ENVIRONMENTAL STUDIES

The social costs of nitrogen

学习引言写作

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Despite growing recognition of the negative externalities associated with reactive nitrogen (N), the damage costs of N to air, water, and climate remain largely unquantified. We propose a comprehensive approach for estimating the social cost of nitrogen (SCN), defined as the present value of the monetary damages caused by an incremental increase in N. This framework advances N accounting by considering how each form of N causes damages at specific locations as it cascades through the environment. We apply the approach to an empirical example that estimates the SCN for N applied as fertilizer. We track impacts of N through its transformation into atmospheric and aquatic pools and estimate the distribution of associated costs to affected populations. Our results confirm that there is no uniform SCN. Instead, changes in N management will result in different N-related costs depending on where N moves and the location, vulnerability, and preferences of populations affected by N. For example, we found that the SCN per kilogram of N fertilizer applied in Minnesota ranges over several orders of magnitude, from less than $0.001/kg N to greater than $10/kg N, illustrating the importance of considering the site, the form of N, and end points of interest rather than assuming a uniform cost for damages. Our approach for estimating the SCN demonstrates the potential of integrated biophysical and economic models to illuminate the costs and benefits of N and inform more strategic and efficient N management.

INTRODUCTION

Human activities have increased the amount of nitrogen (N) in the environment by more than 100% above preindustrial levels (1), a far greater increase compared to atmospheric CO_2 (~40% above preindustrial levels) (2). Only 25% of the anthropogenic N produced each year by industrial N fixation and fossil fuel burning returns to inert N_2 gas (3). Much of the remaining 75% of anthropogenic N remains in reactive forms and continues to accumulate and cycle through systems for years or decades. This widespread human alteration of the global N cycle comes with both benefits and costs. N contributes to the crop and energy production needed to meet the food and fuel needs of billions of people. However, the accumulation of N is also associated with degraded air and water quality, biodiversity loss, stratospheric ozone depletion, soil and water acidification, and climate change (1, 4, 5).

Effective management of N requires information about the magnitude and distribution of N-related benefits and costs. The benefits of fertilizer use for food production and of burning of fossil fuels for energy are largely known, but the environmental cost and the social cost of nitrogen (SCN) are less well quantified. Translating environmental changes to damage costs requires an integrated approach that links specific interventions with the cascade of N-related damages over space and time. An inability to fully quantify and incorporate these N-related costs in decisions underscores N management as one of the critical environmental challenges of the 21st century (6, 7).

Recent studies have attempted to fill this gap by monetizing N-related damages for the European Union (8, 9), the United States (10, 11), and China (12, 13). These studies effectively highlight the potential magnitude of N damages and the urgent need to improve N cost accounting. One limitation of these assessments is their reliance on simplifying assumptions that neither account for the spatial dependencies of N-related damages nor track the transport and transformation of N between the source and those who receive benefits or suffer from damages (14). Here, we build on this work, proposing a framework where a unit of N applied as fertilizer in a given location can be tracked over space and time, through different reactive forms, to the unique economic impacts it has on human well-being at specific locations. This approach adds complexity and increased data requirements relative to earlier damage cost assessments. Because our approach links the costs specific to each form of N with associated impacts to different groups, we develop the possibility for a more comprehensive and targeted approach to N management and policy analysis.

A prime motivation for this work is an identified need to elevate N accounting to the same level of rigor and uptake as carbon (C) accounting. Our aim is to enable decision-makers to estimate the SCN for any given N-related intervention, similar to how the social cost of carbon (SCC) has been applied to C mitigation (2, 15, 16). There has been progress on estimating individual components of the SCN using air emissions and transport models (17) or hydrologic models (18–20). These models have the complexity to account for the form, location, and transport of N but are not integrated in a way that can account for transformations among different pools and end points of interest. A further challenge is that even the most sophisticated models often fall short of linking changes in N with impacts to human well-being (21). We present both a theory and an empirical application using existing data of an approach to estimating the SCN that is actionable and generates information that can be used to better target interventions, evaluate alternative policies for N management, and illuminate the distribution of N-related costs and benefits.

Comparing the SCC and the SCN

The SCC is defined as the present value of the monetary damages caused by an incremental increase in emitted CO_2 or equivalent greenhouse gas. There are more than 200 published estimates of the SCC, largely based on outputs from three widely used integrated assessment models (IAMs): the Dynamic Integrated Climate and Economy model (22, 23), the Climate Framework for Uncertainty, Negotiation,

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and Distribution model (24), and the Policy Analysis of the Greenhouse Effect model (25). These models assume future trajectories of net greenhouse gas emission quantities, convert emissions into changes in average global temperature, and then apply damage functions to convert temperature into changes in the monetary value of impacts. There are numerous assumptions and simplifications required at each step, large uncertainties in the SCC estimates, and huge data gaps, and there is an ongoing debate about how to improve the IAMs and the resulting SCC values (26–28).

