Quantifying On-farm Nitrous Oxide Emission Reductions in Food-Supply Chains

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Key Points:

- Nitrogen balance is a robust indicator of nitrous oxide emissions from agricultural cropland.
- Food-supply-chain companies and other entities can scale up field-level N balance values to measure progress toward sustainability goals over time.
- The relationship between N balance and N_2O emissions is non-linear, such that the greatest environmental benefit will come from reducing high field-scale N balances

Abstract

Reducing nitrous oxide (N_2O) emissions from agriculture is critical to limiting future global warming. In response, a growing number of food retailers and manufacturers have committed to reducing N_2O emissions from their vast networks of farmer suppliers by providing technical assistance and financial incentives. A key challenge for such companies is demonstrating that their efforts are leading to meaningful progress towards their climate mitigation commitments. We show that a simplified version of soil surface nitrogen (N) balance, the difference between N inputs to and outputs from a farm field (e.g., fertilizer N minus crop N), is a robust indicator of N_2O emissions. Furthermore, we present a generalized environmental model which will allow food-supply-chain companies to translate aggregated and anonymized changes in average N balance across their supplying farms into aggregated changes in N_2O emissions. This research is an important first step, based on currently available science, in helping companies demonstrate the impact of their sustainability efforts.

Plain Language Summary

As a powerful greenhouse gas, nitrous oxide emissions from agriculture contribute to climate change. Reductions in these emissions are not only possible – they are critical to addressing climate change. Food companies and others wanting to reduce nitrous oxide emissions in their food supply chains are looking for a way to show evidence of progress. Our research shows that a simple calculation of nitrogen (N) balance in crop fields (N in fertilizer minus N in the harvested crop) can be used as an indicator of nitrous oxide emissions. At the large scale, reducing high N balances will reduce overall emissions. We demonstrate the strong relationship between N balance and nitrous oxide emissions and show how this simple model can be used at scale to bring about positive environmental change.

1 Introduction

Agriculture is the dominant anthropogenic global source of nitrous oxide (N_2O) emissions (Tian et al., 2019), a long-lived greenhouse gas 265 times more powerful than carbon dioxide. Given the global imperative of limiting warming to 1.5^{o}C (Masson-Delmotte et al., 2018) there is a desire for immediate action to reduce N_2O and other greenhouse gas (GHG) emissions across large scales. N_2O emissions from N-fertilizer use, from both its manufacturing and field usage, dominate the greenhouse gas (GHG) footprint of cereal-based food products (Goucher et al., 2017) and play an important role in the environmental impact of livestock production (Herrero et al., 2016). Food-supply-chain companies, with their influence on millions of hectares of crop production, could play an important role in reducing these emissions. As food-supply-chain companies seek to reduce their overall GHG emissions (Krabbe et al., 2015), they must translate improvements in agricultural management on their supplier farms to changes (reductions) in N_2O emissions.

Quantifying such changes is challenging. Nitrous oxide is most commonly produced in agricultural soils through the microbial processes of nitrification and denitrification (Butterbach-Bahl et al., 2013). Rapid response of these microbial processes to variations in the environmental factors governing N_2O emissions gives rise to so-called "hot spots" and "hot moments" of N_2O emissions (Groffman et al., 2009), whereby N_2O production varies dramatically over short distances (meters) and timescales (hours). The existence of "hot spots" and "hot moments" creates high variability in measured emission values, thereby complicating efforts to measure emissions and/or relate overall changes in N_2O emissions to changes in agricultural management.

To date, relating agricultural management to N_2O emissions has primarily relied on two broad approaches: (1) empirical relationships at global, national or regional scales between N_2O emissions and N fertilizer rate (a partial measure of N availability; IPCC, 2006; Millar et al., 2010); and (2) complex biogeochemical models that attempt to simulate the impact of agricultural management practices on processes governing N_2O emissions at field- or site-specific scales (e.g., American Carbon Registry, 2013). The challenge to the first approach is that, by focusing exclusively on reduction in fertilizer rate, it risks jeopardizing yield, which makes it unattractive to farmers (Zhao et al., 2017). It also overlooks the potential role in reducing N_2O emissions of a broader set of farming practices that can improve N cycling in cropping systems (for example, recycling N through cover cropping; Han et al., 2017).

The challenge to the second approach is the need to parameterize, calibrate and validate complex models for specific crops and regions to be sure that models are correctly simulating N_2O emissions. Several dozen site-specific input parameters potentially affect simulated emissions, but data on these parameters is not routinely collected on working farms. Likewise, the availability of field measurements to support model calibration and validation is quite limited across the range of crop-soil-climate-practice combinations likely to be of interest (Tonitto et al., 2018). Emissions responses to many practices have not yet been validated in these models (Tonitto et al., 2018), and research shows that some of these practices could generate different (and even opposite) emission responses within different regions or cropping systems (Venterea et al., 2012).

Here we present an approach to quantifying the N_2O emission impacts of agricultural management that is uniquely aligned with food-supply-chain company needs. These needs include the ability to: (1) estimate aggregated changes in N_2O emissions across large (> 10,000 km^2) sourcing regions, based on readily-available and anonymized field-level data from participating farmers; (2) capture the impact of a broad array of farm-management practices on N_2O emissions, recognizing that farmers want flexibility to tailor management to their specific conditions; and (3) easily quantify and aggregate emission reductions across a variety of cropping systems, soils and climate regions, ideally through use of a single (generalized) model. The challenge is to develop an N_2O quantification approach that is robust at large scales, requires minimal input data, and aligns with farmers' interests in increased productivity and profitability.

Our quantification approach is based on a field-level measure of the amount of N potentially available for N_2O losses: N balance (McLellan et al., 2018). Previous research suggests that N_2O emissions are better predicted by the amount of N in excess of crop needs than by total N rate (Chantigny et al., 1998; van Groenigen et al., 2010; Omonode et al., 2017). This excess or "surplus" N (van Eerdt and Fong 1998) is a measure of the extent to which N inputs remain in the crop field and are therefore vulnerable to loss by microbial processes such as denitrification and volatilization, or by physical processes such as leaching and runoff. Using mass balance principles, this excess N can be quantified as the difference between N inputs to the crop field and N removed in harvested crops (including N removed in any harvested residue) at an annual or crop-cycle scale (whichever is shorter).

