ENVIRONMENTAL RESEARCH
LETTERS

LETTER • OPEN ACCESS

Dynamic model-based N management reduces surplus nitrogen and improves the environmental performance of corn production

IOP Publishing Environ. Res. Lett. 13 (2018) 054010 https://doi.org/10.1088/1748-9326/aab908

Environmental Research Letters

OPEN ACCESS

RECEIVED
21 December 2017

REVISED
5 March 2018

ACCEPTED FOR PUBLICATION
23 March 2018

PUBLISHED
26 April 2018

LETTER

Dynamic model-based N management reduces surplus nitrogen and improves the environmental performance of corn production

S Sela[1,2], P B Woodbury[1] and H M van Es[1]

1 Soil and Crop Sciences Section, School of Integrative Plant Science, Cornell University, Ithaca, NY, United States of America
2 Author to whom any correspondence should be addressed.

E-mail: ssela@cornell.edu

Keywords: N surplus, corn, yield-scaled N losses, crop simulation, dynamic model-based N management

Supplementary material for this article is available online

Abstract

The US Midwest is the largest and most intensive corn (*Zea mays*, L.) production region in the world. However, N losses from corn systems cause serious environmental impacts including dead zones in coastal waters, groundwater pollution, particulate air pollution, and global warming. New approaches to reducing N losses are urgently needed. N surplus is gaining attention as such an approach for multiple cropping systems. We combined experimental data from 127 on-farm field trials conducted in seven US states during the 2011–2016 growing seasons with biochemical simulations using the PNM model to quantify the benefits of a dynamic location-adapted management approach to reduce N surplus. We found that this approach allowed large reductions in N rate (32%) and N surplus (36%) compared to existing static approaches, without reducing yield and substantially reducing yield-scaled N losses (11%). Across all sites, yield-scaled N losses increased linearly with N surplus values above ~48 kg ha^{-1}. Using the dynamic model-based N management approach enabled growers to get much closer to this target than using existing static methods, while maintaining yield. Therefore, this approach can substantially reduce N surplus and N pollution potential compared to static N management.

1. Introduction

The US produces 29% of global corn (*Zea mays*, L.; FAO 2014), with 83% located in the Midwest corn belt (USDA 2017). However, inefficiencies in nitrogen management lead to substantial losses of N to the environment, including nitrate (NO_3) leaching from the soil, causing groundwater pollution (Ferguson 2015, Struffert *et al* 2016), contamination of waterways (David *et al* 2010), and impairment of aquatic ecosystems (Diaz and Rosenberg 2008). Transport of NO_3 to the Gulf of Mexico creates a dead zone which was the largest ever recorded in 2017 (NOAA 2017). Loss of ammonia gas (NH_3) from N fertilizer application contributes to fine particulate air pollution, an important cause of respiratory diseases (Pinder *et al* 2007, Heo *et al* 2016). Nitrous oxide (N_2O) is a potent greenhouse gas and contributes significantly to global warming (Millar *et al* 2010). Other gaseous N species contribute to formation of ozone, an important air pollutant damaging plant and human health (Kampa and Castanas 2008, Avnery *et al* 2011). Altogether, N pollution from anthropogenic sources is very costly to society (Erisman *et al* 2013), estimated at $210 billion per year for the USA alone during recent decades (Sobota *et al* 2015). Costs of damages from N fertilizer alone exceeded $50 million per year for many counties in Minnesota (Keeler *et al* 2016).

N surplus—the difference between N inputs and the N removed from the field at harvest—can be used as an index of the efficiency of N management in cropping systems (Van Groenigen *et al* 2010, Cui *et al* 2013, Chen *et al* 2014, Zhang *et al* 2015). N surplus was found to be positively correlated with both NO_3 leaching losses (Zhou and Butterbach-Bahl 2014, Zhao *et al* 2016) and gaseous N_2O losses (Van Groenigen *et al* 2010, Decock 2014, Venterea *et al* 2016). N losses are typically curvilinear related to N surplus, with yield-scaled losses increasing rapidly above N surplus values of 0-to-50 kg ha^{-1} (Van Groenigen *et al* 2010, Pittelkow *et al* 2014, Walter *et al* 2015, Venterea *et al* 2016, Zhao *et al* 2016). From a nutrient management perspective, N surplus values should be positive—i.e. not mining the soil of N (EU Nitrogen Expert Panel 2015)—but as low as possible without reducing yields.

N surplus is being used in global analyses to track progress over time for individual countries to reduce environmental impacts of crop production (Zhang *et al* 2015). N surplus is also reported for countries by the OECD (OECD 2013). In the US, McLellan *et al* (2018) recently suggested N surplus as a suitable index for tracking the sustainability of US maize production in a supply-chain context. However, setting appropriate N surplus targets requires knowledge of the realistic and achievable N surplus values.

The majority (68%) of US corn fields do not apply fertilizer to the crop during the active growing season, and instead rely on large applications of N before or at planting (USDA ERS 2010). While this approach reduces logistical considerations associated with in-season N application, it increases the risk of N losses, especially in humid climates (van Es *et al* 2007). There are multiple recommendation tools currently available for US corn production (see Morris *et al* 2018 for a recent review). University Cooperative Extension services, crop consultants and retailers typically make fertilizer recommendations that are static regardless of seasonal weather, and have limited adaptation to the local production environment. While this approach is easy to implement, it can lead to excessive N application and losses (Sela *et al* 2017).

Recent advances in computational and information technologies stimulated a new generation of dynamic in-season N recommendation tools based on the application of mechanistic models. For US maize production, application of such tools include the APSIM model (Jin *et al* 2017), the Maize-N model (Thompson *et al* 2015), or the Adapt-N tool (Sela *et al* 2016). These tools allow continuous modeling of biogeochemical interactions to estimate soil nutrient levels, and use this information to calculate real-time fertilizer recommendations. Adapt-N's model-based N recommendations have been compared with static N rates in commercial US maize production where they were found to be economically and environmentally advantageous (Sela *et al* 2016, 2017).

There is a pressing need to reduce losses of N to the environment in order to improve water quality and mitigate atmospheric losses. Our study uses a combination of data from 127 on-farm field experiments along with site-specific simulation results to better understand the potential of advanced dynamic model-based tools (in this case Adapt-N, henceforth 'dynamic approach') to reduce N surplus and consequently N losses, compared with the current grower practice. The driving hypothesis is that such a dynamic approach to N management that is also adapted to the local production environment can lower N fertilizer rates without yield losses, and thereby reduce N surplus and pollution and its cost to society.