Despite these limitations, the SCC values represent the best available knowledge to inform climate change policy and regulatory assessments on local to global scales (16). For example, monetized benefits of C emission reductions using the SCC values have been included in at least seven major rules across three U.S. federal departments and agencies, in testimonies and declarations used in court cases, and in setting new fuel efficiency standards for U.S. vehicles (15, 29). Canada, Mexico, United Kingdom, France, Germany, and Norway have also adopted an SCC for use in their regulatory and rule-making processes, and numerous corporations use the SCC metrics to evaluate their C mitigation and offset programs (30).

Another common application of the SCC is in ecosystem services assessments where C sequestration is one of the few nonmarket benefits that can be readily monetized [for example, Nelson et al. (31) and Polasky et al. (32)]. It is unclear whether C-related costs indeed make up the largest proportion of the total value of services affected or whether this result is due to a lack of monetizable impacts to other costs, such as changes in air quality, water quality, biodiversity, or recreation (21). What is clear is that in many of these economic assessments, costs attributable to changes in N remain in biophysical terms or are left out entirely, not for a lack of interest but because there is no equivalent estimate of social cost to apply.

Although it is appealing to directly transfer the methodologies for estimating the SCC to the SCN, there are several key differences between C and N (mostly related to the biogeochemistry of N) that require a different approach (Table 1). The SCC models typically account for C damage costs related to a single proximate driver—globally averaged temperature change from baseline (25, 33, 34). C in the atmosphere is assumed to mix uniformly; thus, damages are independent of the spatial location of emissions. There is no equivalent single driver of damages for N. For example, N damages are related to changes in water quality (for N as NO_3^-), changes in climate (for N as N_2O), and changes in air quality [for N as NO_x, NH_3, NH_4NO_3, and $(NH_4)_xSO_4$]. In contrast to CO_2, each form of N requires its own unique damage function specific to the end points and impacts associated with that form of N and the subsequent transformations of one form of N into another. Because most forms of N are not uniformly mixed in the environment, the costs of N cycling through each pool are highly dependent on the form and location of N.

Both the SCC and the SCN are subject to considerable uncertainty. The social costs of climate change are largely driven by the risks of low-probability, high-consequence events that may occur far in the future. Transforming the flow of these potential future damages into a single value applied to present-day emissions also requires assumptions about the appropriate discount rate (35). For the SCN, impacts are largely driven by the location where new N is emitted or applied, the transport and transformation of N into different forms, and the expected damages along the flow path. A further complication is that the long-term consequences of N accumulation are poorly understood, including impacts to coastal eutrophication and food webs, soil fertility, terrestrial and aquatic food webs, climate change, ozone formation, and implications for disease, pests, and parasite abundances (6). Even for known impacts of N on air and water pollution, there is uncertainty about the degree of damages caused, the shape of the relationship between changes in N in each form and expected impacts to human well-being, and the associated monetary value of those damages.

RESULTS
A general framework to assess the SCN

We propose a theoretical framework for estimating the SCN that considers not only specific forms of N (i) at specified sites (j) at certain times (t) but also how N converts into a future form (k) and site (l) at a particular time ($t + 1$), and then relates changes in specific N forms

Table 1. Comparing the SCC and the SCN.

SCC	SCN
Assumes uniform spatial distribution of atmospheric C, regardless of spatial location of emissions	The location where N enters the system needs to be known to route N to end points of interest where damages may occur.
Costs only associated with C in atmospheric pool	Costs associated with N in atmospheric, surface water, groundwater, and coastal pools
All forms of greenhouse gases can be aggregated into a single equivalent form (CO_2).	Different forms of N must be accounted for separately based on their differential impacts.
Damages are spatially explicit; populations vary in their exposure to climate risks and vulnerability to impacts.	Damages are spatially explicit; populations vary in their exposure to N-related risks and vulnerability to impacts.
Climate impacts are experienced globally. The most-damaging impacts are in the distant future.	N impacts are local to regional to global and occur over shorter and longer time scales; long-term impacts are poorly characterized.
Damage functions driven by a single proxy variable (changes in temperature)	Multiple damage functions driven by changes in multiple forms of N in different locations
Uncertainty driven by climate sensitivity, expected damages, and discounting	Uncertainty driven by location of emissions, flow, routing, expected damages of N in different pools, and discounting

2 of 9

at those sites to costs using a damage function specific to that form, site, and time.

