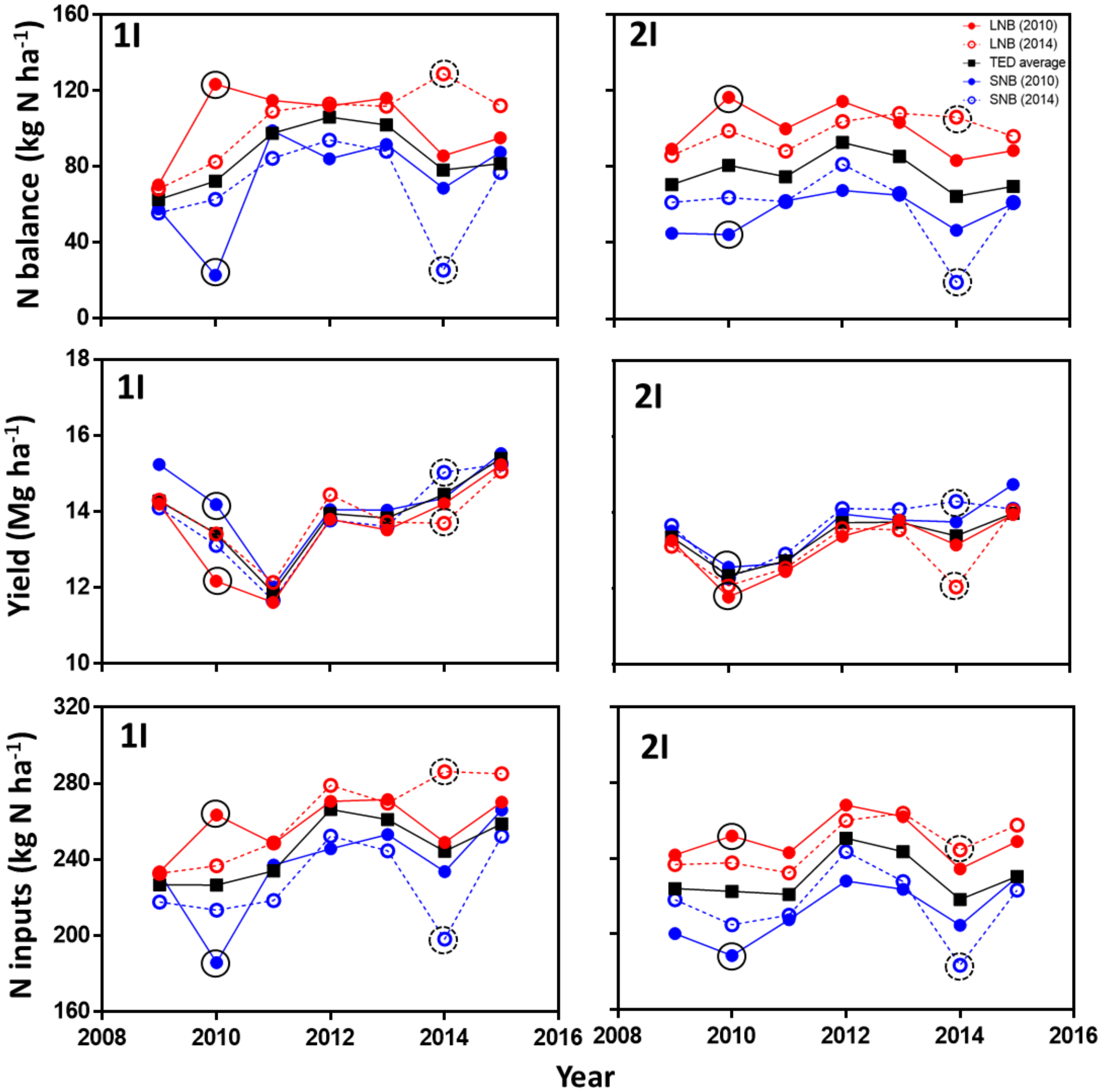

Figure 4-8. Nitrogen (N) balance, yield, and N inputs persistency based on two years: 2010 and 2014 (“ranking years”), in irrigated (I) maize fields located in technology extrapolation domain (TED) 1 and 2. Fields were classified in large N balance (LNB) and small N balance (SNB) categories based on top and bottom quartiles of producer fields N balance distribution in ranking years, respectively. Average N balance of fields in LNB (red) and SNB (blue) categories selected for 2010 (solid symbols and lines) and 2014 (open symbols, dashed lines) were tracked across other years (“non-ranking years). Annual TED average is shown (square symbols). Encircled datapoints represent the average estimate for 2010 (solid) and 2014 (dashed) ranking years.

CHAPTER 5: ASSESSING EXPLANATORY FACTORS FOR VARIATION IN ON-FARM NITROGEN BALANCE IN THE WESTERN US CORN BELT

ABSTRACT

Previous studies have shown large variation in N balance among maize producer fields in the US Corn Belt. However, it is still unknown the degree to which such variation is explained by differences in soil and/or crop management factors. This study aimed to identify soil and management factors influencing N balance in irrigated and rainfed maize producer fields in Nebraska (USA). Driving factors for variation in N balance were assessed using a database containing yield and management data from 311 fields sown with maize during two years (2010-2011). The N balance was estimated as the difference between N inputs (from fertilizer and applied irrigation) and grain N removal. Random forests and regression tree analyses were used to relate variation in N balance to soil and management factors. We derived a boundary function for the relationship between yield and N inputs with a slope of 40 kg N ha^{-1}, reaching a yield plateau for N inputs > 255 kg N ha^{-1}. Water regime, sowing date, soil organic matter (SOM), N application timing, and spring N split application explained 41% of observed variation in N balance. On average, irrigated fields exhibited 48% higher N balance relative to rainfed fields, with 68% of irrigated fields showing N balance ≥ 75 kg N ha^{-1}. In rainfed fields, sowing date, N application timing, and SOM were main variables

influencing N balance while, in the case of irrigated fields, SOM and spring N split application were the most important drivers. Irrigated fields located in sandy soils exhibited the largest N balance as a result of high N rates and N from irrigated water. Our analysis suggests that producer risk perception plays an important role at explaining the variation in N balance across fields and that there is room to improve yield *and* reduce N surplus by fine tuning management factors.

Keywords: maize, nitrogen, nitrogen balance, management, soil

5.1. INTRODUCTION

Agriculture has the challenge of meeting expected increase in food demand on existing cropland while minimizing the environmental impact (Tilman et al., 2002). Addition of nitrogen (N) fertilizer is essential to attain high yields in cereal crops but can also lead to N pollution (Goolsby et al., 2000; Erisman et al., 2013; Zhang et al., 2015; Cui et al., 2018). Hence, achieving synchrony between nitrogen (N) supply and crop demand, so that there is no N excess (*i.e.*, N surplus) or deficiency (*i.e.*, N deficit) is key to attain high yields and reduce N losses (Cassman et al., 2002). Along these lines, there is an increasing demand for robust, cost-effective indicators that could be used to assess progress of agricultural systems towards productivity and environmental goals (Thomson et al., 2017). The N balance, that is, the difference between N inputs and grain N removal, is one of those indicators (Treacy et al., 2008; Oenema et al., 2012; McLellan et al., 2018; Tenorio et al., 2019a, b). It can be estimated using readily available information by crop producers as it only requires data on yield and N inputs. Potential N losses increase with large N balance ($\geq$ 75 kg N ha^{-1}). Thus, the N balance approach can be used to benchmark current yield performance of producer fields in relation with N fertilizer use.

The Corn Belt is located in the US North Central region, accounting for *ca.* 30% of global maize production. A number of studies have assessed N balance in maize producer fields in this region (*e.g.,* McLellan et al., 2018; Basso et al., 2019; Tenorio et al., 2019a). For example, Tenorio et al. (2019a, b) study found variability in N balance across fields to be as high as variation across years, suggesting potential room for improving N balance through fine tuning of management practices. The same study identified crop sequence and water regime as important factors influencing N balance. However, we are not aware of any study that has explicitly assessed management practices (*e.g.,* sowing date, fertilizer management, etc.) and soil properties (*e.g.,* soil organic matter, texture) on their influence on N balance in producer fields. Such analysis would be of value to identify opportunities for reducing N balance for those fields exhibiting large N surplus.

As an starting point to identify suites of practices that can help producers meet productivity and environmental goals, we assessed here mangement and soil properties explaining variation in N balance. As a study case, we used an on-farm database collected in Nebraska (USA)— this state produces 43 million MT of maize annually in *ca.* 4 million ha (USDA-NASS, 2014-2018). The database incuded field-specific detailed data on yield, applied inputs, and management practices collected during two cropping seasons (2010-2011) from rainfed and irrigated maize fields.

5.2. MATERIALS AND METHODS

5.2.1. Description of study area, and producer data

This study used data collected from rainfed and irrigated maize fields in Nebraska during 2010 and 2011 (Figure 5-1). Nebraska ranks third amongst maize producing states, with irrigated and rainfed area accounting for 65 and 35% of NE maize production (USDA-NASS, 2014-2018). Each field was mapped using Google Earth® and the following information was available for each fied: grain yield (at standard moisture content of 155 g H_2O kg^{-1} grain), total irrigation water, amount and time of fertilizer applications, fertilizer inputs, hybrid relative maturity, sowing date, tillage method, plant density, and previous crop. Reported yield and applied N fertilizer were representative of NE producer's fields as determined by comparing values against other independent data sources (Grassini et al., 2015; Tenorio et al., 2019a).

Only fields sown with maize for grain that reported complete data on yield and N fertilizer were included in our study. In addition, only pivot-irrigated fields were considered as surface (flood) irrigation accounts for a small fraction of irrigated maize area in NE (*ca.*14%) and its area has steadily declined over time (USDA-ERS, 2010). Because the majority (>85%) of maize across the US Corn Belt region is grown continuously or in a maize-soybean rotation (Farmaha et al., 2016), fields sown with maize after wheat, alfalfa, or other crops besides maize and soybean were excluded from the analysis. Similarly, we also exclude a small number of fields that received manure application as this is not a frequent practice in NE and also because determination of amount and time of N released from manure is difficult. Associated data were screened for erroneous and incomplete entries using quality control measures that set acceptable ranges for yield and N inputs. For example, fields that reported incidence of unmanageable production site adversities (*e.g.*, hail, frost, wind) *and* achieved yield < 6 Mg ha^{-1} were excluded in the database (*ca.* 3% of total observations). The aforementioned method ensured to only exclude fields with substantial yield losses due to the reported adversity and maintain those fields which yield loss were negligible. After the quality control, our database contained a total of 202 and 109 field-year observations for irrigated and rainfed maize fields, respectively.