2. Materials and methods

2.1. Field trials

We used data from 127 on-farm field trials (appendix 1 available at stacks.iop.org/ERL/13/054010/mmedia) conducted during the years 2011–2016. In all trials a static N rate, obtained from the grower or from a state recommendation system, was compared to a dynamic N rate developed by the Adapt-N tool. Two types of trials were used: (i) a side by side strip trial where two N rates (generated either by a static or dynamic approach) were applied and the resulting yield was compared; and (ii) a multi-N rate trial, where a series of N rates were applied, covering a wide range of N values. A response function was then constructed via regression analysis relating N rate to yield in each specific trial. Using this response function the yield from either the static or Adapt-N recommendation was calculated and used in the analysis.

All trials used a replicated, spatially-balanced randomized complete block design (van Es *et al* 2007). The experiments were located in seven US states (figure 1): Iowa, Indiana, Wisconsin, Ohio, New York, Maine, and North Carolina, and spanned different soil types, soil organic matter contents and weather patterns. In 91% of trials corn was grown for grain and in 9% for silage. The type of fertilizer and the amount of N applied prior to planting varied among experiments according to grower practices. Manure was applied in 20% of the trials in varying quantities and timing following grower practices. The experiments differed only in the in-season N application amount, decided either dynamically by the Adapt-N tool or following a static approach. Data on the experimental sites, N treatments, yields, and literature references are in appendix 1, and details of the static N rates for the different regions are in appendix 2. All statistical analyses in this study were performed using the R language and environment for statistical computing (R Core Team 2015).

2.2. Dynamic model-based N management

The dynamic approach to managing N is demonstrated here using the Adapt-N tool (www.Adapt-N.com), which is a modeling framework to monitor crop N availability in maize fields (Sela *et al* 2016). The core of the Adapt-N tool is the Precision Nitrogen Management (PNM) biogeochemical model (Melkonian *et al* 2007, Marjerison *et al* 2016), an amalgamation of the LEACHN soil hydrology and chemistry model (Hutson and Wagenet 1995) and a corn growth model (Muchow and Sinclair 1995) that has received extensive subsequent adjustments, parameter calibrations, and field testing. The PNM model runs on a daily time-step,

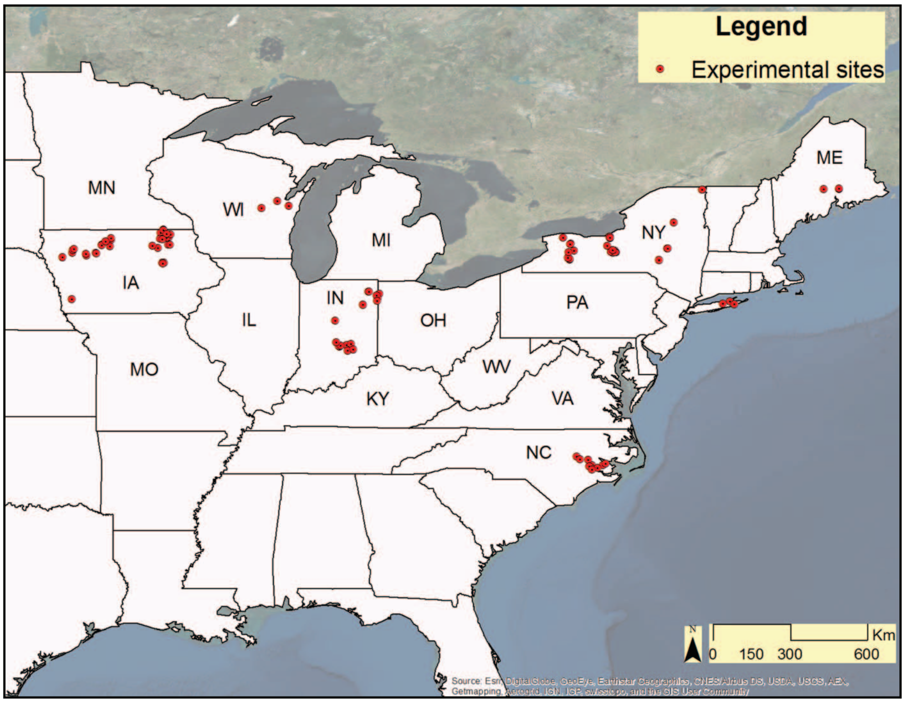

Figure 1. 127 experimental sites used for the analysis. Background image source credits: ESRI world imagery base map.

and solves in one dimension (depth) the biochemical transformations of N as modified by environmental conditions such as soil water content and temperature. The PNM model and its constituent modules were calibrated and validated in previous studies under different production environments, presenting good agreement against measured N leaching, soil N mineralization, and crop N uptake (Jabro *et al* 1995, Sogbedji *et al* 2001a, Sogbedji *et al* 2001b, Jabro *et al* 2006, Sogbedji *et al* 2006, Marjerison *et al* 2016, Melkonian *et al* 2017). The Adapt-N tool uses daily simulation results of soil N availability and crop N uptake from the PNM model to derive N recommendations to reach a target prescribed yield goal based on an N mass balance approach. The tool uses high-resolution climate data (4 × 4 km) derived from routines using the US National Oceanic & Atmospheric Administration's Rapid Refresh (NOAA RAP) weather model and operational Doppler radars. Detailed description of the Adapt-N tool, the main governing equations, and the data needed to run a simulation, are in appendix 3.

2.3. N surplus and NUE calculation

N surplus and NUE were calculated using the following equations:

$$N_{surplus} = N_{input} - N_{output} \tag{1}$$

$$NUE = N_{output}/N_{input} \tag{2}$$

where N_{input} is the sum of N fertilizer rate in each treatment and N credits from manure applications and previous crops as determined by Adapt-N, and N_{output} is the amount of N removed from the field at harvest. For trials where silage was grown it was assumed that all above-ground crop N is removed at harvest, while in the corn grain trials it was assumed that only the grain is removed from the field and the stover is returned to the system. Crop N content was not measured in the reported field experiments, but is expected to vary depending on field conditions and crop N availability. To account for this variability, in the trials involving silage corn N was estimated by the PNM model. For corn grain trials, grain N was estimated using the following equation (McLellan *et al* 2018), developed based on analysis of 163 observations from 17 previously published Midwest corn cropping studies ($R^2 = 0.22$; $P < 0.0001$):

$$\text{Grain\_N\%} = 1.0974 + 0.00124 \times \text{Fertilizer N Inputs } (\text{kg N ha}^{-1}) \tag{3}$$

where Grain_N% is the percentage of grain N out of the total oven-dry grain. The amount of N removed by grain harvest was consequently estimated by multiplying Grain_N% with the measured grain yield, adjusted to oven-dry weight (2% moisture). ANOVA analysis found the overall model highly significantly different from a null model of the mean ($p < 0.0001$). The mean and standard deviation values found for our data (dynamic and static dataset combined) using this regression equation (1.33% ± 0.06), are similar to the values found for aggregated US data ($n = 2483$) published by the US Grain Council for the 2013–2016 corn growing seasons (1.36% ± 0.09; USGC 2016, 2013, assuming a ratio of 6.25 of grain protein to grain N (Belitz *et al* 2009)).