The amount of N of form i at site j at time t is defined as N_{ijt}, $i = 1, 2, …, I$; $j = 1, 2, …, J$; $t = 1, 2, …, T$, and we define the vector $N_t = (N_{11t}, N_{12t} …, N_{1Jt}, N_{21t}, N_{22t} …, N_{2Jt}, …, N_{I1t}, N_{I2t}, …, N_{I1Jt})$, to summarize the state of N at time t where the $I \times J$ elements represent the amount of each form of N at each site.

The net cost of an additional unit of N of form i at site j at time t is given by C_{ijt}. If additional N of a particular form at a particular site has positive net benefits, such as boosting crop yields with little N loss to the environment, then $C_{ijt} < 0$. Because fertilizer application rates exceed plant demand for N, net benefits decrease and losses of N_2O, NO, and NO_3^- increase exponentially (36–38).

N cascades through ecosystems, changing forms in both water (NO_2^-, NO_3^-) and air [N_2O, NO_x, NH_3, NH_4NO_3, $(NH_4)_xSO_4$] before it is immobilized in organic matter, it is denitrified to unreactive N_2 gas, or it accumulates in oceans or groundwater (39). Methods ranging from mass balance models or emission factors to more complex process-based biogeochemical models can be used to estimate stocks, flows, and transformation of N among different pools (12, 40, 41). For N-related climate emissions, emission factors translate units of fertilizer to emissions of N_2O (38, 42, 43). Similar approaches convert N emissions into other constituents [for example, NO_x and NH_3 are converted into fine particulate matter ($PM_{2.5}$) equivalent emissions for air pollution costs]. For airborne N, atmospheric models track the transport, transformation, and removal of pollution across space and time and estimate the resulting human health damages (17, 44–46). For hydrologic N, water quality models route N through freshwater or coastal systems using varying levels of complexity in estimating N processing and retention along flow paths (18, 19, 47).

We define m_{ijt}^{kl} to be the proportion of N form i at site j at time t that becomes form k at site l at time $t + 1$. In general, m_{ijt}^{kl} can depend on conditions at site j at time t, such as the site-specific plant demand for N, soil pH, microbial composition, temperature, wind patterns, and other factors (1). We summarize the evolution of N from period t to period $t + 1$ with the matrix M: $N_{t+1} = N_t M_t$, where M_t is defined as follows

$$M_t = \begin{pmatrix} m_{11t}^{11} m_{11t}^{12} \cdots m_{11t}^{1J} m_{11t}^{21} m_{11t}^{22} \cdots m_{11t}^{2J} \cdots m_{11t}^{I1} m_{11t}^{I1} \cdots m_{11t}^{IJ} \\ m_{12t}^{11} m_{12t}^{12} \cdots m_{12t}^{1J} m_{12t}^{21} m_{12t}^{22} \cdots m_{12t}^{2J} \cdots m_{12t}^{I1} m_{11t}^{I1} \cdots m_{12t}^{IJ} \\ \vdots \\ m_{IJt}^{11} m_{IJt}^{12} \cdots m_{IJt}^{1J} m_{IJt}^{21} m_{IJt}^{22} \cdots m_{IJt}^{2J} \cdots m_{IJt}^{I1} m_{IJt}^{I1} \cdots m_{IJt}^{IJ} \end{pmatrix}$$

We note that $\sum_{l=1}^{L} \sum_{k=1}^{K} m_{ijt}^{kl} \leq 1$ with strict inequality if some portion of N_{ijt} becomes unreactive nitrogen (N_2).

The SCN of adding a particular form of N to the environment at a particular site is then given by

$$SCN_{ij} = \sum_{t=0}^{\infty} \sum_{j=1}^{J} \sum_{i=1}^{I} N_{ijt} C_{ijt} \delta^t$$

with $N_{t+1} = N_t M_t + n_{t+1}$, where $0 < \delta < 1$ is the discount factor.

The framework outlined above represents a comprehensive approach to estimating the SCN in all of its forms at all locations, different costs associated with different forms and different locations, and the transformation and transport of N through space and time. The approach accommodates the complex biogeochemistry of N, including the ability of a single atom of N to cascade through multiple forms. This explicit accounting of form, location, and the differential damages caused by differences in form or location distinguishes the SCN from the SCC described above.