Soil variables including percentage of soil organic matter (SOM), plant available water holding capacity (PAWHC), and topographic wetness index (TWI) were retrieved for each field from the Soil Survey Geographic database (SSURGO, https://websoilsurvey.nrcs.usda.gov). PAWHC represents the amount of water (mm) that the soil can hold between field capacity and wilting point within the rootable depth. TWI indicates the likelihood of surface runoff (run-on) from (to) an area based on slope and surrounding area, with bottom and upland areas having highest and lowest values, respectively (Sørensen et al., 2006).

5.2.2. Calculation of nitrogen balance

A simple maize N balance was calculated as the difference between N inputs and grain N removal. The N inputs include N from fertilizer and, in the case of irrigated fields, also groundwater NO_3^--N from irrigation water (hereafter referred to 'N irrigation'). As explained elsewhere (Tenorio et al., 2019a), N fertilizer and N irrigation inputs accounted for the largest portion of total N inputs (which also include manure, atmospheric deposition, soil organic matter mineralization) and they are readily available from producer fields. The N irrigation was calculated from reported irrigation amount for each field-year (typically measured using flowmeters installed at each irrigation well) and average NO_3^--N concentration in groundwater estimated for each NE Natural Resources District (www.nrdnet.org). Maize grain N removal was estimated based on producer yield, assuming a grain N concentration of 11.5 g kg^{-1} grain (Tenorio et al., 2019c). Detailed description of N balance estimation is provided elsewhere (Tenorio et al. (2019a).

5.2.3. Yield potential simulation for each field-year

Yield potential (Yp) is the yield attained by an adapted crop cultivar when grown with non-limiting nutrient and water supplies and with pests and diseases effectively controlled (Evans, 1993; van Ittersum et al., 2013). Water-limited yield potential (Yw) is influenced by the same factors that define Yp but also determined by precipitation amount and distribution and soil properties that influence water availability such as PAWHC and field slope. In our study, Yp (irrigated) and Yw (rainfed) were estimated using Hybrid-Maize model for each field-year. Simulations were based on field-specific input variables, including daily weather data (precipitation, maximum and minimum temperature, solar radiation, wind speed, relative humidity, and ETo), crop management (sowing date, relative maturity, and plant density) and soil and terrain properties (soil depth, texture, bulk density, soil surface residue cover, and field slope). Weather variables, including maximum and minimum temperature, solar radiation, wind speed, and relative humidity, were retrieved from the High Plains Regional Climate Center (www.hprcc.unl.edu) and interpolated for each field using inverse distance weighting using the data from the three nearest weather stations to each field (Yang and Torrion, 2014; Franke and Nielson, 1980). Hybrid-Maize model has been widely evaluated for its ability to estimate yield potential in well-managed crops that grew without nutrient limitations and kept free of biotic stresses (Yang et al., 2004; Grassini et al., 2009).

5.2.4. Random forests and regression tree analyses

Distribution of yield, N inputs, and N balance were assessed separately for irrigated and rainfed fields, and deviation from normality was tested using D'Agostino-Pearson test. We used a number of machine-learning techniques to identify candidate soil and management factors explaining variation in N balance among producer fields. Machine learning analysis has been increasingly used in different areas of research due to some advantages over other (more frequently used) statistical methods (*e.g.*, multiple regression). Some of the advantages of machine learning are: (i) no assumption on distribution of response and predictor variables and robust in the presence of multicollinearity; (ii) it can handle missing data and combinations of categorical and continuous variables; and (iii) it has the ability to reveal variable interactions (Strobl et al., 2009). Two types of machine learning recursive partitioning techniques were used to investigate the influence of management and soil variables on N balance. The first technique was regression tree analysis, which is a non-parametric method that recursively partitions the data into successively smaller groups with binary splits based on a single continuous predictor variable using the "rpart" package in R (Breiman et al., 1984; Verbyla, 1987; Clark and Pregibon, 1992; Hothorn et al., 2006; Prasad et al., 2006). Regression tree analysis produces a tree-diagram output, with branches determined by splitting rules and a series of terminal nodes (TN) that contain the mean response (*i.e.*, N balance) and the number of observations (n) that fall within each TN. Here, a maxdepth validation technique was used to prune the regression tree to an optimal size (Therneau and Atkinson, 1997). The regression tree analysis handled missing values in the explanatory factors (*na.rpart* function), excluding cases only if the response variable (*i.e.*, N balance) or all explanatory factors were missing. When missing values were encountered in considering a split, they were ignored and predictions are calculated from the non-missing values of that factor (Venables and Ripley, 2002).

While regression trees produce simple model, they are unstable. For example, a few changes in dataset can give a different first splitting variable, which when changed can drastically modify the entire tree structure. Hence, we also performed random forest analysis using “randomForest” function in R, which overcomes the instability problem of the regression tree analysis (Breiman, 2001). Random forests uses an ensemble learning technique (bootstrap sampling) to create many trees and make final prediction as the average of the predictions across the trees. Random forests quantifies the variable importance, which was based on how much the mean accuracy decreases when a variable is excluded. To normalize values between water regimes, relative variable importance was determined by setting the variable with the highest importance to 1 and calculating individual values as a percentage of the most important variable. In general, while random forests analysis improves accuracy, the simple regression tree analysis gives a model that is easy to interpret and presents the value of variables used to split data and predict outcome. Given the advantages and limitations of each machine learning technique, we used both techniques in our study. Overall, seven continuous and nine categorical variables were used as potential explanatory factors for variation in N balance across producer fields (Tables 5-1 and 5-2). In addition, the most important factors affecting N balance were further analyzed based on their influence on yield and N inputs. Finally, quantile linear-plateau regression was used to determine a boundary function (quantile: 0.95) for the relationship between yield and N inputs.

5.2.5. Framework to benchmark yield and N balance in producer fields

Analysis of yield variation across field-years, for a given N balance level, is confounded by year-to-year and site-to-site variation in weather. Hence, expressing producer yields as percentage of Yp (or Yw) for a given field-year (hereafter referred to as 'relative yield') allows a fair comparison of producer yields and N balance across years and regions. Some cases with relative yield greater than one (*i.e.*, 15% of total field-years) were likely associated with inaccuracies in weather, soil, or producer yield data; in those cases, the relative yield was set at one. Relative yield (as percentage of Yp or Yw) *versus* N balance plots were assessed to determine the frequency of fields with small or large N balance and low or high yield. Fields were subsequently grouped in four categories: (A) high relative yield, N balance <75 kg N ha^{-1}; (B) low relative yield, N balance <75 kg N ha^{-1}; (C) high relative yield, N balance ≥75 kg N ha^{-1}; (D) low relative yield, N balance ≥75 kg N ha^{-1}. Following Lobell et al. (2009) and van Ittersum et al. (2013), we used 80% and 70% of Yp and Yw as thresholds to distinguish high *versus* low yields in irrigated and rainfed fields, respectively. These values represent reasonable yield goals, with the smaller yield goal in the case of rainfed crops aiming to account for the higher production risk associated with erratic rainfall across years. Finally, the framework was used to assess available room to improve N balance by identifying different agronomic practices between the four groups of fields. Differences in averages of fields that exhibited small (SNB) *versus* large N balance (LNB) and achieved low (LRY) *versus* high relative yield (HRY) for each continuous variable were tested for statistical significance using *t*-tests, while Chi-square (χ^2) test was used for categorical variables.

5.3. Results

5.3.1. On-farm yield, N inputs, and N balance in irrigated and rainfed conditions

The study included two crop seasons (2010 and 2011) with above-normal precipitation, except for 2011 in the south-central region, which exhibited near-normal precipitation (Figure 5-2). Cumulative GDD for both years did not deviate from the long-term average in the three regions. Average irrigated fields had 23% and 33% higher yield and N inputs, respectively, relative to rainfed fields (Figure 5-3). The N inputs averaged 162 and 240 kg N ha^{-1} in rainfed and irrigated fields, respectively. In irrigated fields, N irrigation represented 11% of the N inputs. Irrigated fields exhibited (48%) higher average N balance compared with rainfed fields (94 *versus* 49 kg N ha^{-1}), with 21% and 68% of rainfed and irrigated fields exhibiting N balance $\geq$ 75 kg N ha^{-1}. Smaller N balance in rainfed *versus* irrigated fields were expected due to a combination of relatively small N inputs in the former and above-average rainfed yields as a result of above-normal precipitation in both years. The opposite would have occurred in a drought year (*i.e.*, large N balance in rainfed fields as a result of low yield). Both water regimes exhibited negatively skewed field yield distributions, indicating that an important number of fields were closer to highest yields (Figure 5-3). In contrast, distribution of N inputs showed contrasting patterns between water regimes: irrigated and rainfed fields exhibited positively and negatively skewed N input distributions. The N balance distribution in irrigated fields was positively skewed, but normally distributed in the case of rainfed fields.

The boundary function fitted for the relationship between yield and N inputs showed that the attainable yields over the range of N inputs increased at a rate of 40 kg per kg N ha^{-1}, reaching a plateau (16 Mg ha^{-1}) for N inputs > 255 kg N ha^{-1} **(**Figure 5-4**)**. Above this value, there was no further increase in grain yield. There were, however, 18% of total fields received N inputs in excess to 255 kg N ha^{-1}; all of them corresponded to irrigated fields exhibiting a large N balance (range: 85 to 228 kg N ha^{-1}). The y-intercept of the fitted boundary function also provides an estimate of the attainable yields without N inputs (5.7 Mg ha^{-1}), which is consistent with data from N-omission trials in Nebraska (Wortmann et al., 2011). Finally, it was clear that, given the same level of N input, maize yields were typically higher in irrigated *versus* rainfed fields. For example, average yield was 1.9 Mg ha^{-1} higher in irrigated than rainfed fields at N inputs ≥ 200 kg N ha^{-1} (*t*-test, p <0.001). A number of factors associated with rainfed fields (*e.g.*, late sowing, less intensive management, insufficient water supply, less suitable soils) can help explain why rainfed yield depart from their attainable yield at a given N input level, even in years with favorable weather conditions as it was the case in this study.