2.4. Simulated environmental N losses

Environmental N losses, i.e. leaching below the rooting zone and gaseous losses to the atmosphere, were simulated for each site using the PNM model for either the Adapt-N or the static N rates. In addition to denitrification, the PNM model simulates ammonia volatilization and the two products are reported as gaseous N losses. In this study we combine leaching and gaseous N losses and report the total simulated N losses. The simulations spanned 365 days, from November 1st of the previous season to November 1st of the experimental season. To ensure that reductions in N losses did not reduce yield, simulation results were coupled with the measured yield at each site to derive yield-scaled (YS) total losses for each treatment (equation 4):

$$\text{Total YS N losses} = \text{area-scaled N losses}/\text{grain yield} \tag{4}$$

where Total YS N losses are in (kg ha^{-1} N/Mg ha^{-1} yield), total area-scaled N losses are in kg ha^{-1} and grain yield is in Mg ha^{-1} (15.5% moisture). Silage yields, originally reported in 65% moisture, were converted to 15.5% moisture to be comparable to grain yield trials.

3. Results and discussion

3.1. Dynamic N management effect on applied N inputs, N surplus and NUE

The static N management approach used in this study represents improved N management practice through timely sidedress fertilizer use, especially compared to fall or spring preplant applications. However, the dynamic approach allows additional flexibility in managing N inputs as it identifies both (1) potential N rate reductions to prevent N excesses or (2) potential N increases to prevent deficiencies. We found that in 83% of the trials the dynamic approach reduced N rates (average −57.3 kg ha^{-1}) compared to a static approach, and increased N rates in the remaining trials (average +35.4 kg ha^{-1}). Overall N inputs were reduced on average by a 18% (−42.0 kg ha^{-1}; $p < 0.0001$; figure 2(*a*), table 1), and lead to a statistically insignificant yield reduction (average −50.4 kg ha^{-1}, 0.5%). Previous studies similarly found that using a dynamic approach for N rate improved profitability compared to a static approach, mostly through decreased fertilizer expense without reducing yield (Sela *et al* 2016, 2017).

In the N mass balance approach of Adapt-N, the recommended N rate accounts for future N availability from site-specific soil organic matter mineralization, thus maximizing utilization of the soil's own N resources (appendix 3). Previous studies had suggested that nutrient removal from the field at harvest should be lower than nutrients inputs, to avoid unsustainable 'mining' of soil nutrients (Sheldrick *et al* 2002, Zhang *et al* 2015). Applying a dynamic approach to N management allowed a significant increase in efficiency (figures 2(*c*) and (*d*) and table 1): a reduction in soil N surplus of 36% (−34.9 kg ha^{-1}; $p < 0.0001$), and an increase in NUE of 17% (+0.1 kg ha^{-1}/kg ha^{-1}; $p < 0.0001$). Across all trials, the average N surplus and NUE values in the dynamic approach are 61.0 kg ha^{-1} and 0.72 kg ha^{-1}/kg ha^{-1}, respectively. Only a minority of trials had N surplus lower than zero or NUE higher than 1 (7 trials, 6%). Scharf *et al* (2011) have reported similar N surplus and NUE using another dynamic N recommendation method, crop canopy sensing, for trials in Missouri (US). These NUE values are higher than those recently reported for corn production in the US (0.68, average for the years 2002–2011; (Zhang *et al* 2015)). Furthermore, (Zhang *et al* 2015) had defined a target NUE of 0.75 by the year 2050 for US crop production to sustainably match growth in corn demand. The NUE values under the dynamic approach are already comparable with this target value.

The results show much higher N surplus values for fields where N management included manure applications, 114.9 and 147.6 kg ha^{-1} compared with 47.8 and 83.3 kg ha^{-1} for trials excluding manure for the dynamic and static datasets, respectively. In all our trials manure was applied before the growing season, either in the previous fall, at early spring before planting, or in both. In 52% of the cases where manure was applied, the dynamic approach recommended no in-season N application, indicating sufficient or excessive soil N at sidedress time.

3.2. Effect of dynamic N management on yield-scaled N losses

Using the Adapt-N tool was found to significantly reduce yield-scaled N losses by 11% (figure 3(*a*), table 1). Most of the large yield-scaled losses occurred under (i) manured applications; and (ii) static N management, demonstrating repeated excessive N applications. The large variation in yield-scaled N losses for a given level of N surplus is in accordance with previous studies (Van Groenigen *et al* 2010, Decock 2014, Zhou and Butterbach-Bahl 2014, Zhao *et al* 2016). Higher variability was found in the lower range of N surplus values, where similar values show a wide range of simulated N losses. Much of this variation is attributed to cases where large residual N was simulated for the soil profile root zone at the end of the growing season (appendix 4), mostly associated with the 2012 growing season, which was much drier than the average. These high residual soil N levels highlight a limitation of N surplus as predictor of N losses, which implicitly assumes most residual N is being lost to the environment. However, this large reservoir of residual N is at high risk of eventually being lost to the environment, as shown by measurements of large N losses in Midwest streams following the anomalous dry season of 2012 (Van Metre *et al* 2016). These N losses could

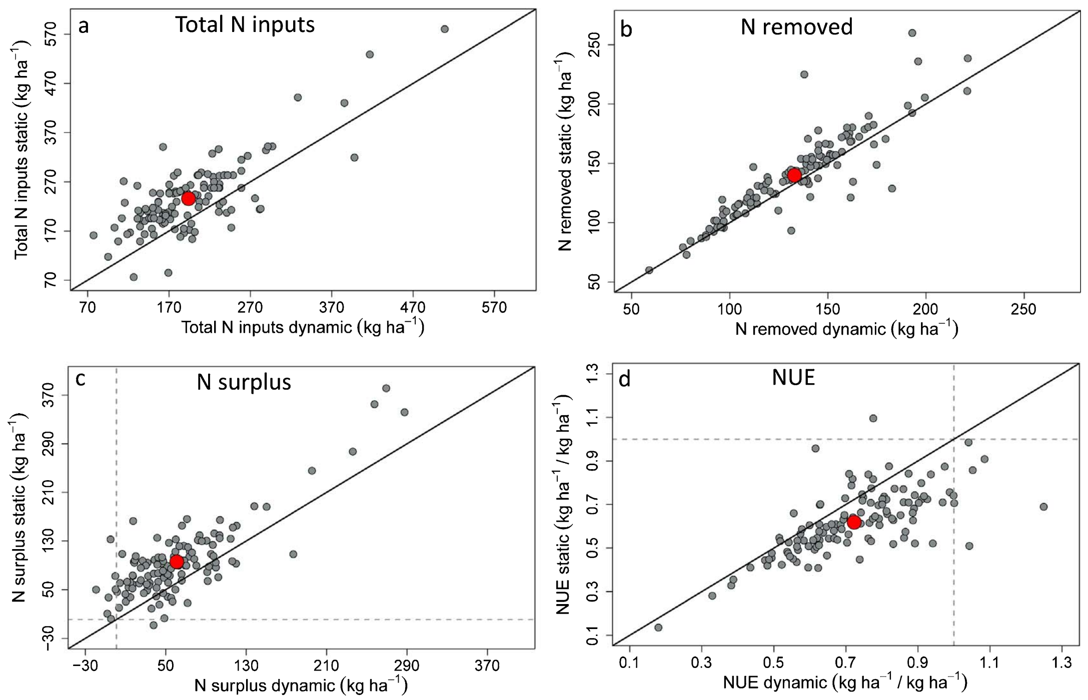

Figure 2. Comparison of Total N inputs, N removed from the field, N surplus and NUE of the static vs dynamic approaches ((*a*), (*b*), (*c*) and (*d*) respectively). Red circles represent mean values. Dashed lines represent N surplus value of zero, and NUE value of one.