We therefore define N balance as the difference between N inputs to a field (from inorganic fertilizer and/or organic amendments and/or N_2-fixing crops and/or irrigation water) and N outputs from a field (as harvested crop and/or residue), calculated as follows:

$$(1) \qquad NBalance\ \left(\frac{kg\ N}{ha}\right) = TotalNApplied\ \left(\frac{kg\ N}{ha}\right) - NRemoved\ \left(\frac{kg\ N}{ha}\right)$$

Where *TotalNApplied* is equal to N from mineral fertilizer plus other N inputs (e.g., manures, N-fixing crops and irrigation water), and *NRemoved* is the N harvested with the crop (for harvested grain, this is calculated from crop yield and measured or estimated grain N concentration). For a major staple grain crop in a rainfed area, receiving only inorganic N fertilizer, the data needed to estimate N balance for a given field are limited to fertilizer N rate and yield, supplemented with estimates of grain N concentration. Measured grain N concentrations may not frequently be available from farmers, but using literature-derived estimates of grain N concentrations would likely be sufficient for calculating N balance (Tenorio et al., 2019). Thus, the calculation of N balance at field scale requires minimal data that are routinely gathered by farmers as part of their business operations.

Previous research has documented that, where N_2O production is N-limited, N_2O emissions are relatively small and constant at negative or small N balances and increase more rapidly as N balance increases (van Groenigen et al., 2010; Venterea et al., 2016; Omonode et al., 2017). Here we propose a simple but robust methodology, based on the empirical relationship between N balance and N_2O emissions, which can be used by food-supply-chain companies and others to quantify regional-scale aggregated changes in N_2O emissions. We focus on the relationship between N balance and N_2O emissions in typical rainfed cropping systems on the most widespread agricultural soils in temperate-climate crop-producing regions of the world. Such systems are the dominant source of grain, oilseed, and forage supply across regionally aggregated sourcing regions.

We previously published a preliminary model for the relationship between N balance and N_2O emissions for maize grown with inorganic N fertilizer (e.g., ammonia, ammonia nitrate, urea) in the U.S. Corn Belt (McLellan et al., 2018*)*. In the present paper, we test the validity of that preliminary model for explaining N balance–N_2O relationships in systems which are more diverse in soil type, N source, crop and/or region. Our objective is to develop a generalized model that integrates variations in the highly site-specific relationship of N balance to N_2O

emissions across fields and years into a broader understanding. A widely applicable and straightforward model, based on biophysical understanding of the drivers of N_2O emissions and easy to implement across tens of thousands of fields, will better enable food-supply-chain companies to track emissions reductions, and thereby motivate greater emphasis on reducing N losses within the food supply chain. Our effort is therefore very different from, although intended to complement, the work done by others to identify the relative impacts of an array of environmental factors (e.g., climate, soil texture) on N_2O emissions (Butterbach-Bahl et al., 2013; Eagle et al., 2017), to create detailed N_2O inventories at a wide range of spatial scales (Fitton et al., 2017), or to identify "hotspot" locations of very high N_2O emissions (e.g., organic soils, flood-prone soil zones; Fisher et al., 2014; Pärn et al., 2018).

2 Materials and Methods

2.1 Literature survey and database compilation

Data collection began with an expansion of the comprehensive literature search conducted for the preliminary model applied to maize on silt loam soils in the Corn Belt (McLellan et al., 2018). A Web of Science search located additional field studies and meta-analyses published since September 2016 and through May 2019, all reporting N_2O emissions from maize and other crops. Potential studies referenced in these articles and in previous cropland N_2O meta-analyses (Abalos et al., 2016b; Bouwman, 1996; DeCock, 2014; Eagle et al. 2017; Kim et al., 2013; Kim & Giltrap, 2017; Omonode et al., 2017; Rochette et al., 2018; Shcherbak et al., 2014; van Groenigen et al., 2010) were also retrieved and examined for relevant data. Selection criteria narrowed the studies to those most representative of typical annual field-crop systems in temperate regions. Atypical cropping systems and minor soil types with small production area are excluded from our analysis because they have limited influence on N_2O emissions at the scale of large grain- and oilseed-sourcing regions. Soils in tropical regions, such as Oxisols in Brazil which have a high anion exchange capacity, may respond quite differently to N additions (Jankowski et al., 2018), and so are excluded from our database. Likewise, N cycling in irrigated systems is likely to be quite different from that in rainfed systems (Trost et al., 2013); our survey was limited to rainfed crops.

The published data available for evaluating the N_2O-N balance relationship are dominated by studies on maize in the North American Corn Belt (inset panel in Figure 1). This is not surprising given the dominance of maize production in North American agriculture. Maize is grown on 26% of the total U.S. cropland area (39% of cropland in Corn Belt states) and received an average of 44% of all N fertilizer used in the U.S. (United States Department of Agriculture, Economic Research Service [USDA ERS], 2018). With maize production having such economic importance to agriculture and associated fertilizer use having a large impact on regional N use and N losses, programs or interventions that target maize have significant potential to influence GHG emissions from crop production. However, recognizing that food companies are interested in a much wider array of crops than maize, we made particular effort to locate studies on other crops and in other regions.