5.3.2. Management and soil factors influencing variation in N balance

Analysis based on conditional random forest indicated that water regime was the most important factor explaining variation in N balance among fields (Figure 5-5a). Separate analysis performed for each water regime revealed that most important factors explaining the remaining variation in N balance were different in irrigated *versus* rainfed fields (Figure 5-5b, c). In irrigated fields, SOM, seeding rate, and spring N split application were most important variables driving differences in N balance among producer fields (Figure 5-5b). Sowing date, N application timing, and foliar fungicide application were the most important factors in the case of rainfed fields (Figure 5-5c). Results from the analysis based on conditional regression trees analysis were consistent with those derived from the conditional random forest analysis. Water regime, sowing date, SOM, N application timing, and spring N split application explained 41% of variation in N balance (Figure 5-6). It was notable that most combinations of management practices and soil properties would lead to an acceptable N balance (≤ 77 kg ha^{-1}), except for two cases (>100 kg N ha^{-1}). These two cases corresponded to irrigated fields with low SOM or receiving spring N split applications. In rainfed fields, early-sown fields receiving fall *and* spring N applications exhibited the largest N balance (77 kg N ha^{-1}).

5.3.3. Impact on yield and N inputs of management factors influencing N balance

Producers growing irrigated maize in sandy soils with low SOM tend to apply larger N inputs (both N fertilizer and N irrigation) compared with producers in fine-textured soils, probably to compensate for the lower indigenous soil N and also as a consequence of higher irrigation water inputs (Figure 5-7). For instance, total N fertilizer applied ranged from 250 – 360 kg N ha^{-1} in sandy soils, while N irrigation varied from 22 to 92 kg N ha^{-1}. This risk-aversion behavior leads to a large N surplus, with N balance ranging from 129 to 228 kg N ha^{-1}. While the number of fields in sandy soils was relatively small, their N balance and N losses is substantially higher compared with the other fields, contributing proportionally more to the total N load in the region.

Producers in rainfed fields who applied N fertilizer in fall only or both in fall *and* spring exhibited high N balance due to 10% higher total N inputs compared with spring N application only and, lesser yield for fall application while a proportionally smaller (+7%) yield advantage for fall *and* spring application (Figure 5-7). In contrast, irrigated fields with only spring N application had higher N input compared with fall or fall *and* spring application (+10 and +2%, respectively), and N input was even larger (+34 kg N ha^{-1}) when the spring application was split (Figure 5-7). In the case of rainfed fields, early-sown fields exhibited higher N balance as a result of larger N inputs compared with late-sown fields, without any detectable change in yield between early and late sowings (Figure 5-8A). In addition, seeding rate had a positive relationship with N balance, N inputs, and yield (Figure 5-8B).

5.3.4. Benchmarking yield and N balance in producer fields

There is ample room for improvement of N balance in irrigated field as indicated by the fact that 68% of the fields exhibited large N balance (categories C and D) and, of these, about half reached yields below their attainable yield level (Figure 5-9). In contrast, about 20% of total rainfed fields exhibited a large N balance. Notably, 23% and 67% of irrigated and rainfed fields attained high yields with small N balance (*i.e.*, < 75 kg N ha^{-1}), indicating that meeting productivity and environmental goals simultaneously is possible.

Analysis of differences in the management practices associated with each field category revealed a number of practices that could potential lead to yield increase, or N surplus reduction, or both (Tables 5-3 and 5-4). It was remarkable that N fertilizer inputs was similar between the high relative yield (HRY) and low relative yield (LRY) fields; indeed, yields were higher in the small N balance (SNB) *versus* large N balance (LNB) field categories. On the one hand, the analysis revealed options to increase yield without trade-offs in terms of N balance. For example, irrigated LRY fields that were sown, on average, three days later had exhibited higher N balance than HRY fields (Tables 5-4). On the other hand, there seem to be opportunities to reduce the N balance without hurting yield. For example, LRY fields tended to exhibit higher N inputs, suggesting that N fertilizer rates can be reduced by using a more realistic yield goal. Some results need to be treated cautiously as they may be confounded by the biophysical background. For example, irrigated fields receiving spring split application exhibited larger N balance and the proportion of these fields was higher in low-yield (LRY) *versus* high-yield (HRY) fields (Tables 5-3 and 5-4). Similarly, K and S fertilizer input application was more frequent in LRY compared with HRY fields. Application of K and S fertilizer and split of spring N application is frequent in fields located in sandy soils with lower SOM and high risk of N leaching. These soils have, in turn, lower indigenous soil N, leading the producer to apply larger N fertilizer rates as indicated previously.

5.4. DISCUSSION

This study assessed the importance of soil and management factors at explaining variation in maize N balance across irrigated and rainfed fields in NE. Random forests and regression tree analyses revealed important factors influencing N balance across fields, including water regime, SOM, sowing date, and timing and split of N fertilizer application, and seeding rate. While this study identified management and soil properties influencing N balance, they only accounted for 41% of field-to-field variation in producer

N balance. Part of unexplained variation might be attributed to factors not available in our database or unaccounted variation in climate and soil among fields. Understanding drivers for N balance in producer fields could be improved in future studies by including other management practices and covering a larger number of fields and years. Still, we found that risk-aversion played a major role at explaining large or small N balance. For example, rainfed fields exhibited smaller N balance due to higher risk as a result of erratic precipitation. In other words, producers typically apply smaller N fertilizer rates in rainfed *versus* irrigated fields, leading to a smaller N balance than irrigated fields, especially when precipitation is above-normal as it was the case of the two years included in our study. Similarly, a risk aversion behavior was also clear for irrigated producers growing maize in sandy soils. In this case, producers applied relatively larger N fertilizer rates to compensate for lower indigenous soil N, which, together with the N from irrigation, lead to a large N balance. Another example of risk aversion was observed in late-sown rainfed fields. Although there was no relationship between rainfed yield and sowing date, producers who sown late probably considered that less N is required for crops with shorter growth period and with a higher risk of early-killing frost, hence, applied smaller N fertilizer rates compared with early-sown fields. Results from irrigated fields in this study are probably applicable to other large maize-producing areas in US Corn Belt since irrigated maize in Nebraska has comparable yield level and stability compared to those of rainfed maize production in the most favorable environments in the eastern and central portions of the US Corn Belt (Grassini et al., 2014).

Variation in N balance across field-years was also explained by timing of N application. In our study, high N balance in rainfed fields was associated with N application in fall only and both in fall *and* spring (Figure 5-7**).** Producers apply N fertilizer during fall due to some economical advantages (*e.g.*, lower N fertilizer price, and more available equipments and applicators); however, previous studies have indicated higher N recovery in spring *versus* fall N applications (Randal and Vetsch, 2005). Hence, moving from fall to spring application can help reduce cases of large N balance in the case of rainfed fields. For irrigated fields, we found larger N balance during spring *versus* fall or fall *and* spring N application and when producers split the N fertilizer spring application. In principle, one would expect the opposite results. However, those same producers who applied N fertilizer in the spring application also used larger N fertilizer rates compared with those that applied N fertilizer in the fall or fall *and* spring. It may be the case that producers applying N fertilizer in the spring would increase the rate to compensate for potential N losses as a result of excessive precipitation early in the season, which they knew before spring N fertilizer application time (Feinerman et al., 1990). We also found that producer splitting the spring N fertilization would also tend to use larger N rates: irrigated fields with spring N split application exhibited same yield and larger N balance compared with those without split application. Consistent with these results, Jaynes and Colvin (2006) reported that split N application (shortly after emergence and midseason) was only beneficiary for yield when lower N rate early in the season is applied compared with a single application. Lastly, while higher seeding rate increased yield, this practice also showed higher N inputs applied which resulted to larger N balance compared to lower seeding rate. For example, 51% of fields that sown greater than 80 seeds m^{-2} applied N inputs rate >255 kg N ha^{-1} at which yield was shown to plateau (Figure 5-4).

The N balance framework was used to identify fields with low/high yield and small/large N balance and recognized soil and management factors that could be improve to increase yield and reduce N balance. Consistent with Tenorio et al. (2019a), there were fields that successfully achieved the goal of simultaneuosly attaining high yield and small N balance (category A in Figure 5-9). The framework can be used for an effective research and extension prioritization by identifying and focusing on fields that have larger room for improvements. For instance, agronomic intervention and policy should be first directed to fields that attained low yield and exibited large N balance (category D in Figure 5-9), which represents 33% of total irrigated fields. Similarly, additional research on manageable practices to reduce N balance should be focused on fields with sandy soil type that showed to exhibit the largest N balance (Figures 5-6, 5-7). The framework can also be used by individual producers to assess their current yield and N balance and identify possible practices to increase N use efficiency. For instance, producers in categories C and D (N balance ≥ 75 kg N ha^{-1}) can look for opportunities to reduce their N balance while maintaining or even increasing their yield. This study provides a first step for a cost-effective assessment of N balance and its drivers at local and regional level based on field-level producer data.

REFERENCES

Bakhsh, A., Kanwar, R.S., Bailey, T.B., Cambardella, C.A., Karlen, D.L., Colvin, T.S., 2002. Cropping system effects on NO3–N loss with subsurface drainage water. Trans. ASAE 45:1789–1797.

Basso, B., Shuai, G., Zhang, J., Robertson, G.P., 2019. Yield stability analysis reveals sources of large-scale nitrogen loss from the US Midwest. Sci. Rep. 9, 5774.

Breiman, L., 2001. Random Forests. Machine Learning 45, 5–32.

Breiman, L., Friedman, J., Olshen, R., Stone, C., 1984. Classification and Regression Trees. Wadsworth, Belmont, CA.

Camp, R., 1989. Benchmarking: The search for industry best practice that lead to superior performance. New York: Quality Resources.

Cassman, K.G., Dobermann, A., Walters, D.T., 2002. Agroecosystems, nitrogen-use efficiency and nitrogen management. Ambio. 31, 132–140.

Clark, L.A., Pregibon, D., 1992. Tree-based models. In: Chambers, J.M., Hastie, T.J. (Eds.), Statistical Models in S. Wadsworth, Pacific Grove (CA), pp. 377–419.

Cui, Z., Zhang, H., Chen, X., Zhang, C., Ma, W., Huang, C., Zhang, W., Mi, G., Miao, Y., Li, X., et al., 2018. Pursuing sustainable productivity with millions of smallholder farmers. Nature 555, 363–368.

Erisman, J.W., Galloway, J.N., Seitzinger, S., Bleeker, A., Dise, N.B., Petrescu, A.M.R., Leach, A.M,, de Vries. W., 2013. Consequences of human modification of the global nitrogen cycle. Phil. Trans. R. Soc. B. 368, 20130116.