Table 1. Mean and standard deviation of N input, output and environmental N losses of the experimental sites. For N surplus and NUE the uncertainty in the values is also presented, based on the 95% confidence envelope of grain N. All reported yields are at standard 15.5% moisture.

Variable	Units	Dynamic		Static		Difference (Dynamic-Static)
		mean	SD	mean	SD	
N rec	kg ha^{-1}	91.2	60.8	133.2	73.1	−42.0 (32%)***
Total N inputs	kg ha^{-1}	194.2	64.2	236.2	70.2	−42.0 (18%)***
N surplus	kg ha^{-1}	61.0±15.4	53.2	95.9±17.26	17.3	−34.9 (36%)***
NUE	kg ha^{-1} / kg ha^{-1}	0.72±0.08	0.18	0.62±0.07	0.07	+0.1 (17%)***
Yield	Mg ha^{-1}	11.4	2.3	11.45	2.22	−0.05 (0.5%) ns
Total YS N loss	kg ha^{-1} N/Mg ha^{-1}	9.91	5.1	11.2	5.5	−1.27 (11%)***

YS=Yield-scaled. Statistical significance levels: *** $p < 0.0001$, ns = not significant. N rec = N recommendation at sidedress time. Total N inputs include organic and inorganic N inputs and credits from previous crops (determined using the Adapt-N tool). Total N does not include input of N from mineralization of soil organic matter or areal deposition.

potentially be reduced by adoption of winter cover cropping, which can consume residual N in the soil remaining from the main growing season and thus reduce N losses by leaching by an average of 54% (Woodbury *et al* 2017).

To test whether an N surplus threshold exists where N losses begin to increase significantly, the data were analyzed by piece-wise regression. Typically, the relationship of N surplus and N losses is characterized in the literature in some form of a non-linear function (e.g. Van Groenigen *et al* 2010, Cui *et al* 2013, Zhao *et al* 2016, McLellan *et al* 2018), but some studies found a linear function to be the best fit (i.e. Decock 2014, Zhou and Butterbach-Bahl 2014). Within a range of low N surplus values, losses are expected to be minimal as any increase in N rate will lead to higher yield (and hence low yield-scaled N losses). In our results, since the Adapt-N tool simulates *total* gaseous losses (including N_2), beyond some threshold of N surplus value losses are expected to increase linearly (i.e. any additional increase in N inputs will be lost to the environment). Therefore, supported by our biophysical understanding of the system, the data were fitted with a discontinuous 'hockey stick' type function comprised of two segments, one a plateau (unchanging) and one linearly increasing:

$$y = \begin{cases} a + (\mathrm{b} \times \mathrm{i}), x < i \\ a + \left(b \times \mathrm{N}_{\mathrm{surplus}}\right), x > i \end{cases} \quad (5)$$

where y is total yield-scaled N losses, and i, a, and b are fitted parameters (table 2). The i parameter represents the breakpoint connecting the plateau and linear segments of the function, i.e. the N surplus value where N losses begin to increase. Combining the dynamic and static N rates into a single dataset offers a wide range of N surplus values and N losses. However, in our data the two N treatments in each trial relate to the same field, and therefore combining them violates the

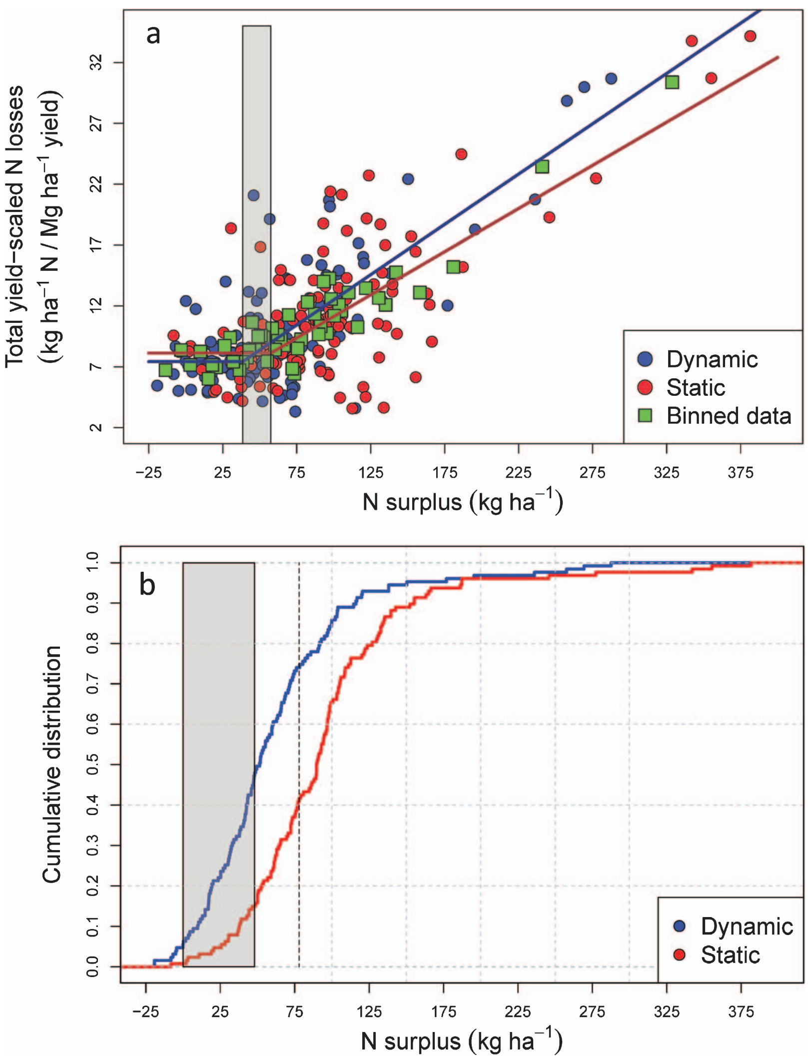

Figure 3. (*a*) The effect of N surplus on total yield-scaled N losses for the dynamic and static N fertilizer management approaches. Binned data (equal size bins of five observations) are presented to illustrate the general trend, but were not used for statistical analysis. Regression analysis was performed separately for the dynamic and static data (blue and red lines, respectively). The shaded area represent the critical N values range of 38.5–57.5, found for the dynamic and static datasets. (*b*) Cumulative distribution of N surplus values for the dynamic and static data. The shaded area represents the N surplus range of 0–48 kg ha^{-1}. The black dashed line represents N surplus values of 78 kg ha^{-1} suggested in Zhang *et al* (2015) as the upper limit for sustainable crop production.