With an emphasis on identifying studies of high experimental quality, we constrained data selection to those experiments that reported fertilizer or manure N application rate, crop yield or harvested N removed, and cumulative annual or growing season N_2O emissions measured for a span of at least 70 days (detailed selection criteria in Table S1). For synthetic fertilizer observations, any plots known to receive manure or to be converted from a perennial in the previous two seasons were also excluded. Laboratory and greenhouse studies were also excluded. In order to best estimate the N_2O emission impact of management changes on working farms where fertilizer N (or manure) is nearly always used for non-legume crops, we excluded data from zero-N plots. We further limited our data to experiments that intentionally varied N balance by monitoring at least two different non-zero N application rates. By eliminating experiments that used only a single rate, we avoid potential bias from over-weighting the data within a limited range of N balance. This approach also ensured that the model dataset represented a wide range of N balance values. For robustness tests, and to evaluate the impact of factors other than N balance, we used an expanded dataset (Table S3) that included zero N observations and those from studies that measured N_2O emissions from only one non-zero N application rate. As a result of the selection criteria, both the model and expanded datasets excluded a number of studies (or portions thereof) that have been used by or mentioned in previous meta-analyses or syntheses (see Table S4).

Data were compiled as reported in published articles or supplemental materials, with some gaps (mostly crop yield and grain N) filled by data provided by study authors. For each site-year-treatment observation (most often the average of 3–4 replicates), data collected included N_2O losses, crop yield, N fertilizer added, plus other management, soil, and environmental conditions. Crop yield values were converted to (or confirmed at) standard moisture content (e.g., 15.5% for grain corn). For maize studies, we used reported grain N values where available; where not reported, we used the standard International Plant Nutrition Institute (IPNI) values (e.g., 12 kg N/Mg grain for maize; see Tenorio et al., 2019, for rationale). For studies on other crops, we only used data which reported crop N uptake.

Nitrogen balance is calculated in the basic system as the total fertilizer N added minus crop N removed. With increasing complexity, the inputs also included manure and the outputs include other harvested material such as straw or, in the case of forage, the full plant biomass. We categorized the data into five subsets, characterized by N source, soil type, and cropping system, as described below. Gaps in soil and weather characteristics were filled first with details from companion publications at the same site, and then from publicly available databases (see supplemental materials for details).

2.2 Statistical analyses

In our analysis we determined the most appropriate relationship between N_2O emissions and N balance on an area-scaled basis. While our previous model (McLellan et al., 2018) followed the work of van Groenigen et al. (2010) and others by using yield-scaled emissions, area-based emissions are more appropriate for the food-supply-chain context because of the climatic imperative to reduce absolute GHG emissions.

Because each data subset comprises a collection of studies that fit particular criteria, each subset has a unique statistical distribution of N balance, soil carbon (C), N_2O monitoring period (e.g., summer vs. annual), long-term mean annual precipitation (MAP), and other factors affecting N cycling. This variability creates challenges in comparing the data across subsets. To address this challenge, we developed a hierarchical model using the STATA *mixed* command, grouping by both location and data subset. Grouping by location (research site) and data subset in the hierarchical model accommodates the non-independent nature of these observations, going beyond a standard multivariate regression model by allowing possible response differences between groups (Woltman et al., 2012). Unless observations from the same research farm clearly came from the same experimental plots, we treated them as separate "locations" in the statistical model. The hierarchical models also address unbalanced data, with between 2 and 41 observations per location.

Data for cumulative N_2O emissions were transformed (natural log) and regressed against N balance, after being statistically adjusted to the mean soil C content, MAP, and N_2O monitoring period. These three covariates consistently explained variability in N_2O emissions within and between data subsets. The final multi-level hierarchical model included 301 observations from the five restricted data subsets, testing for differences between data subsets by allowing both the slope and intercept of the N balance–N_2O relationship to vary between them.

Model specifications were varied to test for the impact of other explanatory variables, including long-term mean annual temperature (MAT), crop species, previous crop species, and fertilizer management (i.e., placement, source, and timing). With a larger number of observations, the expanded dataset served as a robustness check on these relationships. Additional details on the testing and selection of confounding variables, between-group testing, and alternate model estimations are given in the Supplemental Materials.

3 Data

Figure 1 shows the locations of study sites in our final model, and Table 1 summarizes the characteristics of the five restricted data subsets. The first three subsets are limited to maize grown for grain using only inorganic N fertilizer. Subset 1 contains data used in our previous N Balance–N_2O model study of maize systems on silt loam soils in the North American Corn Belt (McLellan et al. 2018). Subsets 2 and 3 of the data augment the subset 1 database with more data from this silt-loam-soil system (subset 2) and data for maize on other soil textures (subset 3). Subset 4 adds observations from studies where maize – for either grain or silage – received manure, rather than inorganic fertilizer, as an N source. Grain N or N removed was reported (or otherwise made available from study authors) for 41% of the 232 observations for Corn Belt maize (CBM). Data for other rainfed crops and regions across the globe comprise 69 observations (subset 5). Across the different subsets, the data represent variations in geography, as well as in environmental and management factors known to affect N cycling and crop production. The expanded dataset that removed the requirement for multiple non-zero N rates within each experiment totaled 780 observations, including 178 from other crops and regions.