Evans, L.T., 1993. Crop Evolution, Adaptation, and Yield (Cambridge, UK: Cambridge University Press).

Feinerman, E., Choi, E.K., Johnson, S.R., 1990. Uncenainty and split nitrogen application in com production, American Journal ofAgricultural Economics 72, 975-84.

Franke, R., Nielson, G., 1980 Smooth interpolation of large sets of scattered data. Int. J. Numer. Methods Eng. 15 1691–704.

Franks, J.R., Collis, J., 2003. On-farm benchmarking: how to do it and how to do it better. Proceedings International Farm Management Congress Farming at the Edge, Perth, Australia.

Goolsby, D.A., Battaglin, W.A., Aulenbach, B.T., Hooper, R.P., 2001. Nitrogen input to the Gulf of Mexico. J. Environ. Qual. 30, 329–336.

Grassini, P., Torrion, J.A., Yang, H.S., Rees, J., Andersen, D., Cassman, K.G., Specht, J.E., 2015. Soybean yield gaps and water productivity in the western U.S. Corn Belt. Field Crops Res. 179, 150–63.

Grassini, P., Thorburn, J., Burr, C., Cassman, K.G., 2011. High-yield irrigated maize in the Western U.S. Corn-Belt: I. On-farm yield, yield-potential, and impact of management practices Field Crops Res. 120, 142–150.

Grassini, P., Yang, H.S., Cassman, K.G., 2009. Limits to maize productivity in the Western Corn-Belt: a simulation analysis for fully irrigated and rainfed conditions. Agric. For. Meteorol. 149, 1254–1265.

Hothorn, T., Hornik, K., van de Wiel, M.A., Zeileis, A., 2006. A lego system for conditional inference. Am. Stat. 60, 257−263.

International Food Policy Research Institute, 2019, "Global Spatially-Disaggregated Crop Production Statistics Data for 2010 Version 1.1", https://doi.org/10.7910/DVN/PRFF8V, Harvard Dataverse, V3.

Jaynes, D. B., and T. S. Colvin. 2006. Corn yield and nitrate loss in subsurface drainage from midseason nitrogen fertilizer application. Agron. J. 98, 1479–1487.

Khanal, S., Anex, R.P., Gelder, B.K., Wolter, C., 2014. Nitrogen balance in Iowa and the implications of corn–stover harvesting. Agric. Ecosyst. Environ. 183, 21–30.

Kucharik, C. J., 2008. Contribution of planting date trends to increase maize yields in the Central United States. Agron. J. 100:328-336.

Lassaletta, L., Billen, G., Grizzetti, B., Anglade, J., and Garnier, J., 2014. 50 year trends in nitrogen use efficiency of world cropping systems: the relationship between yield and nitrogen input to cropland. Environ. Res. Lett. 9, 105011.

Lauer, J.G., Carter, P.R., Wood, T.M., Diezel, G., Wiersma, D.W., Rand, R.E., Mlynarek, M.J., 1999. Corn hybrid response to planting date in the northern Corn Belt. Agronomy Journal, 91, 834– 839.

Lobell, D.B., Cassman, K.G., Field, C B., 2009. Crop yield gaps: their importance, magnitudes, and causes. Annu. Rev. Environ. Resour. 34, 179–204.

McLellan, E.L., Cassman, K.G., Eagle, A.J., Woodbury, P.B., Sela, S., Tonitto, C., Marjerison, R.D., van Es, H.M., 2018. The nitrogen balancing act: tracking the environmental performance of food production. Biosci. 68, 194–203.

Mitchell, J.K., McIsaac, G.F., Walker, S.E., Hirshi, M.C., 2000. Nitrate in river and subsurface drainage flows from an east central Illinois watershed. Trans. ASAE 43:337–342.

Mourtzinis, S., Kaur, G., Orlowski, J.M., Shapiro, C.A., Lee, C.D., Wortmann, C., et al. 2018. Soybean response to nitrogen application across the United States: A synthesis-analysis. Field Crops Res. 215:74–82.

Oenema, J., van Ittersum, M., van Keulen, H., 2012. Improving nitrogen management on grassland on commercial pilot dairy farms in the Netherlands. Agric. Ecosyst. Environ. 162, 116–126.

Pittelkow, C.M., Linquist, B.A., Lundy, M.E., Liang, X., van Groenigen, K.J., Lee, J., van Gestel, N., Six, J., Venterea, R.T., van Kessel, C., 2015. When does no-till yield more? A global meta-analysis. Field Crops Res. 183:156–168.

Prasad, A.M., Iverson, L.R., Liaw, A., 2006. Newer classification and regression tree techniques: bagging and random forests for ecological prediction. Ecosystems 9, 181−199.

Randall, G.W., Vetsch, J.A., Huffman, J.R., 2003. Corn production on a subsurface-drained mollisol as affected by time of nitrogen application and nitrapyrin. Agron. J. 95, 1213–1219.

Sørensen, R., Zinko, U., Seibert, J., 2006. On the calculation of the topographic wetness index: Evaluation of different methods based on field observations. Hydrol. Earth Syst. Sci. 10, 101–112.

Spendolini, M., 1992. The Benchmarking Book. New York: American Management Association.

Strobl, C., Malley, J., Tutz, G., 2009. An introduction to recursive partitioning: rationale, application, and characteristics of classification and regression trees,bagging, and random forests. Psychol. Methods 14, 323–348.

Tenorio, F.A.M., Eagle, A.J., McLellan, E.L., Cassman, K.G., Howard, R., Below, F.E., Clay, D.E., J Coulter, J.A., Geyerg, A.B., Joos, D.K., Lauer, J.G., Licht, M.A., Lindsey, A.J., Maharjan, B., Pittelkow, C.M., Thomison, P.R., Wortmann, C.S., Sadras, V.O., Grassini, P., 2019c. Assessing variation in maize grain nitrogen concentration and its implications for estimating nitrogen balance in the US North Central region. Field Crop Res. 240, 185–193.

Tenorio, F.A.M., McLellan, E.L., Eagle, A.J., Cassman, K.G., Grassini, P., 2019a. Benchmarking nitrogen input use in producer fields in the western US Corn Belt. Agr. Ecosyst. Environ. *Submitted.*

Tenorio, F.A.M., McLellan, E.L., Eagle, A.J., Cassman, K.G., Grassini, P., 2019b. Data requirements for estimation of on-farm maize nitrogen balance. *To be submitted.*

Therneau, T.M., Atkinson, E.J., 1997. An Introduction to Recursive Partitioning Using the RPART Routine. Technical Report 61, Mayo Clinic, Section of Statistics.

Thomson, A. M., Ramsey, S., Barnes, E., Basso, B., Eve, M., Gennet, S., Grassini, P., Kliethermes, B., Matlock, M., McLellan, E., Spevak, E., Snyder, C.S., Tomer, M.D., van Kessel, C., West, T., Wick, G., 2017. Science in the supply chain: Collaboration opportunities for advancing sustainable agriculture in the United States. Agric. Environ. Lett. 2, 170015.

Tilman, D., Balzer, C., Hill, J., Befort, B. L. 2011. Global food demand and the sustainable intensification of agriculture. Proc. Natl Acad. Sci. USA 108, 20260–20264.

Tilman, D., Cassman, K.G., Matson, P.A., Naylor, R., Polasky, S., 2002. Agricultural sustainability and intensive production practices. Nature. 418, 671–677.

Treacy, M., Humphreys, J., Mc Namara, K., Browne, R., Watson, C.J., 2008. Farm-gate nitrogen balances on intensive dairy farms in the south west of Ireland. Irish J. Agr. Food Res. 47, 105–117.

van Ittersum. M.K., Cassman, K.G., Grassini, P., Wolf, J., Tittonell, P., Hochman, Z., 2013. Field 349 Crops Research Yield gap analysis with local to global relevance — A review Field Crops Res. 350 143 4–17.

Venables, W.N., Ripley, B.D., 2002. Modern Applied Statistics with S, fourth edition. Springer-Verlag, New York.

Verbyla, D.L., 1987. Classification trees: a new discrimination tool. Can. J. Res. 17 (1150), 1152.

Waterfield, W., 2002. Benchmarking as a means of improving the financial wellbeing of organic dairy farms. UK Organic Research 2002: Proceedings of the COR Conference. 26-28 March 2002. Aberystwyth.

Wortmann, C.S., Tarkalson, D.D., Shapiro, C.A., Dobermann, A.R., Ferguson, R.B., Hergert, G.W., Walters, D.T., 2011. Nitrogen use efficiency of irrigated corn for three cropping systems in Nebraska. Agron. J. 103, 76–84.

Yang, H.S., Dobermann, A., Lindquist, J.L., Walters, D.T., Arkebauer, T.J., Cassman, K.G., 2004. Hybrid-maize: a maize simulation model that combines two cropmodeling approaches. Field Crops Res. 87, 131–154.

Yang, H.S., Torrion, J.A., 2014 Weather Interpolator: Version 2014.2 © 2012-2014 University of Nebraska – Lincoln (https://hybridmaize.unl.edu/weatherDataUtilities).

Zhang, X., Davidson, E., Mauzerall, D., Searchinger, T., Dumas, P., 2015. Managing nitrogen for sustainable development. Nature. 528, 51–5

Table 5-1. Summary statistics for continuous management and soil variables in the surveyed producers maize fields in Nebraska, USA. Maximum, minimum, median and lower(P25) and uper quartiles (P75) are shown for each variable. Number of observations in each variable ranged from 309 to 311.

Continuous variables	Minimum	P25	Median	Mean	P75	Maximum
Sowing date (DOY)	94	111	119	118	123	149
Relative maturity	98	110	113	107	114	133
Seeding rate (m^{-2})	7.3	10.5	12.1	9.3	12.9	17.4
Soil organic matter (%)	0.5	1.4	1.9	2.1	2.8	6.0
pH	1.9	6.1	6.5	5.9	6.7	8.7
PAWHC (mm)	93	245	275	260	311	343
TWI	7.6	8.8	9.7	8.4	10.4	12.2

PAWHC: plant available water hoding capacity; TWI: topographic wetness index; DOY: day of year

Table 5-2. Summary statistics for categorical management variables in the surveyed producers maize fields in Nebraska, USA.