Table 2. Regression parameters and their associated uncertainty, calculated using bootstrapping for the static and dynamic datasets ($n = 127$). Details regarding the uncertainty analysis are presented in appendix 5.

	Dynamic			Static		
Parameter	Estimate	SE	95% CI	Estimate	SE	95% CI
i	38.54[a]	8.41	27.76–56.59	57.47[a]	12.77	40.40–81.66
a	4.24[a]	0.69	2.55–5.32	4.04[a]	0.85	2.64–5.24
b	0.082[a]	0.007	0.0686–0.0972	0.070[a]	0.007	0.0597–0.081
RSE (DF)		3.29 (124)			3.86 (124)	

[a] $P < 0.001$. SE = standard error. CI = confidence interval. RSE = residual standard error. DF = degrees of freedom.

regression assumption of independent observations. We therefore analyzed each dataset independently.

Figure 3(*a*) and table 2 present the regression lines and parameters calculated for the dynamic and static datasets. Both yielded slightly different estimates of the critical N surplus value, 38.5 kg ha^{-1} and 57.5 kg ha^{-1} for the dynamic and static datasets, respectively. This range is in line with those found in previous studies for corn and other crops (Van Groenigen *et al* 2010, Pittelkow *et al* 2014, Walter *et al* 2015, Venterea *et al* 2016, Zhao *et al* 2016). It is worth noting that there is substantial uncertainty associated with these inflection points, as explored using a bootstrapping approach (95% confidence range of 29 and 41 kg ha^{-1}, for the dynamic and static datasets, respectively; table 2, appendix 5). For the remainder of this paper we chose to use 48 kg ha^{-1}—the mean value of the dynamic and static dataset estimates—as an environmental N surplus target to reduce N losses. On the lower end, N surplus should be higher than

Table 3. Factors affecting N surplus based on multiple regression analysis ($n = 127$).

	Dynamic		Static	
Parameter	Estimate	SE	Estimate	SE
Intercept	−89.00[b]	18.00	−86.57[b]	20.81
Total N applied	0.73[b]	0.04	0.74[b]	0.04
SD_{ratio}	−16.66[a]	7.43	−16.02 ns	9.87
Soil texture factor 2[c]	12.85 ns	6.67	16.07[a]	8.05
Soil texture factor 3[d]	17.18 ns	10.09	18.62 ns	11.98
Annual rainfall	−0.005 ns	0.01	−0.010 ns	0.01
Organic matter %	3.59 ns	2.36	4.19 ns	2.74
Adjusted R^2 (p-value)	0.79 ($p < 0.001$)		0.77 ($p < 0.001$)	

[a] $P < 0.05$

[b] $P < 0.001$; ns = not significant. SE = Standard Error.

[c] Difference between fine and medium soil textures.

[d] Difference between fine and coarse soil textures. Also note that the difference between the coarse and medium soil textures (data not shown) was found not statistically significant in both datasets.

zero to prevent N mining of the soil. Therefore the environmental N target range used in this study is 0–48.0 kg ha^{-1}.

It appears challenging to manage N in rain-fed agriculture systems with an N surplus lower than 48.0 kg ha^{-1}. Analysis of the cumulative distribution of N surplus (figure 3(*b*)) indicates that 42% of values in the dynamic dataset are within the 0–48.0 kg ha^{-1} target range, a threefold increase compared with the static case where only 14% of the cases are within this range. Applying dynamic N management allows for a statistically significant ($p < 0.0001$) reduction in both N surplus and N losses, with mean values of 61.0 kg ha^{-1} (36% reduction) and 9.9 kg ha^{-1}/Mg ha^{-1} yield (11% reduction) in N surplus and N losses, respectively. Zhang *et al* (2015) have translated the 'safe' planetary boundary for N (Steffen *et al* 2015) into a globally averaged N balance compatible with a boundary of 39-to-78 kg ha^{-1}. Using the upper limit of this range as a sustainable N surplus target (dashed line in figure 3(*b*)) includes 69% of the trials in the dynamic dataset, compared with 41% of the cases of the trials in the static dataset. In any case, a dynamic approach enables a reduction in the gap between the achievable N surplus values and the designated target.

We do not suggest, however, that an N surplus value of 48 kg ha^{-1} should be a uniform target used to manage N across all production environments. While this N surplus value emerges as a threshold for N losses in our data, there might be situations where higher N surplus is needed to maintain profitability, possibly necessitating higher environmental N losses. This value may vary based on local climate, crop potential yield, soil texture, soil organic matter, and other factors. Identifying such local N surplus targets is beyond the scope of this paper.

3.3. Factors affecting N surplus under dynamic and static N management approaches

To better understand the factors that affect N surplus and identify approaches to reducing it, multiple regression analysis using different predictors was performed. The static and dynamic datasets were analyzed separately. Five predictors where chosen: (i) total N applied; (ii) annual rainfall; (iii) soil texture class (coarse, medium or fine; see appendix 6 for classification table); (iv) the ratio of N applied during in-season sidedress to the total N applied (SD_{ratio} = SD N/Total N); and (v) soil organic matter.

The predictors showed little multicollinearity when tested using variance inflation factors (GVIF < 1.9; (Fox and Monette 1992, R package CAR; Fox and Weisberg 2011)). The total N applied was found to be a significant predictor of N surplus for both the static and dynamic datasets. The positive relation between total N applied and N surplus is expected from equations (1) and (3), and is evident in figures 4(*a*) and (*b*): excessive N application and high N surplus was associated with trials where manure was applied before the growing season. In the static dataset, a second significant predictor of N surplus was soil texture (figure 4(*c*)). N surplus is highest for medium textured soils, although there was large variability in N surplus values in each texture class. For the dynamic dataset, a significant second predictor is SD_{ratio} (figure 4(*d*)). Results suggest that manure applications outside the growing season typically lead to high N surplus and low SD_{ratio} values, corroborating that a mismatch between timing of N application and crop N needs increases N losses (Robertson and Vitousek 2009). As noted previously, USDA data (USDA ERS 2010) suggests that only 32% of US maize growers apply fertilizer N during the growing season, and the rest use large fall or spring preplant applications. In a multi-year simulation study involving 19 Midwest locations, split applications where the bulk of N is applied within the growing season required on average 50% and 40% less N than fall and spring preplant N applications, respectively (McLellan *et al* 2018). Shifting from applying most N fertilizer and manure before planting to applying within the growing season is expected to better synchronize N availability and crop N needs and reduce N surplus. Importantly, this shift enables the use of dynamic N management tools to adjust N rates according to the location-specific seasonal conditions, and facilitate further reduction of N surplus to reach the environmental targets.