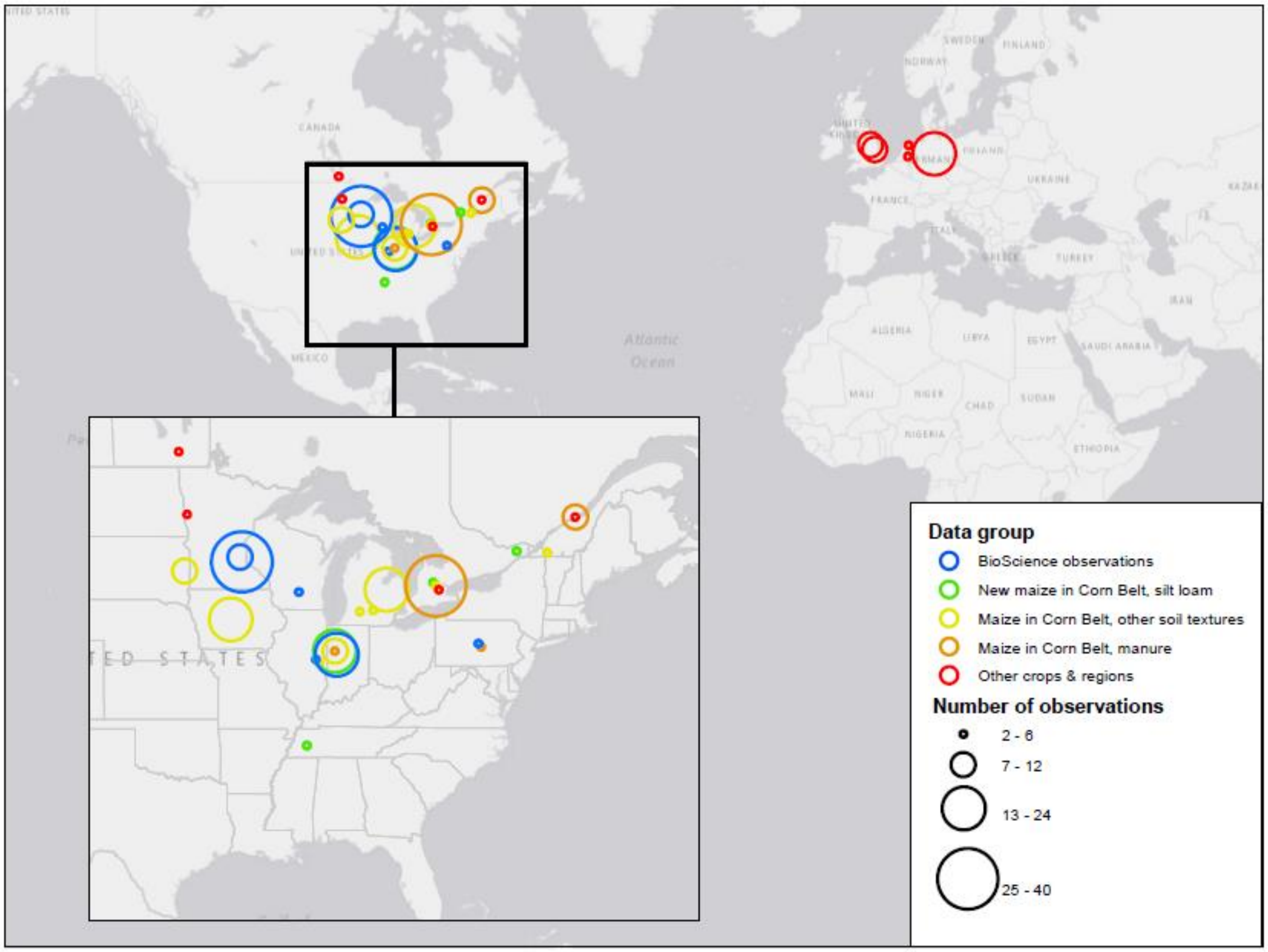

Figure 1. Map illustrating the locations of study sites from which data were compiled to assess the relationship between N balance and N_2O emissions in rainfed cropping systems. The inset shows the location of studies in the North American Corn Belt.

Table 1. Selected characteristics defining five data subsets used to test relationship between N_2O emissions and N balance

Data subset[a]	Crop(s)	States & Provinces[b,c]	Soil texture(s)	N source(s)	N_2O monitoring time-frame, per year
A (n=76)	maize – grain	MN (66%), IN (20%), IL (7%), WI (5%), PA (3%)	silt loam	urea (62%), UAN (25%), SuperU (5%), anhydrous ammonia (AA; 4%), ammonium nitrate (AN; 3%), polymer-coated urea (PCU; 1%)	<6 mo (70%), ≥6mo (30%)
B (n=29)	maize – grain	IN (55%), ON (38%), TN (7%)	silt loam	UAN (62%), urea (31%), AN (7%)	<6 mo (74%), ≥6mo (26%)
C (n=82)	maize – grain	MI (37%), IA (20%), IN (15%), SD (10%), ON (7%), IL (7%), QC (5%)	loam (52%), silty clay loam (27%), sandy clay loam (10%), fine sandy loam (6%), clay loam (5%)	urea (39%), UAN (27%), AA (17%), AN (15%), PCU (2%)	<6 mo (55%), ≥6mo (45%)
D (n=45)	maize – grain (82%) or silage (18%)	ON (64%), QC (18%), IN (9%), PA (9%)	loam (62%), silt loam (20%), clay (9%), silty clay loam (9%)	Manure – cattle (91%), hog (9%)	<6 mo (9%), ≥6mo (81%)
E (n=69)	wheat (39%), silage maize (17%), canola (13%), sugarbeet (13%), barley (10%), other (7%)	Germany (35%), UK (28%), Netherlands (12%), MB (9%), MN (9%), QC (6%), ON (3%)	silt loam (46%), clay (17%), clay loam (7%), loamy sand (7%), sandy loam (7%), sand (6%), silty clay loam (6%), loam (3%)	UAN (35%), unspecified (28%), urea (16%), calcium ammonium nitrate (CAN; 12%), AN (6%), PCU (3%)	<6 mo (48%), ≥6mo (52%)

[a] Data sources:

1: Fernández et al. (2015), Osterholz et al. (2014), Smith et al. (2011), Smith et al. (2013), Venterea and Coulter (2015), Venterea et al. (2016)

2: Burzaco et al. (2013), Congreves et al. (2017), Nangia et al. (2013), Thornton and Valente (1996), Wagner-Riddle et al. (2007)

3: Fernández et al. (2015), Hernandez-Ramirez et al. (2009), Hoben et al. (2011), Iqbal et al. (2015), Lehman and Osborne (2013), Omonode et al. (2015), Parkin and Hatfield (2010), Pelster et al. (2011), Roy et al. (2014)

4: Abalos et al. (2016a), Adviento-Borbe et al. (2010), Cambareri et al. (2017a), Cambareri et al. (2017b), Hernandez-Ramirez et al. (2009), Rochette et al. (2008b)

5: Asgedom et al. (2014), Kaiser et al. (1998), Rochette et al. (2008b), Thapa et al. (2015), van Groenigen et al. (2004), Wagner-Riddle et al. (2007), Webb et al. (2004)

[b] Two-letter abbreviations correspond to postal system identifiers for U.S. states and Canadian provinces, with the exception of UK (United Kingdom).