Categorical variables	% fields
Water regime (n= 311)	
irrigated	65
rainfed	35
Previous crop (n= 311)	
maize	18
soybean	82
Tillage method (n= 310)	
conventional	28
no-till	72
Time of N application (n = 306)	
fall	8
spring	70
fall and spring	22
Spring N split application (n= 306)	49
P application (n= 311)	80
K application (n= 311)	27
S application (n= 311)	36
Fungicide application (n= 311)	26

P: phosphorus; K: potassium; S: sulfur

Table 5-3. Average nitrogen (N) balance, yield, N inputs, and management and soil variables in irrigated and rainfed fields exhibiting small (SNB; pooled categories A and B) and large N balance (LNB, pooled categories C and D) as shown in Figure 5-9. Difference (Diff.) between SNB and LNB and their statistical significance are shown.

	Irrigated			Rainfed		
Variables	SNB	LNB	Diff.	SNB	LNB	Diff.
N balance (kg N ha^{-1})	53	114	-61^{***}	38	92	-55^{***}
Yield (Mg ha^{-1})	13.0	12.5	0.5^{**}	9.9	9.2	0.7
N inputs (kg N ha^{-1})	204	258	-54^{***}	152	199	-47^{***}
N fertilizer (kg N ha^{-1})	182	233	-51^{***}	152	199	-47^{***}
Continuous variables						
Sowing date (DOY)	117	117	nil	119	115	4^{*}
Relative maturity	112	112	nil	112	112	nil
Seeding rate (m^{-2})	7.7	7.8	-0.1	6.1	6.3	-2
Soil organic matter	2.1	2	0.1	2.3	2.6	-0.3
pH	6.6	6.5	0.1	6.6	6.4	0.2
PAWHC	257	259	-2	267	267	0.99
TWI	9.7	9.7	0	9.7	9.6	0.67
Categorical variables (% fields)						
Soybean as previous crop	83	73	10	93	95	-2
No-till method	67	61	6	85	100	-15
Time of N application						
fall	17	5	12^{**}	7	9	-2
spring	69	80	-11^{**}	62	41	21
fall and spring	14	15	-1^{**}	31	50	-19
Spring N split application	48	68	-20^{**}	26	18	8
P application	75	82	-7	78	91	-13
K application	32	31	1	21	9	12
S application	34	38	-4	34	45	-11
Fungicide application	23	31	-8	20	23	-3

PAWHC: plant available water hoding capacity; TWI: topographic wetness index; DOY: day of year
Asterisks indicate significance of t-test or Chi-square (χ^2) test at p-value * <0.10, ** <0.05, and *** <0.001.

Table 5-4. Average nitrogen (N) balance, yield, N inputs, and management and soil variables in irrigated and rainfed fields exhibiting high (HRY; pooled A and C categories) and low relative yield (LRY; pooled B and D categories) as shown in Figure 5-9. Differences (Diff.) between HRY and LRY fields and their statistical significance are shown.

	Irrigated			Rainfed		
Variables	HRY	LRY	Diff.	HRY	LRY	Diff.
N balance (kg N ha^{-1})	84	109	-25^{***}	47	58	-11
Yield (Mg ha^{-1})	13.2	12.0	1.2^{***}	10	7.3	3^{***}
N inputs (kg N ha^{-1})	236	247	-11^{**}	164	144	20^{**}
N fertilizer (kg N ha^{-1})	215	220	-4	164	144	20^{**}
Continuous variables						
Sowing date (DOY)	116	119	-3^{**}	118	121	-3
Relative maturity	112	112	0	112	112	nil
Seeding rate (m^{-2})	7.7	7.8	-1	6.2	6.1	1
Soil organic matter	2.1	1.8	0.3^{**}	2.3	2.3	nil
pH	6.4	6.7	-0.3^{**}	6.5	6.5	nil
PAWHC	262	252	10	270	253	17
TWI	9.6	9.7	-0.1	9.7	10	-0.3
Categorical variables (% fields)						
Soybean as previous crop	75	79	-4	96	82	14^{**}
No-till method	61	67	-6	88	88	nil
Time of N application						
fall	14	1	13^{**}	8	6	2
spring	70	85	-15^{**}	54	76	-22
fall and spring	16	14	2^{**}	38	18	20
Spring N split application	55	72	-17^{**}	27	12	15
P application	77	85	-8	78	88	-10
K application	21	44	-23^{**}	16	29	-13
S application	29	48	-19^{**}	37	29	8
Fungicide application	32	24	8	21	18	3

PAWHC: plant available water hoding capacity; TWI: topographic wetness index; DOY: day of year
Asterisks indicate significance of t-test or Chi-square (χ^2) test at p-value * <0.10, ** <0.05, and *** <0.001.

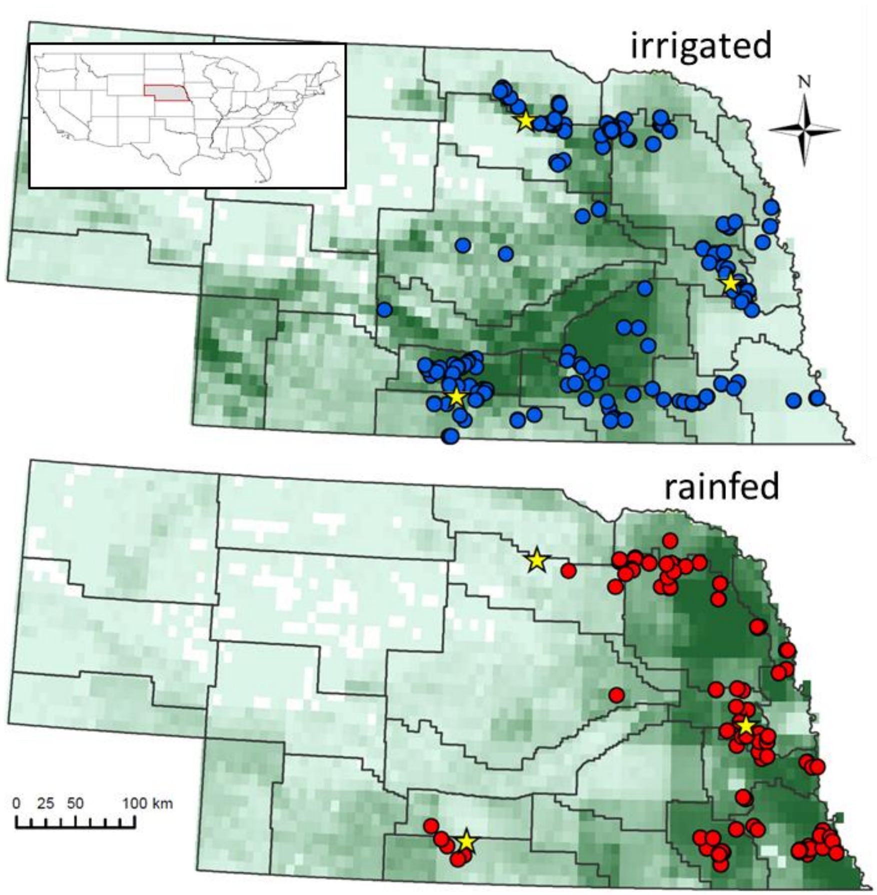

Figure 5-1. Map of Nebraska showing location of surveyed irrigated (upper panel) and rainfed (bottom panel) producer fields. Stars show the representative meteorological stations used to describe weather patterns in Figure 5-2. Maize harvested area distribution is shown in green (IFPRI, 2019). Inset shows the location of NE within the conterminous USA (highlighted in red).

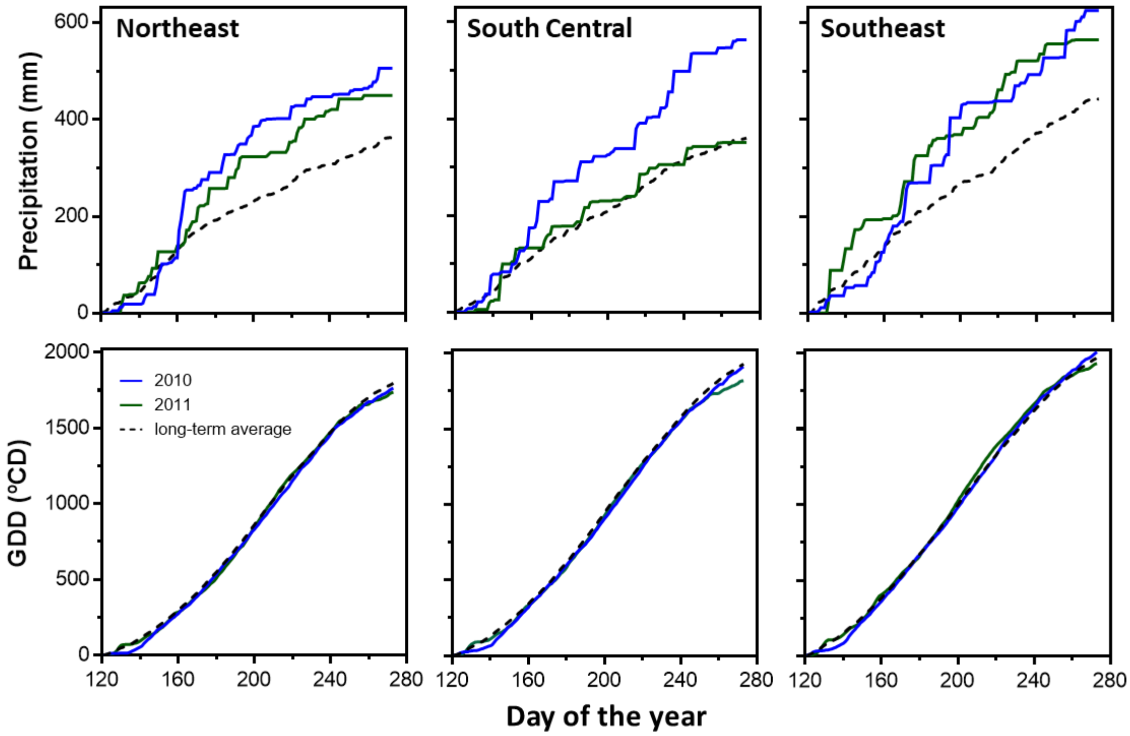

Figure 5-2. Cumulative precipitation and growing-degree days (GDD, T_{base} and T_{max} = 8 °C and 30 °C, respectively) for the period between May 1st and Sep 30th, which roughly coincides with maize emergence and physiological maturity, respectively, in years 2010 (blue), and 2011 (green), at three representative locations: O'Neill, NE (northeast region), Holdrege, NE (south central region) and, Mead, NE (southeast region). Dashed black lines represents long-term (1997- 2011) average.