Figure 3(*b*) suggests that even with in-season N management using Adapt-N, 58% of the N surplus values are outside the target N surplus range of 0–48 kg ha^{-1}. To further explore the role of SD_{ratio} on N surplus in our datasets, figure 5 presents the effect of two levels of SD_{ratio} within our datasets—SD_{ratio} <0.5 and SD_{ratio} >0.5—on the cumulative distribution of N surplus. Under the dynamic N management approach, shifting to a higher SD ratio nearly doubled the fraction of values within the target 0–48 kg ha^{-1} N surplus range from 27% to 51%. However, for the static dataset, shifting to higher values for SD_{ratio} only had a minor effect on N surplus, increasing from 12% to 15% the percentage of trials within the target N surplus

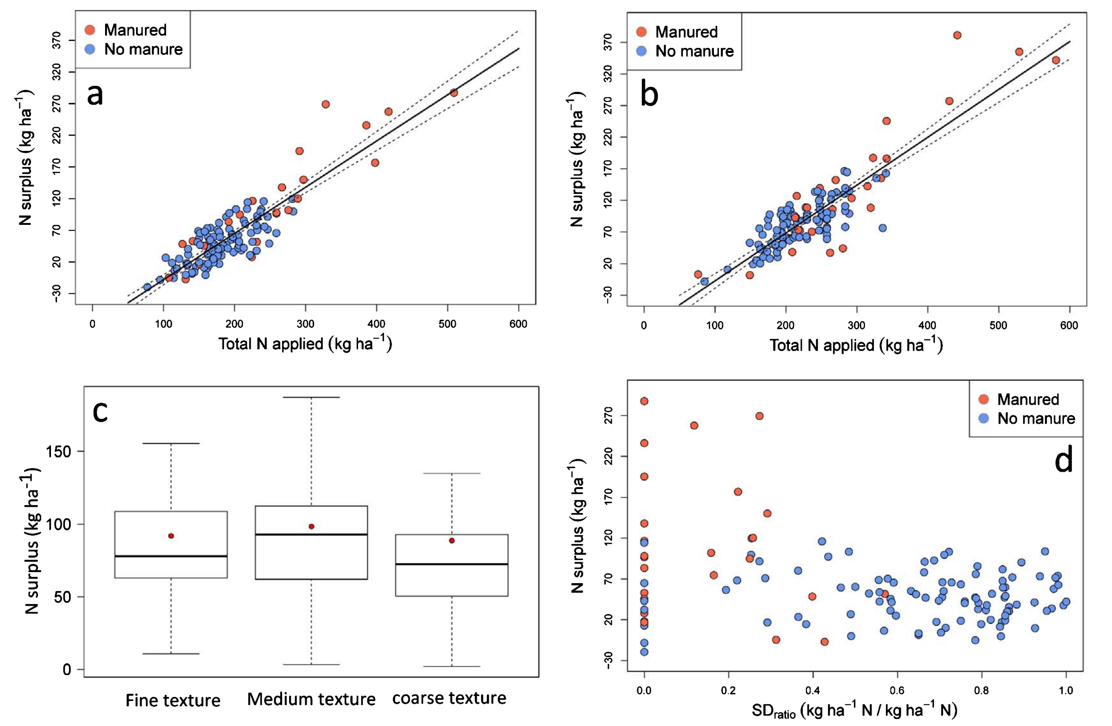

Figure 4. N surplus versus total N applied for the dynamic (*a*) and static (*b*) datasets, and the effect of soil texture on N surplus for the static dataset (*c*); red points and black lines represent the mean and median N surplus values in each texture group, respectively). Panel (*d*) presents the effect of the ratio of side-dress N fertilizer to total fertilizer (SD_{ratio}) on N surplus in the dynamic dataset.

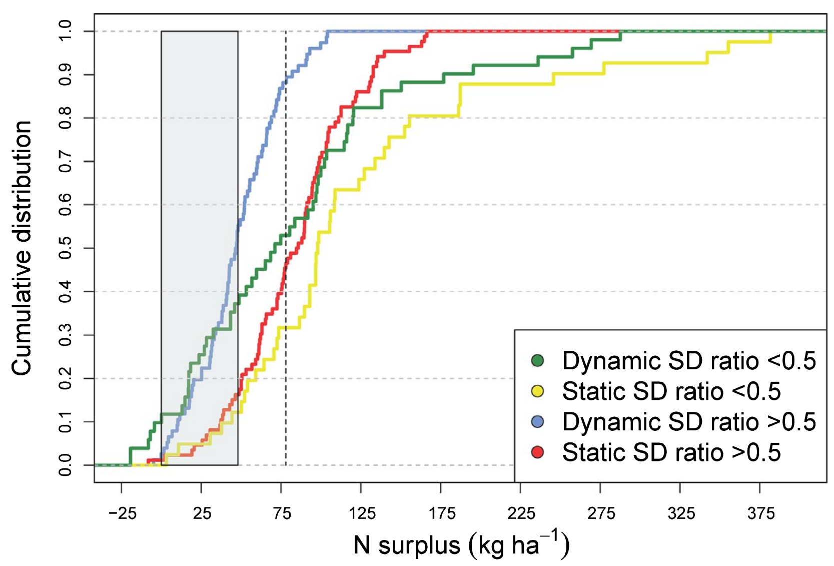

Figure 5. Cumulative distribution of N surplus values for two levels of the ratio of side-dress N fertilizer to total fertilizer (SD_{ratio}) for the dynamic and static datasets. The shaded area is the N surplus range from 0–48 kg ha^{-1}. The dashed black line is the 78 kg ha^{-1} N surplus limit from the literature (Zhang *et al* 2015).

range. Applying the upper value of the N surplus range suggested by Zhang *et al* (2015) for sustainable production (78 kg ha^{-1}) lead to inclusion of 88% of the dynamic results with SD_{ratio} higher than 0.5, but only 45% for the static results. Supported by the lack of significance of the SD_{ratio} for the static dataset in the regression analysis, these results suggest that increasing the amount of N applied within the growing season without dynamically adjusting the rate will only marginally contribute to sustainable N surplus limits.