[c] Totals may not sum to 100% due to rounding.

4 Results

4.1 N balance–N_2O relationships for an individual site-year

Figure 2 shows data on N balance and associated N_2O emissions for one site-year (data from Venterea and Coulter 2015). This is the only site-year in our database with more than three non-zero N rates that also reported actual grain N content. With multiple N rates, treatments at this site provided a large range in measured N balance and allowed us to explore the impact of changes in N balance under otherwise constant conditions. Despite the scatter, a general relationship can be seen in which N_2O emissions are relatively constant at low N balance values but increase markedly at higher N balance values.

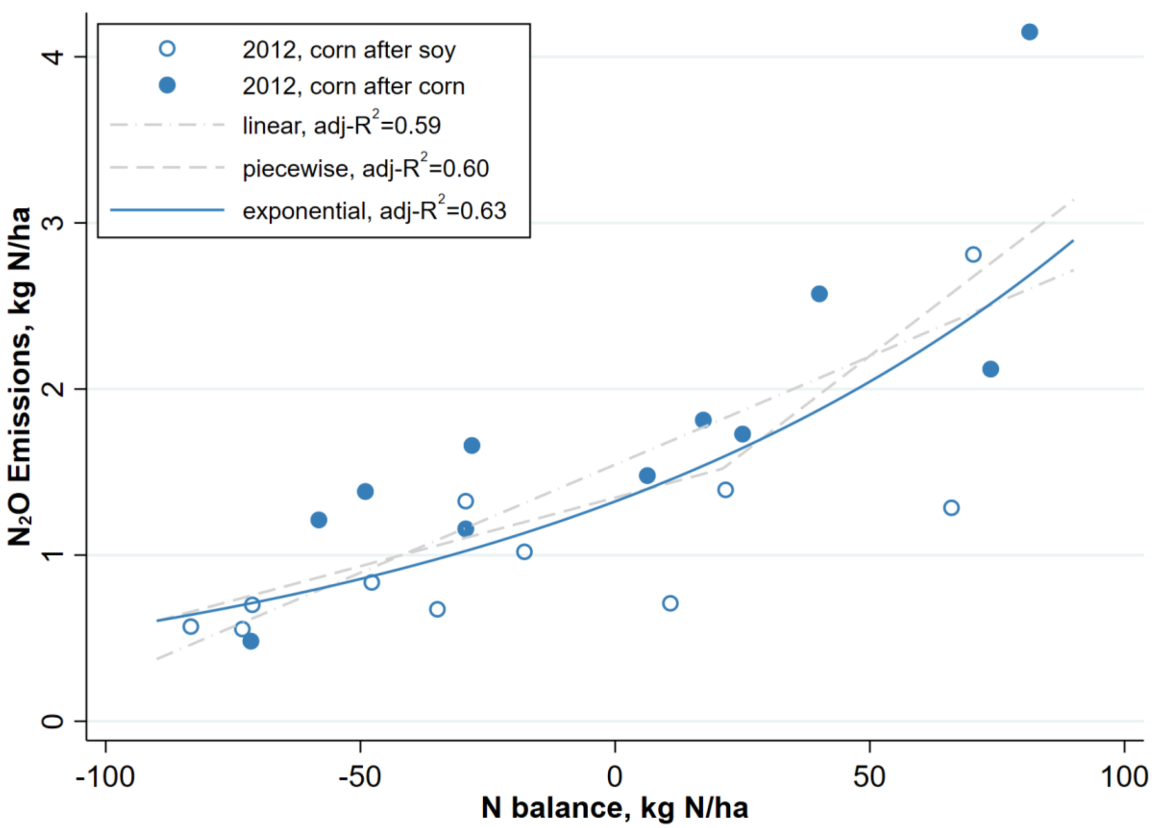

Figure 2. Example of N_2O emissions related to N balance at a single site-year with a wide range in N balance due to multiple N fertilizer rates. Drawn from data reported in Venterea and Coulter (2015), with full-factorial data received from authors. R^2 = 0.81.

We tested a variety of N balance–N_2O relationships – linear, exponential (log-linear) and piecewise (broken-stick) regressions – and found that an exponential form most consistently fit the data for this site-year. Both the Akaike information criterion (AIC) and Bayesian information criterion (BIC) for piecewise and linear models were approximately double those for exponential models, and R^2 values were also higher for the exponential model.

4.2 N balance–N2O relationships across soil types, N sources and cropping systems

An exponential form also fit best for the combined dataset. Moreover – and despite differences in soil types, regions, and N sources – the curvilinear shape of the relationship between N_2O emissions and N balance was similar across all maize datasets (curves A–D in Figure 3). Likewise, the relationship between N_2O emissions and N balance for other crops and regions (curve E in Figure 3) was consistent with the relationships for Corn Belt maize (curves A–D). Equally important, none of the relationships from individual data subsets were statistically different from one another or from the combined dataset (note in Figure 3 that the curves for each data subset lie within the confidence interval for the combined dataset). Therefore, we can identify a generalized relationship between N balance and N_2O losses for a wide variety of cropping systems and regions, with the following equation:

$$N_2O = \exp(0.326 + 0.0045 * NBal) \quad (2)$$

where N_2O is annual cumulative N_2O emissions and *NBal* is the annual N Balance, both in units of kg N ha^{-1} (or lb N $acre^{-1}$, if preferred).