In theory, the SCN should capture all sources and transformations of N, track net benefits over time, and be applicable across different scales and resolutions of analysis from field-level interventions to regional accounting of N flows and impacts. In practice, empirically tracking the evolution of different forms of N through space and time is computationally challenging and data-intensive. In even the most well-studied systems, data and models that can quantitatively track N as it moves from terrestrial to aquatic to atmospheric pools over spatial and temporal scales, which are fine enough to relate to specific damages, are not available. For example, N applied as fertilizer to a corn crop in a Midwestern U.S. farm field may end up in atmospheric, soil, surface water, and groundwater pools directly or through food supply chains. Some of this N will be volatized as ammonia, causing local or regional air pollution impacts; some will be denitrified to N_2O, contributing to climate change; some will be lost to surface water and transported to the Gulf of Mexico where it may be further denitrified along the way or cause hypoxia and eutrophication; and some will enter groundwater, potentially affecting drinking water. There is uncertainty over the rates and drivers of these transformations; the residence times of different forms of N in each pool; the transport, dilution, and retention processes that affect N as it cascades through systems; and the shape of the damage functions that relate changes in N at a given end point to expected costs (1, 39).

Further research on N biogeochemistry and socioeconomic damages will improve our ability to model the complexity of N that is consistent with the framework outlined above. Despite these challenges, we argue that, with simplifications, data and models currently exist to estimate an approximate value of the SCN that is roughly comparable in accuracy to currently used approaches to estimating the SCC.

Empirical application of the SCN

To demonstrate how SCN can be estimated using available data and simplified modeling approaches, we quantified the spatially explicit SCN for N applied as fertilizer to agricultural fields in the U.S. state of Minnesota. N management in this region is emblematic of broader conflicts between agricultural productivity, water quality, and pollution reduction goals designed to protect human health and the environment. We evaluated the SCN at the county level because it represented the best match between data resolution, model complexity, and decision relevance for this system. Outputs were designed for ready uptake into current N management and policy decisions at the state level.

To estimate the SCN for N applied as fertilizer in Minnesota, we focused on three end points of interest assumed to make up the greatest fraction of total N-related costs: greenhouse gas emissions (N_2O), air pollutants ($PM_{2.5}$ formed from NO_x and NH_3), and groundwater contamination (NO_3^-). There are well-established valuation approaches for estimating costs associated with greenhouse gas emissions (16) and air pollutants (17), and previous assessments have found that these costs often exceed costs associated with other N-related impacts (10). We focused on groundwater because most of the drinking water in this region is from groundwater sources, and therefore, most of the exposure and associated health impacts are linked to N in groundwater (48). A significant proportion of fertilizer N ends up in surface

water, and this N may cause eutrophication or hypoxia, especially in coastal systems. The economic impacts of hypoxia are poorly quantified, precluding attempts to monetize any potential damages due to N export to coastal systems (*49*).

To make the comprehensive accounting framework outlined above actionable, we applied several simplifying assumptions. We only estimated costs associated with the first transformation of N from fertilizer to atmospheric or aquatic pools. For example, N fertilizer transformed into NO_3^- and entering groundwater was accounted for but not the subsequent denitrification of that N into N_2O and the associated damages to climate. We did not track N that ended up in crops and resulted in damages elsewhere in the food supply chain. Similarly, we could not account for the differential residence time of N in each pool and instead presented average annual values of the damage costs of N associated with each form and end point of interest. For the air and water quality costs, we estimated total damages based on the best available published rates of current N application. We estimated the per-unit N damages as costs associated with increases in N application above current application rates. We will further discuss the limitations and assumptions of our proposed approach in the Discussion.

In summary, the computational steps for estimating our simplified version of the SCN are as follows:

(1) Allocation: For a given intervention or action that changes the flux of new N entering the environment (for example, fertilizer application), we allocate N flows into the appropriate quantity and form (that is, N_2O, NO_x, NH_3, and NO_3^-).

(2) Transport: We spatially route each form of N to end points where costs and/or benefits occur (for example, drinking water wells, population centers, source water intake pipes, and atmosphere).

(3) Damages: We convert changes in each form of N at each identified end point into costs using individual damage functions for that form, consequence, and affected population (for example, water treatment costs to comply with federal drinking water standards).

Following these steps, we estimated the total and marginal costs of N applied as fertilizer as a function of damages to water quality, air quality, and climate change (Fig. 1). Water quality damages reflect costs incurred to drinking water consumers in Minnesota, air quality damages are assessed regionally on the basis of health impacts incurred in Minnesota and downwind in adjacent states, and climate change damages reflect global costs. Total costs illustrate the magnitude and distribution of damages associated with current annual N fertilization rates across space. The per-unit N costs indicate where future investments in reducing N are likely to yield the greatest benefits to society. We found that the potential savings that could be obtained by reducing or preventing future N damages vary widely depending on location. We estimated that the SCN per kilogram of N fertilizer applied in Minnesota ranges over several orders of magnitude, from less than $0.001/kg N to greater than $10/kg N, illustrating the importance of considering the site and form of N rather than assuming a uniform damage cost (Fig. 1 and table S1).