4. Conclusions

We evaluated the effects of dynamic vs. static N management approaches and the relationship between N-surplus and environmental losses from multi-year on-farm trials ($n = 127$) conducted in the Midwest, Northeast, and Mid-Atlantic US using PNM model simulations. The dynamic approach allowed a significant reduction in N application rate (32%) and N surplus (36%), without reducing yield, which led to significantly lower yield-scaled N losses (11%). Losses increased linearly with N surplus values above $\sim$48 kg ha^{-1}. N surplus was affected by the rate of N application, soil texture, and the fraction of total N applied during the growing season. Dynamic tools can account for these factors and reduce the gap between environmental N surplus targets and N surplus values achievable by growers, based on local conditions such as climate, potential yield, soil texture, and prior management. Future environmental policy that aims at using N surplus as a sustainability performance indicator should take into account both the temporal and the spatial variability of achievable N surplus values at the field scale. Dynamic N management tools allow for an overall reduction in N application and losses without reducing yield, thus offering multiple sustainability benefits. Further reduction in N surplus and concomitant reductions in N losses could be achieved by using such tools with slow-release fertilizers, better adjustment of pre-plant fertilizer rates, and reducing N rate to maintain profitability rather than yield.

Acknowledgments

We acknowledge funding support from the Walton Family Foundation (2013–1219), The McKnight Foundation (13-060), USDA-NRCS (2010 CIG; 69-3A75-10-157), the New York Farm Viability Institute (OAR 14 016), the USDA-AFRI Water Quality Program (2013–51130-21490), and the Atkinson Center for a Sustainable Future at Cornell University. Data from trials in North Carolina were obtained through a collaborative effort with Deanna Osmond and Shelby Shelton of NC State University. We are grateful for the cooperation in field activities from Keith Severson, Sandra Menasha, Anita Deming, Paul Cerosaletti and Dale Dewing of Cornell Cooperative Extension, David DeGolyer, Dave Shearing and Jason Post of Western NY Crop Management Association, Eric Young at Miner Institute, Peg Cook of Cook's Consulting in New York, Hal Tucker, Michael McNeil, and Frank Moore in Iowa, Shannon Gomes of Cedar Basin Crop Consulting (IA), Jeff Polenske of Tilth Agronomy Group (WI), Jordan Seger of the Indiana Department of Agriculture, and Erin Roche and Ellen Mallory of the University of Maine Cooperative Extension. Dr. Erika Mudrak from the Cornell Statistical Consulting Unit (CSCU) is gratefully thanked for her advice on statistical analysis.

Potential conflict of interest

The Adapt-N tool was developed at Cornell University by Harold van Es and colleagues. Agronomic Technology Corporation (now part of Yara International ASA) received a license for its commercialization and partially sponsors Cornell research related to Adapt-N. All potential conflicts of interest are actively managed per Cornell University guidelines.

ORCID iDs

S Sela https://orcid.org/0000-0002-8919-5937

References

Avnery S, Mauzerall D L, Liu J F and Horowitz L W 2011 Global crop yield reductions due to surface ozone exposure: 1. Year 2000 crop production losses and economic damage *Atmos. Environ.* **45** 2284–96

Belitz H D, Grosch W and Schieberle P 2009 Cereals and cereal products *Food Chemistry* 4th edn (Berlin: Springer) pp 670–745

Chen X *et al* 2014 Producing more grain with lower environmental costs *Nature* **514** 486–9

Cui Z L, Yue S C, Wang G L, Zhang F S and Chen X P 2013 In-season root-zone N management for mitigating greenhouse gas emission and reactive n losses in intensive wheat production *Environ. Sci. Technol.* **47** 6015–22

David M B, Drinkwater L E and McIsaac G F 2010 Sources of nitrate yields in the Mississippi River Basin *J. Environ. Qual.* **39** 1657–67

Decock C 2014 Mitigating nitrous oxide emissions from corn cropping systems in the Midwestern US: potential and data gaps *Environ. Sci. Technol.* **48** 4247–56

Diaz R J and Rosenberg R 2008 Spreading dead zones and consequences for marine ecosystems *Science* **321** 926–9

Erisman J W *et al* 2013 Consequences of human modification of the global nitrogen cycle *Phil. Trans. R. Soc. B-Biol. Sci.* **368** 20130116

EU Nitrogen Expert Panel 2015 Nitrogen use efficiency (NUE) *An Indicator for the Utilization of Nitrogen in Agriculture and Food Systems* (Alterra: Wageningen University)

FAO 2014 Maize production by country (www.fao.org/faostat/en/#data) (Accessed: 1 December 2017)

Ferguson R B 2015 Groundwater quality and nitrogen use efficiency in Nebraska's central Platte River Valley *J. Environ. Qual.* **44** 449–59

Fox J and Monette G 1992 Generalized collinearity diagnostics *J. Am. Stat. Assoc.* **87** 178–83

Fox J and Weisberg S 2011 *An {R} companion to applied regression* 2nd edn (Thousand Oaks CA: Sage)

Heo J, Adams P J and Gao H O 2016 Public health costs of primary PM2.5 and inorganic PM2.5 precursor emissions in the United States *Environ. Sci. Technol.* **50** 6061–70

Hutson J L and Wagenet R J 1995 An overview of LEACHM: a process based model of water and solute movement, transformations, plant uptake and chemical reactions in the unsaturated zone *Chemical Equilibrium and Reaction Models* ed R H Loeppert, A P Schwab and S Goldberg (Madison, WI: Soil Science Society of America, American Society of Agronomy Special Publication 42) pp 409–22

Jabro J D, Jabro A D and Fox R H 2006 Accuracy and performance of three water quality models for simulating nitrate nitropen losses under corn *J. Environ. Qual.* **35** 1227–36

Jabro J D, Toth J D, Dou Z X, Fox R H and Fritton D D 1995 Evaluation of Nitrogen version of LEACHM for predicting Nitrate leaching *Soil Sci.* **160** 209–17

Jin Z N, Prasad R, Shriver J and Zhuang Q L 2017 Crop model- and satellite imagery-based recommendation tool for variable rate N fertilizer application for the US Corn system *Precis. Agric.* **18** 779–800

Kampa M and Castanas E 2008 Human health effects of air pollution *Environ. Pollut.* **151** 362–7

Keeler B L *et al* 2016 The social costs of nitrogen *Sci. Adv.* **2** e1600219

Marjerison R D, Melkonian J, Hutson J L, van Es H M, Sela S, Geohring L D and Vetsch J 2016 Drainage and nitrate leaching from artificially drained maize fields simulated by the precision nitrogen management model *J. Environ. Qual.* **45** 2044–52

McLellan E *et al* 2018 The nitrogen balancing act: tracking the environmental performance of food production *BioScience* **68** 194–203

Melkonian J, Poffenbarger H J, Mirsky S B, Ryan M R and Moebius-Clune B N 2017 Estimating nitrogen mineralization from cover crop mixtures using the precision nitrogen management model *Agron. J.* **109** 1944–59