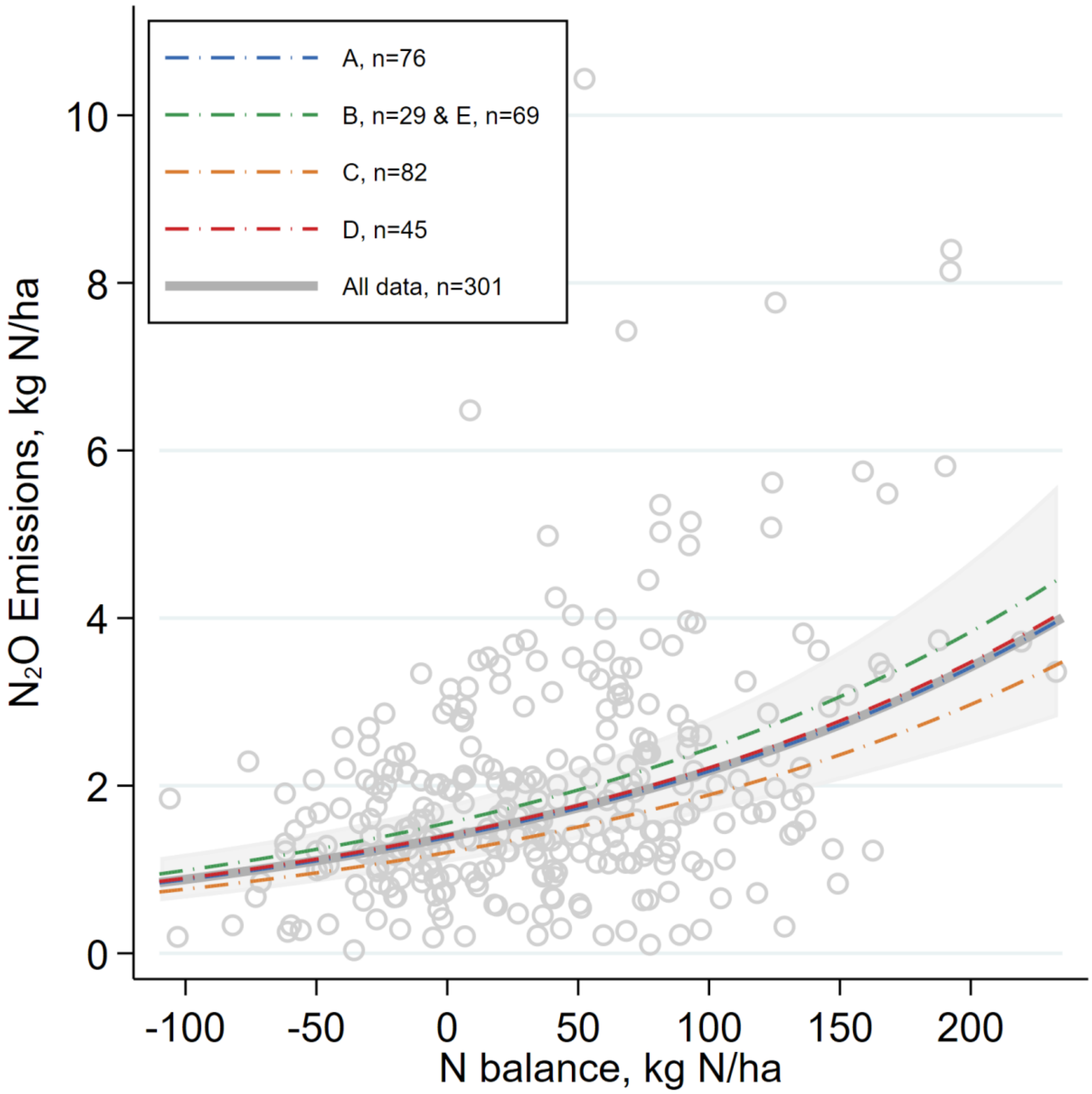

Figure 3. Generalized relationship (grey curve) between N_2O emissions and N balance for all data: data from Corn-Belt maize (CBM) systems. Line A is for the data subset from McLellan et al. (2018), B is for CBM on other silt loam soils, C is for CBM on other soil textures, D is for CBM receiving manure as fertilizer, and E is for other crops and regions. Since data subsets B and E share the same equation, they are shown as one line. Individual observations, adjusted to mean soil C, N_2O measurement timeframe, and average yearly precipitation, are shown as open circles. To better show the majority of data points, two N_2O observations with extreme measures are excluded from the graph (even though they are not excluded from the empirical model).

5 Discussion

The microbial processes that drive N_2O production are highly sensitive to changes in environmental conditions, and high N_2O fluxes can be brought on by rewetting of dry soils, drying of wet soils, thawing of frozen soils, temporary flooding and ponding, and increased availability of nitrogen substrates after fertilizer addition (Butterbach-Bahl et al., 2013). As a result, field-scale fluxes of N_2O vary dramatically over hours, days and seasons. This, coupled with the high spatial heterogeneity of soil physical, chemical and biological properties that influence microbial activity leads to a large scatter in measured N_2O emissions at individual sites (Chadwick et al., 2014; Reeves & Wang, 2015; Wagner-Riddle et al., 2017). This is illustrated in Figure 2, where there is considerable scatter even for a single site-year.

Despite this scatter, the relationship between N balance and N_2O emissions for the data shown in Figure 2 is of the "hockey-stick" type to be expected based on N saturation theory (Gardner & Drinkwater, 2009). When N inputs are small, "internal" sinks (i.e., crop uptake and short-term soil sinks) are larger than the N supply and N losses are also small. Once crop uptake demand has been satisfied, the remaining N in excess of this amount is most likely lost to the environment via leaching, runoff or gaseous loss pathways (the alternative fate of this nitrogen, incorporation into soil organic matter, appears to be minimal, at least in the Corn-Belt maize-soybean production systems that dominate our database; Verma et al., 2005). Hence, the rate of N loss accelerates as applied N exceeds crop N demand (i.e., once N balance exceeds a threshold value). Thus, for most cropping systems the relationship between N inputs, crop growth and N losses is expected to be of a "hockey-stick" shape: linear, with low losses at low N inputs (and low N balance), where much of the added N is taken up by the growing crop, and with N losses increasing more rapidly at higher N input values (and higher N balance) once crop uptake is saturated. The "hockey-stick" shape of our Figure 2 is consistent with previous site-specific studies, such as the work of Broadbent (1978).