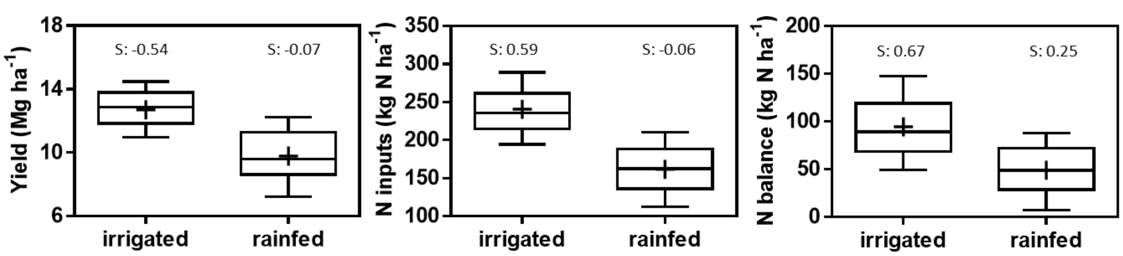

Figure 5-3. Distribution of producer yield, nitrogen (N) inputs, and N balance for irrigated and rainfed fields. Data from the two years (2010 and 2011) were pooled. Upper and lower boundaries of boxes indicate 75th and 25th percentile, respectively. Vertical bars are 10th and 90th percentile. Horizontal line and cross within boxes are the median and mean value, respectively. Skewness (S) of the field data distribution is indicated in each case.

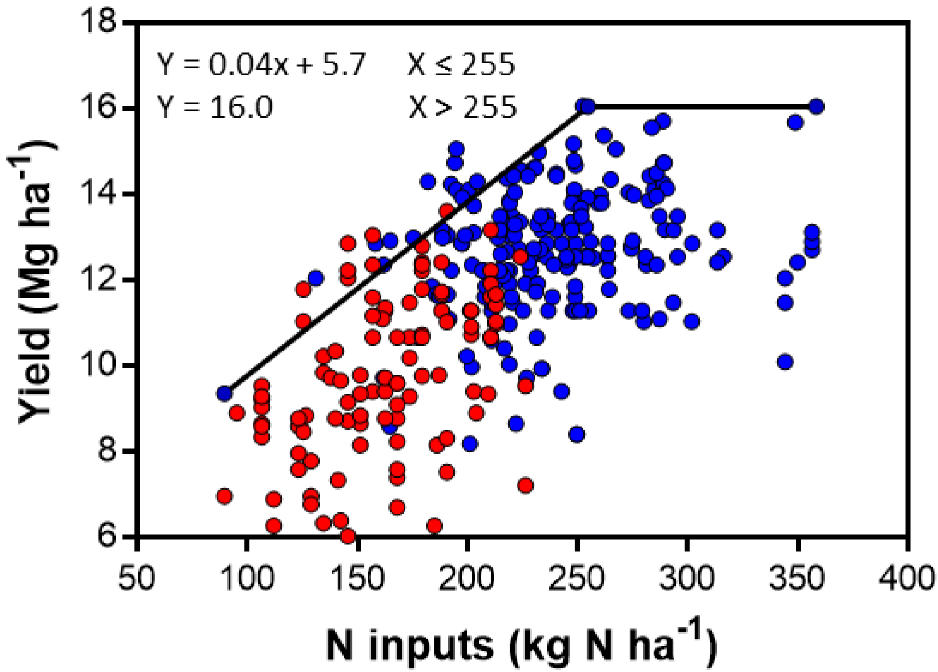

Figure 5-4. Yield and N inputs for irrigated (blue) and rainfed (red) fields. Parameters of the fitted linear-plateau model using quantile regression are shown (quantile: 0.95; p<0.01).

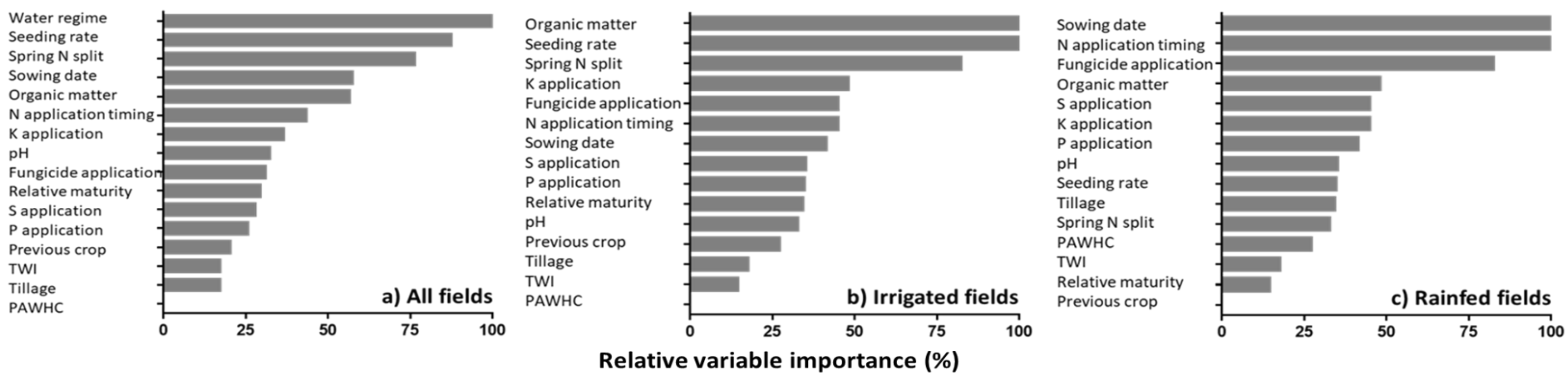

Figure 5-5. Relative variable importance ranking for the influence of soil and management factors on nitrogen balance based on conditional random forest for (a) pooled data, (b) only irrigated fields, and (c) only rainfed fields.

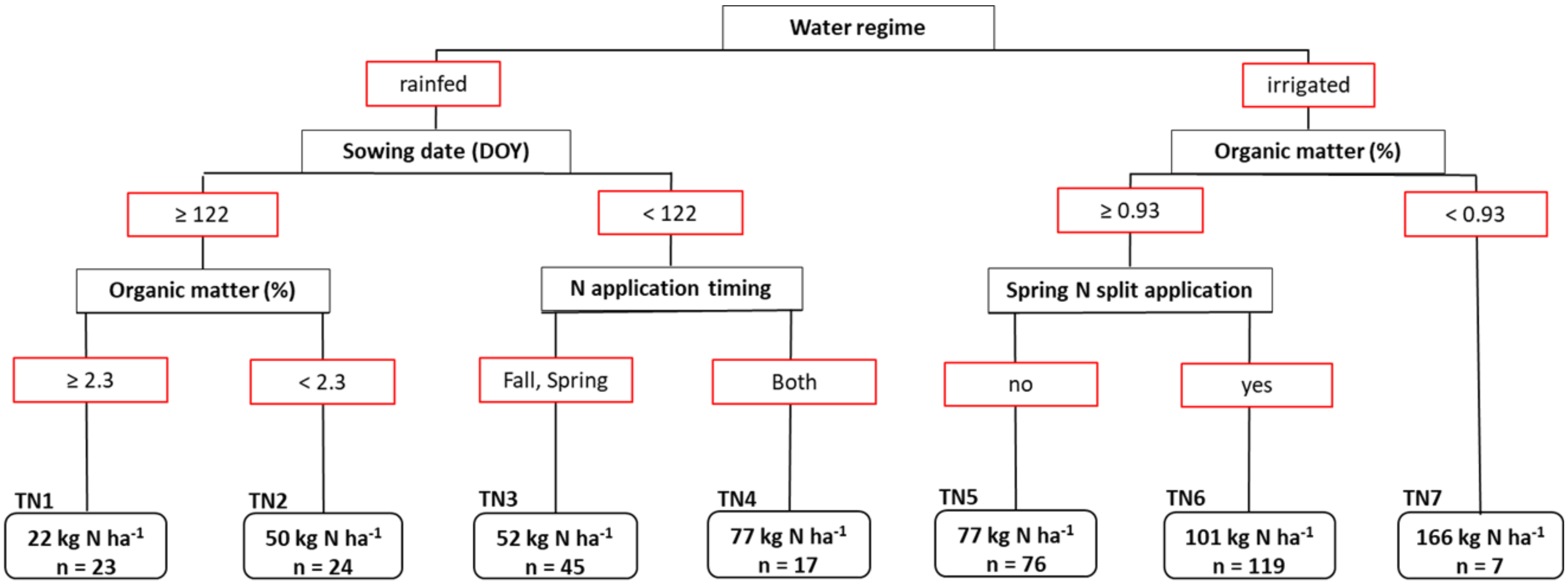

Figure 5-6. Regression tree model showing sources of variation in nitrogen (N) balance due to management and soil factors (overall R^2=0.41). Boxes are splitting nodes, with bottom boxes representing terminal nodes (TN). Values within each of the seven TN TN1 to TN7) indicates average N balance and the number of observations (n).

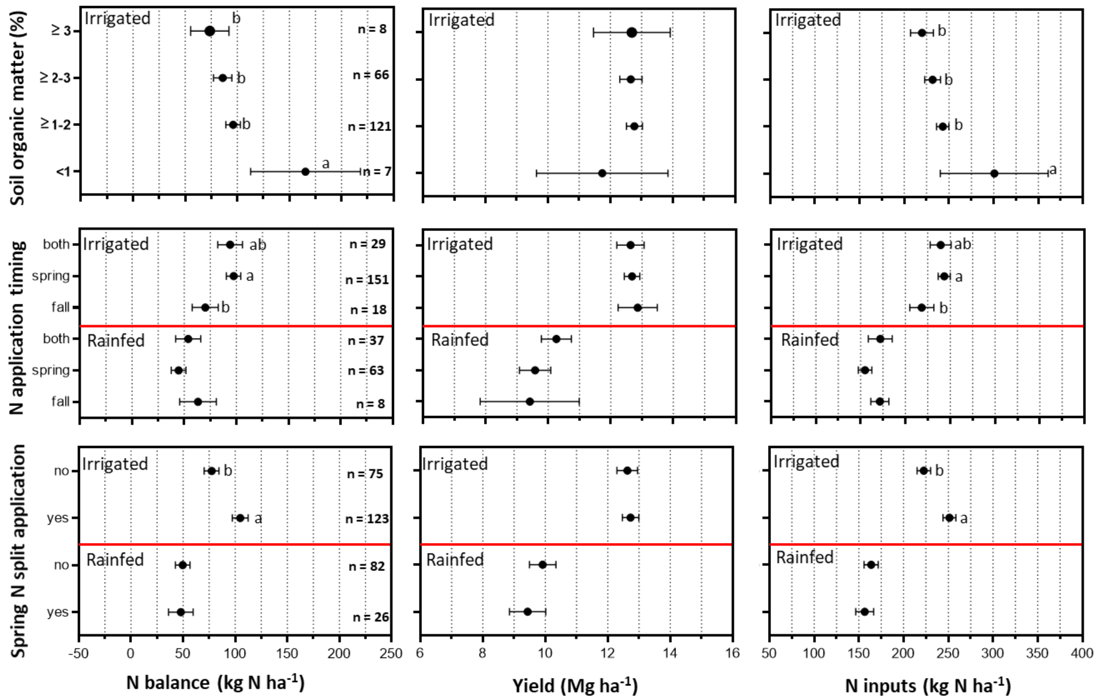

Figure 5-7. Nitrogen (N) balance, yield, and N inputs for irrigated and rainfed fields for soil organic matter (SOM) classes, N application timing, and spring N split application. Only irrigated fields were shown for SOM since it is unusual to have rainfed fields with SOM <1%. Data points represent means and error bars denote the 95% confidence intervals. Different letters indicate statistically significant differences (Tukey's test, $p < 0.05$). Number of fields (n) in each category is also shown.