Melkonian J, van Es H M, DeGaetano A T, Sogbedji J M and Joseph L 2007 Application of dynamic simulation modeling for nitrogen management in maize *The SSSA Symposium on Integrating Weather Variability into Nitrogen Recommendations* ed T Bruulsema (Indianapolis, IN: Int. Plant Nutr. Inst.) pp 14–22

Millar N, Robertson G P, Grace P R, Gehl R J and Hoben J P 2010 Nitrogen fertilizer management for nitrous oxide (N_2O) mitigation in intensive corn (Maize) production: an emissions reduction protocol for US Midwest agriculture *Mitig. Adapt. Strateg. Glob. Change* **15** 185–204

Morris T F *et al* 2018 Strengths and limitations of nitrogen rate recommendations for corn and opportunities for improvement *Agron. J.* **110** 1–37

Muchow R C and Sinclair T R 1995 Effect of nitrogen supply on maize yield. 2. Field and model analysis *Agron. J.* **87** 642–8

NOAA 2017 Media relaease: Gulf of Mexico dead zone largest ever measured (www.noaa.gov/media-release/gulf-of-mexico-dead-zone-is-largest-ever-measured) (Accessed: 14 October 2017)

OECD 2013 *OECD Compendium of Agri-Environmental Indicators* (Paris: OECD Publishing)

Pinder R W, Adams P J and Pandis S N 2007 Ammonia emission controls as a cost-effective strategy for reducing atmospheric particulate matter in the eastern United States *Environ. Sci. Technol.* **41** 380–6

Pittelkow C M, Adviento-Borbe M A, van Kessel C, Hill J E and Linquist B A 2014 Optimizing rice yields while minimizing yield-scaled global warming potential *Glob. Change Biol.* **20** 1382–93

R Core Team 2015 *R: A Language and Environment for Statistical Computing* (Vienna: R Foundation for Statistical Computing)

Robertson G P and Vitousek P M 2009 Nitrogen in agriculture: balancing the cost of an essential resource *Annu. Rev. Env. Resour.* **34** 97–125

Scharf P C, Shannon D K, Palm H L, Sudduth K A, Drummond S T, Kitchen N R, Mueller L J, Hubbard V C and Oliveira L F 2011 Sensor-based nitrogen applications out-performed producer-chosen rates for corn in on-farm demonstrations *Agron. J.* **103** 1683–91

Sela S, van Es H M, Moebius-Clune B N, Marjerison R, Moebius-Clune D, Schindelbeck R, Severson K and Young E 2017 Dynamic model improves agronomic and environmental outcomes for maize N management over static approach *J. Environ. Qual.* **46** 311–9

Sela S, van Es H M, Moebius-Clune B N, Marjerison R, Melkonian J J, Moebius-Clune D, Schindelbeck R and Gomes S 2016 Adapt-N outperforms grower-selected nitrogen rates in northeast and Midwest USA strip trials *Agron. J.* **108** 1726–34

Sheldrick W F, Syers J K and Lingard J 2002 A conceptual model for conducting nutrient audits at national, regional, and global scales *Nutr. Cycl. Agroecosys.* **62** 61–72

Sobota D J, Compton J E, McCrackin M L and Singh S 2015 Cost of reactive nitrogen release from human activities to the environment in the United States *Environ. Res. Lett.* **10** 025006

Sogbedji J M, van Es H M and Hutson J L 2001a N fate and transport under variable cropping history and fertilizer rate on loamy sand and clay loam soils: I. Calibration of the LEACHMN model *Plant Soil.* **229** 57–70

Sogbedji J M, van Es H M, Hutson J L and Geohring L D 2001b N rate and transport under variable cropping history and fertilizer rate on loamy sand and clay loam soils: II. Performance of LEACHMN using different calibration scenarios *Plant Soil.* **229** 71–82

Sogbedji J M, van Es H M, Melkonian J J and Schindelbeck R R 2006 Evaluation of the PNM model for simulating drain flow nitrate-N concentration under manure-fertilized maize *Plant Soil* **282** 343–60

Steffen W *et al* 2015 Planetary boundaries: guiding human development on a changing planet *Science* **347** 1259855

Struffert A M, Rubin J C, Fernandez F G and Lamb J A 2016 Nitrogen management for corn and groundwater quality in upper midwest irrigated sands *J. Environ. Qual.* **45** 1557–64

Thompson L J, Ferguson R B, Kitchen N, Frazen D W, Mamo M, Yang H and Schepers J S 2015 Model and sensor-based recommendation approaches for in-season nitrogen management in corn *Agron. J.* **107** 2020

USDA 2017 Quickstats database (https://quickstats.nass.usda.gov/) (Accessed: 1 December 2017)

USDA ERS 2010 Tailored Reports: Crop Production Practices (https://data.ers.usda.gov/reports.aspx?ID=17883) (Accessed: 1 December 2017)

USGC 2016 2016/2017 Corn harvest quality report (https://grains.org/key-issues/corn-harvest-quality-report) (Accessed: 1 December 2017)

USGC 2013 2013/2014 Corn export cargo quality report (www.grains.org/sites/default/files/books/importer_manual/USGC-Corn-Export-Cargo-Quality-Report-2013-14-Final.pdf) (Accessed: 1 December 2017)

van Es H M, Kay B D, Melkonian J J and Sogbedji J M 2007 Nitrogen management under maize in humid regions: case for a dynamic approach *Managing Crop Nutrition for Weather* ed T Bruulsema (Peachtree Commons, GA: International Plant Nutrition Institute) pp 6–13

Van Groenigen J W, Velthof G L, Oenema O, Van Groenigen K J and Van Kessel C 2010 Towards an agronomic assessment of N_2O emissions: a case study for arable crops *Eur. J. Soil Sci.* **61** 903–13

Van Metre P C *et al* 2016 High nitrate concentrations in some Midwest United States streams in 2013 after the 2012 drought *J. Environ. Qual.* **45** 1696–704

Venterea R T, Coulter J A and Dolan M S 2016 Evaluation of intensive 4R strategies for decreasing nitrous oxide emissions and nitrogen surplus in rainfed corn *J. Environ. Qual.* **45** 1186–95

Walter K, Don A, Fuss R, Kern J, Drewer J and Flessa H 2015 Direct nitrous oxide emissions from oilseed rape cropping—a meta-analysis *GCB Bioenergy* **7** 1260–71

Woodbury P B, Kemanian A R, Jacobson M and Langholtz M 2017 Improving water quality in the Chesapeake Bay using payments for ecosystem services for perennial biomass for bioenergy and biofuel production *Biomass Bioenergy* in press

Zhang X, Davidson E A, Mauzerall D L, Searchinger T D, Dumas P and Shen Y 2015 Managing nitrogen for sustainable development *Nature* **528** 51–9

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

Zhou M H and Butterbach-Bahl K 2014 Assessment of nitrate leaching loss on a yield-scaled basis from maize and wheat cropping systems *Plant Soil* **374** 977–91