Given the multitude of factors which influence N_2O emissions, it would not be surprising if the breakpoint in the "hockey-stick" curve (the point at which N_2O emissions begin to dramatically increase) varied at a given site from year to year, and across sites in response to differences in soil type, cropping system and climate, In the supply chain context, where the interest is in quantifying aggregated change across a variety of soils, climates, cropping systems, and management practices, it would be unrealistic to attempt to determine a site- and year-specific relationship between N balance and N_2O emissions. More important is to determine an average relationship that integrates across multiple site-years of different "hockey-stick" curves, each of which may have different intercepts, breakpoints, and slopes above and below the breakpoint. As shown in Figure 3, this average relationship takes on a shape best fit to an exponential curve.

Of note in Figure 3 is the general congruence in shape and position of the generalized curves for maize cropping systems (curves A–D) across a variety of soil types and N sources, suggesting that a single curve could represent all rainfed maize cropping systems in the North American Corn Belt. Perhaps even more intriguing is that the generalized curve for other crops and other regions (curve E) is also congruent with the various curves for Corn Belt maize. This suggests that, rather than needing to develop separate relationships for each crop and soil type, climatic region and management practice, a single combined curve [represented by equation (2)] could represent the generalized relationship for all rainfed crops on a global basis.

The R^2 value for the N balance–N_2O losses model [equation (2)] is 0.58; this value reflects the variable environments across which measurements were made, recalling that several environmental factors influence emissions even at small spatial and temporal scales. We believe that despite this modest R^2 value, our model is sufficiently robust when used to estimate N_2O emissions (and changes in N_2O emissions) at the scale of hundreds or thousands of fields, where the influence of extreme high or low values from individual fields will cancel each other out (Philibert et al., 2012). The model is not intended for precise quantification at the scale of an individual field, but for predicting the impact of aggregated management change(s) (i.e., changes in N balance values) across a large, regional, food-supply chain. In this context, the most important aspect of the model is its ability to predict average emissions, and changes in emissions resulting from a management change, for a group of fields from a given region or watershed, or in fields that provide maize or other crops for a specific grain elevator, feedlot, mill or another type of large grain buyer. In such circumstances, it is most important that the model be unbiased (i.e., neither over- nor under-estimating average N_2O values).

Exceptions to the general relationship between N balance and N_2O emissions presented in Figure 3 certainly exist, even within the U.S. For example, researchers have measured extremely high N_2O emissions from crops and pasture on histosols (peat or high-organic-matter soils), ranging upwards of an order of magnitude greater than emissions from typical mineral soils (Duxbury et al., 1982; Velthof & Oenema, 1995). Emissions much higher than the norm are also seen in heavily fertilized, irrigated vegetable crops (Duxbury et al., 1982) and in poorly drained, heavy clay soils (Rochette et al., 2008a; Gagnon et al., 2011). While these situations represent a small proportion of total crop production area in the U.S. – histosols and clay soils comprise 1.1% and 2.8%, respectively, of maize-producing cropland in the U.S., and irrigated vegetables take up only 0.9% of total U.S. cropland – they may be of greater importance in other countries (Deng et al., 2012; He et al., 2007). From a global perspective, therefore, the greatest climate (greenhouse gas reduction) benefits may be realized by reducing emissions from these anomalous (by U.S. standards) situations.

Having a science-based, generalized relationship like equation (2) is of critical importance in the food-supply-chain context, where a food processor or retailer is likely to be sourcing multiple ingredients and products, each being supplied from tens of thousands of individual fields. The generalized N balance–N_2O model of Figure 3 and equation (2) allows a food company to calculate the aggregate N_2O emissions associated with the production of major annual food and forage crops over a large geographic area knowing only the mean N balance across participating fields as reported by aggregators, such as participating agri-tech software companies. For example, a company manufacturing breakfast cereal might need to be able to easily and robustly quantify the annual N_2O emissions associated with, variously, oats produced in Minnesota, wheat produced in Washington, and maize produced in Iowa. They could use the generalized N balance–N_2O model to do so without needing to know which crops are sourced from which fields, and without needing location-specific information on each field. Similarly, a meat-processing company could use our generalized model to quantify changes in aggregate N_2O emissions following the provision of agronomic services or farmer incentives to a specific region, for various feed grains. While some differences in the N balance–N_2O relationship are expected between crops, soil types, weather conditions, and N sources, any precision gained by applying different N balance–N_2O relationships for each situation would need to be assessed in relation to the effort and cost required to collect and interpret the additional data that would be required.

Figure 4 shows the data flow pathway through the agri-food value chain, from farmer to food company, so as to maintain both data integrity and farmer privacy. We see crop consultants and farm software providers as being critical to this information management system: crop consultants facilitate high-quality data entry at the scale of the individual field; while software providers deliver low-effort solutions that balance traceability and anonymity, automate and standardize the calculation of the field's N balance value, calculate average N balance across different levels of desired aggregation, and automate the translation of an average aggregated N balance to aggregated N_2O emissions. An individual food company working within a sourcing region can ensure emissions-accounting integrity and avoid the risk of artificially inflating the total amount of data collected – commonly referred to as double-counting – by a) using a single information management system that ensures any given field boundary is genuinely unique among all others for which N balance is calculated, or b) integrating multiple information management systems and utilizing a web-based service to identify and remove duplicate field boundaries for which N balance is calculated, The farm- or field-level results can then be shared with growers and their trusted advisors to stimulate and inform continuous improvement in N management, while aggregated, anonymized results can be provided further up the supply chain to help companies track the impact of their efforts.