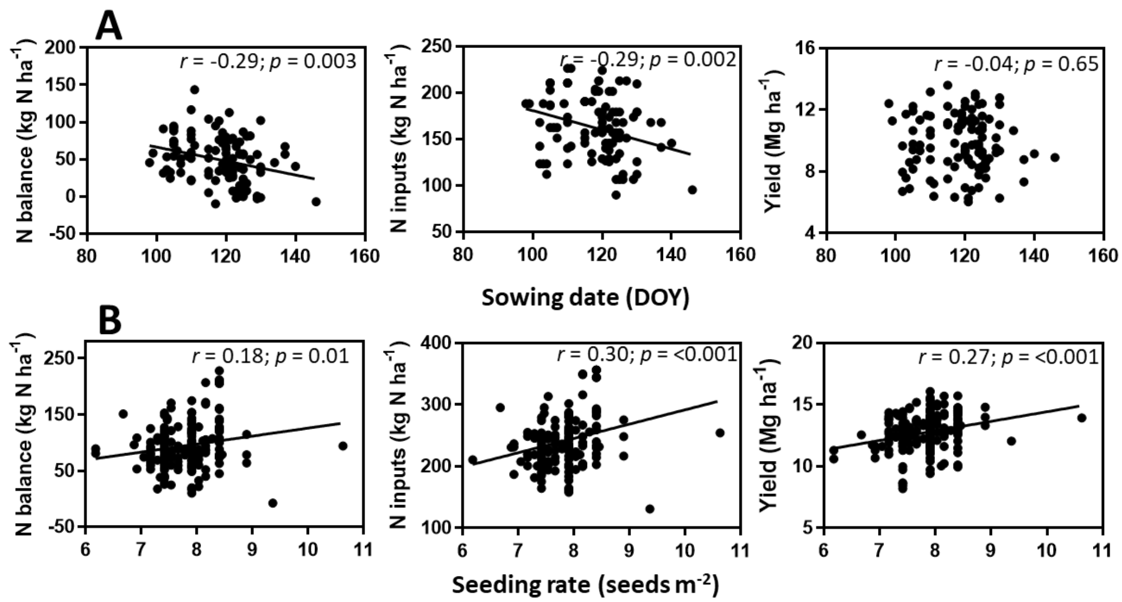

Figure 5-8. Influence of (A) sowing date in rainfed fields and (B) seeding rate in irrigated fields on nitrogen (N) balance, N inputs, and yield. Person's correlation coefficient (r) is shown.

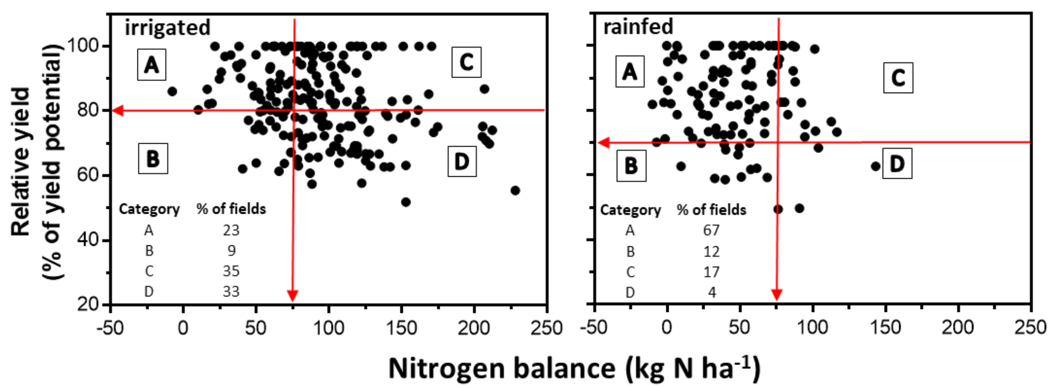

Figure 5-9. Relative yield and nitrogen (N) balance in irrigated and rainfed fields. Relative yield was calculated based on producer yield expressed as percentage of yield potential (Yp; irrigated) or water-limited yield potential (Yw; rainfed). Each data point represents a field-year case. Red vertical line indicates N balance = 75 kg N ha^{-1}, which was used as a threshold to identify fields with small and large N balance. Red horizontal lines indicate 80% and 70% of Yp and Yw, which are reasonable yield goals for irrigated and rainfed maize fields, respectively. Frequency of fields in each of the four (yield x N balance) categories is show

CHAPTER 6: SUMMARY AND FUTURE RESEARCH PRIORITIES

6.1. Key findings from this study

The present research applied the nitrogen (N) balance approach to benchmark the performance of a maize cropping system in the western US Corn Belt in terms of productivity and environmental outcomes using field-level data across a large number of fields in multiple years. A spatial framework (technology extrapolation domain [TED]) was used to upscale the N balance estimates from field to regional level with same soil-climate domain. Overall, this study provides a foundation to develop a platform to monitor potential N losses associated with maize-based systems in the US Corn Belt and, more broadly, to any cropping system in the world.

On-farm N balance assessment requires accurate estimation of grain N concentration (GNC), which was rarely measured by producers. Along these lines, this study found that GNC varied from 0.76 % to 1.66% across experiments conducted in the US North Central region, causing uncertainty in the resulting estimates of grain-N removal and N balance (Chapter 2). A predictive model was developed to refine estimates of grain-N removal and N balance for specific site-years based on key biophysical and management factors explaining variation in GNC (*e.g.,* N fertilizer rate and air temperature and water balance in July and August). In absence of measured GNC data, the predictive model can be applied although its advantage needs to be balanced out against the extra data requirements. Estimates of N balance from the model seem to be more accurate when aggregated to climate-soil domains compared with individual fields; in that case, using a fixed GNC value to estimate grain-N removal would work reasonably well. Here, an average estimated GNC value of 11.5 g kg^{-1} grain (at standard moisture content of 155 g H_2O kg^{-1} grain) was used for field-level maize N balance estimation.

This study demonstrated the value of a comprehensive field-level assessment of yield and N input use in producer fields, which could be useful for producers, supply-chain companies, and policy makers in improving yield and reducing N losses from agricultural production. We found a wide range of N balance across producer maize fields, even within the same year and climate-soil domain, suggesting a substantial room for improvement (Chapter 3). For example, fields in a region of similar domain exhibited an N balance ranging from -50 to 230 kg N ha^{-1}. We used a benchmarking framework for N balance to identify fields that are most likely to benefit from improved management practices. Of the total 8413 irrigated and 867 rainfed field-years, 58% (irrigated) and 14% (rainfed) exhibited N balance $\geq$ 75 kg N ha^{-1}. Similarly, there were irrigated fields that consistently exhibited large N balance as a result of consistent high N inputs and/or low yield (Chapter 4). The proportion of fields with maize in rotation with soybean was, on average, consistently smaller in fields that exhibited large N balance compared with the other fields (15 *versus* 75%). In addition, there were 8% of rainfed fields that exhibited N deficit across years (Figure 3-5), which may possibly benefit from additional N fertilizer application.

Further analysis of the N balance in relation with producer soil and management practices brought new insights about drivers of potential N losses in agro-ecosystems. We found that, in rainfed fields, sowing date, N application timing, and SOM were main variables influencing N balance while, in the case of irrigated fields, SOM and spring N split application explained the largest portion of the variation in N balance (Chapter 5). There were number of practices that could potential lead to yield increase, or N surplus reduction, or both. For example, relative to late-sown fields, early-sown irrigated fields had higher yield without any trade-off in terms of N balance. Likewise, there was opportunity to reduce N balance without sacrificing yield. For instance, irrigated fields with low yield (*i.e.*, yield < 80% of yield potential) had applied higher N inputs compared to fields that attained high yield, suggesting that N fertilizer rates can be reduced by using a more realistic yield goal. Achieving high yields with relatively small positive N balance are not conflicting goals since there were already producers reaching these goals simultaneously.

The producer risk perception plays an important role at explaining the variation in N balance across fields (Chapter 5). For example, rainfed fields exhibited smaller N balance due to higher risk as a result of erratic precipitation, leading rainfed producers to typically apply smaller N fertilizer than irrigated fields. Likewise irrigated producers with sandy soil type exhibited higher N balance since they applied high N fertilizer rates to compensate for lower indigenous soil N and high N from irrigation water as compared to producers with fine-textured soils. Results from this study showed the importance of evaluating the influence of management practices on N balance to properly assess opportunities for improvement.

This study also provide valuable information on data requirements for robust estimation of N balance for a given climate-soil domain (Chapter 4). At least four (irrigated) and six (rainfed) years and 100 fields per year per climate-soil domain were needed to derive an estimate of maize N balance that was ±10% of N balance estimated using all field-years observations available in our database. These information, together with the spatial framework used in this study, can serve as basis to develop a strategy to collect field-level data to monitor productivity and environmental performance over large agricultural areas. Such information would be useful to prioritize research and extension programs that aimed to reduce N footprint in agro-ecosystems as well as to quantify the *ex-ante* and *ex-post* impact derived from these programs. Although Nebraska was used as a case study for proof of concept, the approach can be extended to other cereal-based systems around the world as long as field-level data on yield and N inputs are available. We expect these databases to become available soon given growing demand to measure the environmental footprint in agricultural systems.

6.2. Developing a N balance baseline for the US Corn Belt

Results from irrigated fields in this study are probably applicable to other large maize-producing areas in US Corn Belt since irrigated maize in Nebraska has comparable yield level and stability compared to those of rainfed maize production in the most favorable environments in the eastern and central portions of the US Corn Belt. To verify this, collection of extra data was necessary across major TEDs where maize is currently grown in the US Corn Belt. For example, targeting yield and N inputs data collection from the 16 major TEDs with largest maize area in USA would allow estimation of N balance for an area that account for 50% of US maize area (18 million ha), which means that collecting producer data in 1600 fields per year in four years is sufficient for robust N balance estimation for half of US maize area.

As a first step for N balance estimation across large US maize-based agroecosystem, producer data on yield and N inputs were collected from collaborators who have access to large, high quality producer databases in other US Corn Belt states. The producer database contained 3,066 rainfed fields sown with maize during 2004-2017 (Figure 6-1). Fields were grouped into 15 TEDs, that accounts for 51% of total US maize harvested area.

The current database was used to perform an initial analysis. Results indicated that (i) a greater proportion of the variation (% sum of squares excluding the error) in N balance was explained by TEDs rather than year (21% *versus* 13%); and (ii) average N balance ranged from 17 to 94 kg N ha^{-1} across TEDs, with larger N balance in the northern and eastern fringes of the US maize producing region (Table 6-1; Figures 6-2, 6-3). Smaller and more variable N balance in the western fringe reflects smaller N input due to high risk associated with lower and more erratic precipitation. In addition, areas with high N balance also exhibited higher frequency of fields with N balance ≥ 75 kg N ha^{-1} (Figure 6-3). As indicated previously, potential N losses increase substantially about this N balance level. Proportion of fields that exhibited N balance ≥ 75 kg N ha^{-1} ranged from 4-78% across TEDs, suggesting available room for improvement.

These maps can help identify hotspots for potential N losses and, in tune, help prioritize research and extension program and inform policy. Further, this N balance baseline can serve as basis to identify management options to reduce N balance while maintaining high productivity and profit, given the availability of biophysical and management factor associated with each field. Complete data on yield, N inputs, management practices, and biophysical factors for a given field-year can give a more robust estimation of N balance at field and regional level.

While these maps gave an initial N balance from large maize areas in US Corn Belt, inclusion of more producer data will give a more accurate assessment of the N balance since few data were currently available for other TEDs in eastern part of US (Figure 6-2). For example covering 75% of US Corn Belt will need 44 TEDs that corresponds to 4400 fields per year. In addition, continuous collection of producer data over the years is important to monitor progress towards the effort in reducing potential N losses from agricultural production across the US Corn Belt.

Table 6-1. Analysis of variance (ANOVA) for the effects of climate-soil domain (domain), year, and their interaction on N balance. Proportion (in %) of total sum of squares (SS) excludes the error.

Source	df	%SS	F Value	Pr > F
domain	14	21	5	<0.001
year	12	13	4	<0.001
domain*year	74	66	3	<0.001

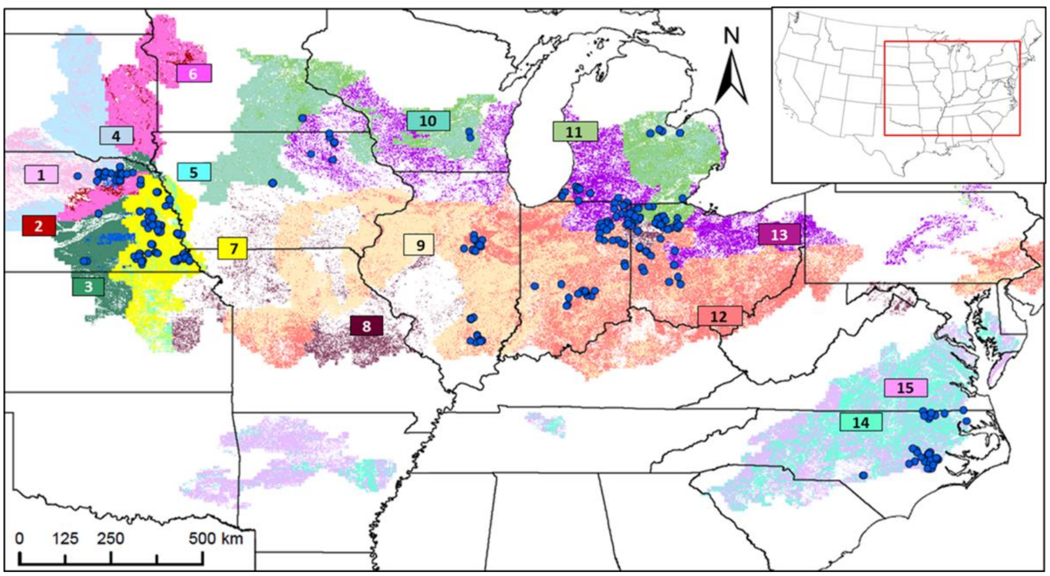

Figure 6-1. Map showing the location of each rainfed maize field (blue points) located within the same soil-climate domain. Each color represents a technology extrapolation domain (TED), and is identified using numeric values (from TED 1 to 15). Inset shows the location of study area (highlighted in red) within the conterminous USA.

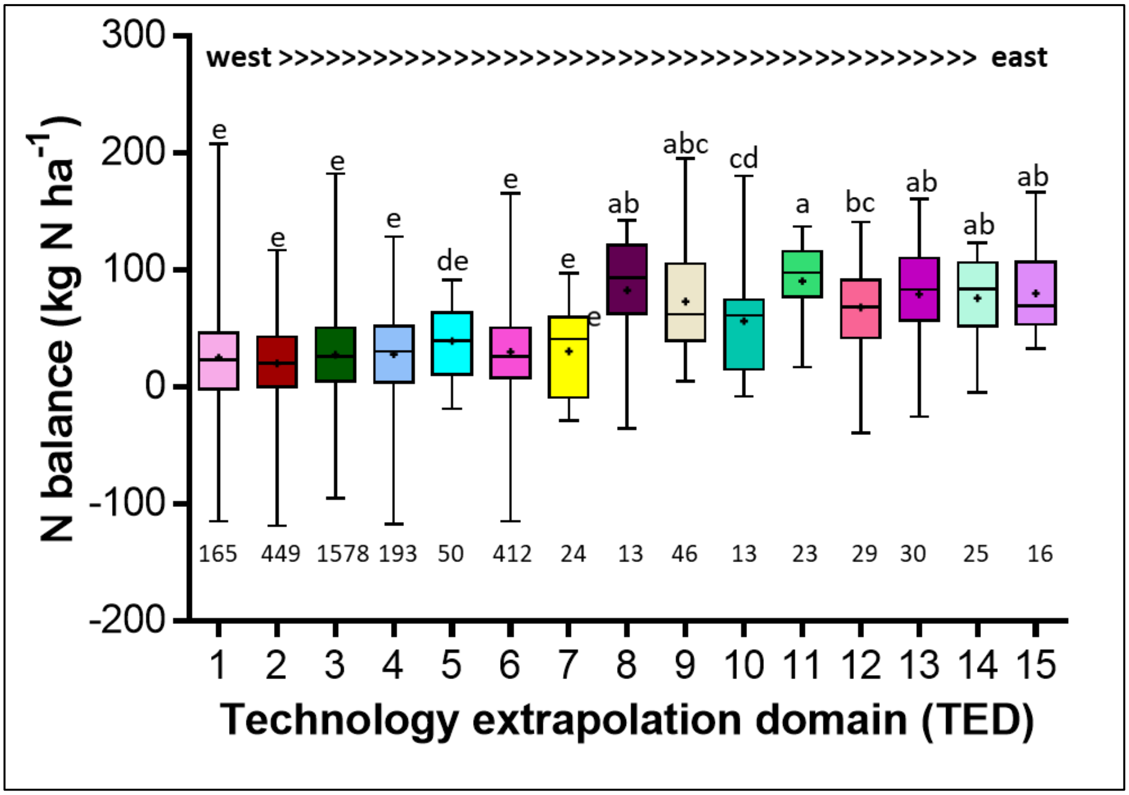

Figure 6-2. Boxplot of nitrogen balance for each technology extrapolation domain (TED). TEDs were arranged from west to east region of US (see Figure 6-1 for TED ID). Below and above box boundary indicates the 25th and 75th percentile, respectively. A black line and a star within the box marks the median and mean, respectively. Whiskers above and below the box indicate the minimum and maximum values. Different letters indicate statistically significant differences (Duncan's test; alpha=0.05). Number of observations were shown in the bottom of each TED.

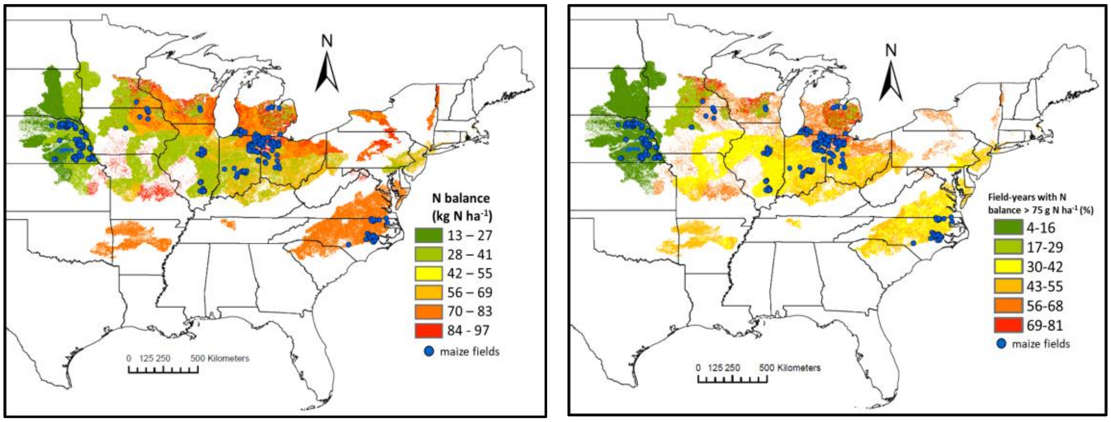

Figure 6-3. Maps showing mean N balance (left) and proportion of fields with N balance $\geq$ 75 kg N ha^{-1} (right) per climate-soil domain. N balance $\geq$75 kg N ha^{-1} was used as a threshold to identify maize fields with large N balance.