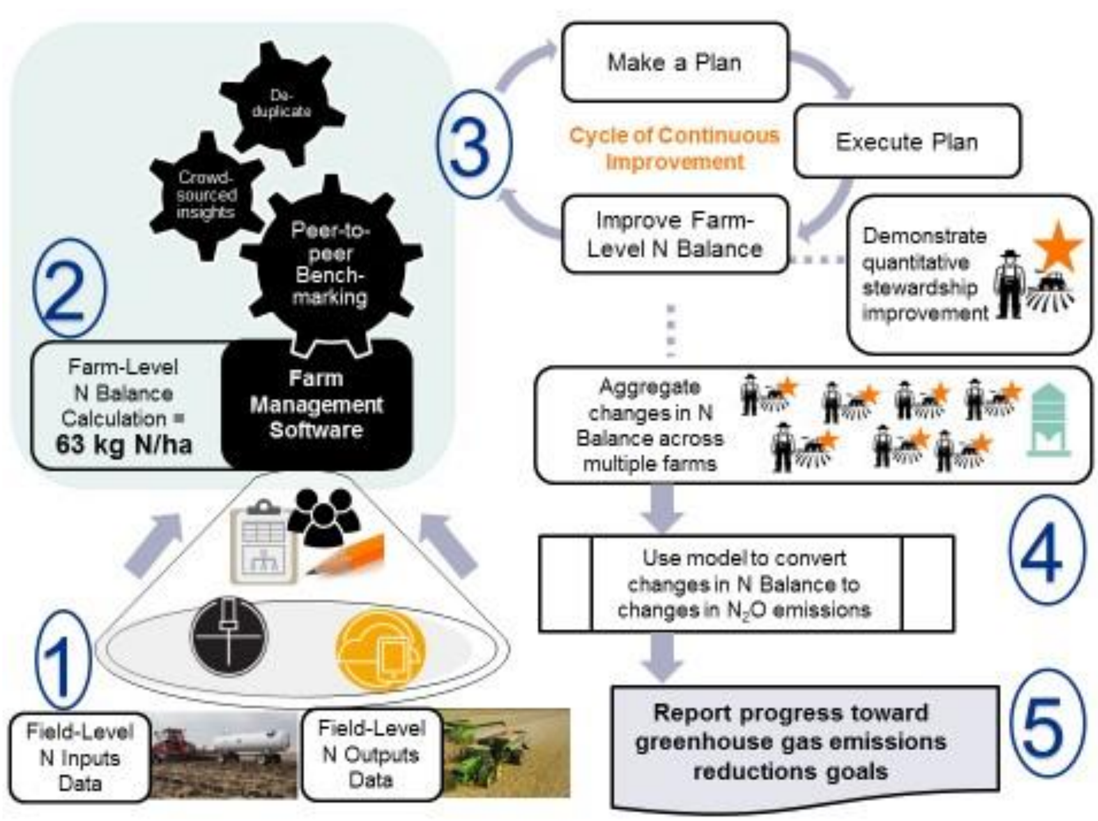

Figure 4. Example of N balance data flow from farm to food company that preserves farmer privacy while allowing important information to pass to both the farm and the purchasing food company. At Step 1, farmers and their advisors enter field-level data on N inputs and N outputs into farm management software, where N balance is calculated (Step 2).Peer-to-peer benchmarking of N balance values across farmer networks can stimulate individual farmers to plan for improvement (Step 3).Crowd-sourced insights on the relationship between N balance and various management practices, supported by data

analytics (Step 2) can inform the continuous improvement plan (Step 3), leading over time to improvements in field- and farm-level N balance. Improvements in N balance over time allow individual farmers to demonstrate and quantify stewardship improvement. Aggregated changes in N balance across hundreds or thousands of fields can be translated into aggregate changes in N_2O emissions using the generalized model described in this paper (Step 4) and food-supply-chain companies can report modelled reductions in N2O emissions to track progress towards their greenhouse gas reduction goals (Step 5).

From an implementation standpoint, important details will need to be considered and standardized across different food supply chains to ensure consistency among public claims of reduced N_2O emissions. For example, a company would need to demonstrate an aggregated reduction in N balance across its supplying farms over a period of time. A multi-year moving average would be needed to smooth out the data and identify the baseline plus any trending change over time (suggesting that several years of data would be needed before making credible claims of emissions reductions). In addition to demonstrating N balance changes in the supplying region or group, a company may need to show evidence of their intervention in the system (e.g., incentives, changes in purchasing, service provision), to claim responsibility for said change.

6 Conclusions

In conclusion, we present a methodology for quantifying regional N_2O emissions from cropping systems based on N balance, centered on a generalized relationship between N balance and N_2O emissions across a wide variety of soils, climates and cropping systems (equation 2). We emphasize N balance over N rate because it (i) better conforms to theoretical relationships between N application, crop growth and N losses, (ii) has been shown by others to out-perform N rate as a predictor of N_2O emissions, and (iii) is more acceptable to farmers, whose business and stewardship interests tend to be aligned with improving N balance. This is because N balance and N losses decline as excess N inputs are reduced (with associated cost-savings), or when yields (and revenue) increase without a concomitant increase in N inputs. Thus N balance as an environmental risk metric also serves as an indicator of farm productivity, resource-use efficiency, and profitability, providing a useful measure of overall sustainability. In addition, focusing on the N balance outcome allows farmers to experiment with an array of conservation practices – related to nutrient management, soil health and cropping system productivity – to determine what works best for their particular location and cropping system.

We outline how the relationship between N balance and N_2O emissions can serve as the foundation for a practical, data-driven approach to achieve meaningful N_2O mitigation in agriculture. Food-supply-chain companies can work with agricultural software providers to facilitate the collection and analysis of aggregated and anonymized field-level N balance data across their supply chains. Analysis of such crowd-sourced data will give farmers insights into opportunities to reduce N losses from their cropping systems, while enabling companies to use our generalized N balance–N_2O model to quantify the environmental outcomes of their efforts to reduce N_2O emissions. Ongoing support for field research will still be necessary to measure N_2O emissions and develop a better, more site-specific understanding of changes in N balance associated with improved genetics, 4R nutrient stewardship, and other management practices, and to confirm the generalizability of the model to other crops and regions. There is a key need for additional field data on N_2O emissions associated with other cropping systems – in experiments that intentionally vary N balance and report complete N uptake and removal as well as management details – as these data are very poorly represented in the current literature. Nevertheless, our results will enable companies to quantify supply chain emissions in the near-term, which is a critical step in helping companies move forward with setting GHG reduction targets across large production regions. Such efforts will help corporate leaders demonstrate the role that the private sector can play in stabilizing global warming (Doda et al., 2015).

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