For NO_3^- in drinking water, the greatest social costs are in the southeast and central regions of the state (Fig. 1). In these regions, the risks to water quality are greater because the underlying aquifers that supply water to households and communities are particularly vulnerable to changes in pollution loads (*50*). For N that contributes to the formation of criteria air pollutants (NH_3, NO_x), costs are highest in and around the Twin Cities because they both house most of the population and are located downwind of agricultural areas. The marginal
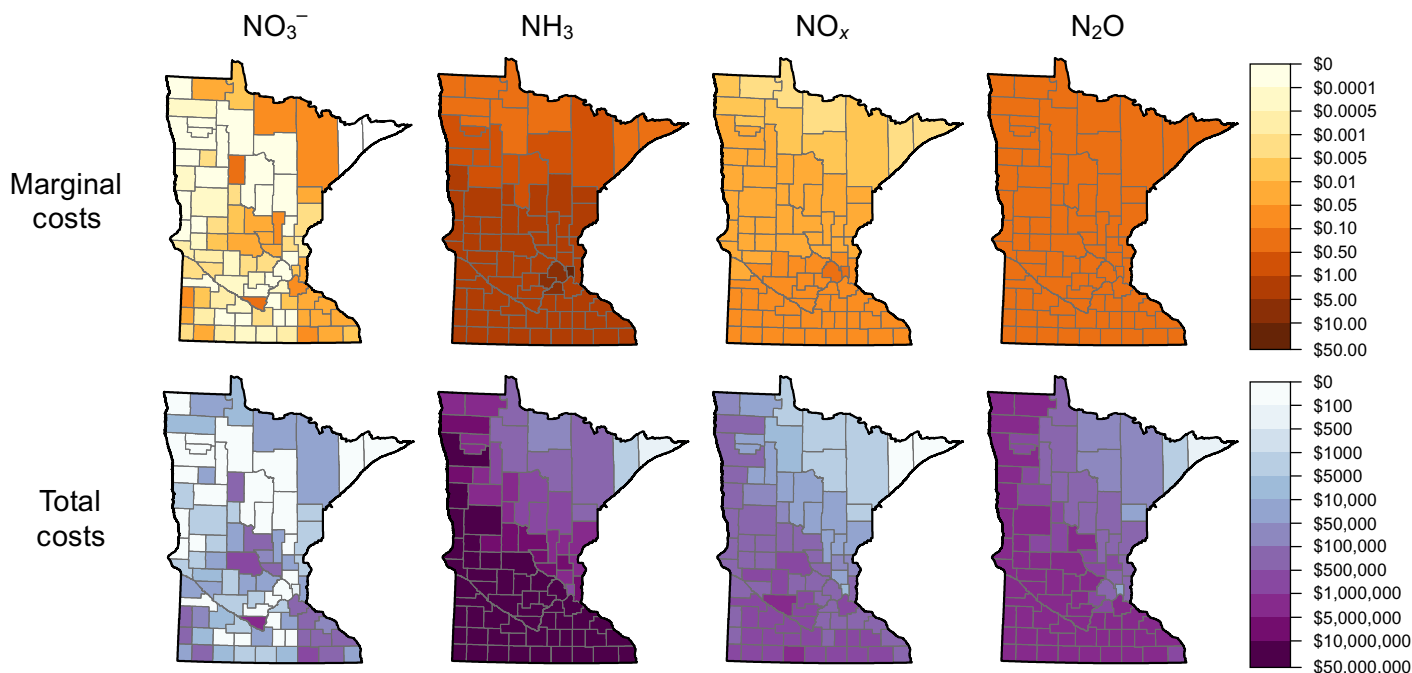
Fig. 1. The marginal and total social costs of N fertilizer applied in each county in Minnesota. Damages from NO_3^- represent the sum of costs in each county in Minnesota due to groundwater contamination of private domestic wells and public water suppliers. Damages from ammonia (NH_3) and N oxides (NO_x) are related to premature deaths from N fertilizer emissions that contribute to the formation and associated impacts of $PM_{2.5}$ and include regional damages within and beyond the borders of Minnesota. Damages from N_2O are estimates of the costs due to global climate change converted into CO_2 equivalents and valued using the SCC. Total costs are average annual values based on reported on-farm N fertilizer inputs assuming a 20-year time horizon and a 3% rate of discount (*59*). Marginal costs are estimated as dollars per kilogram of N fertilizer.
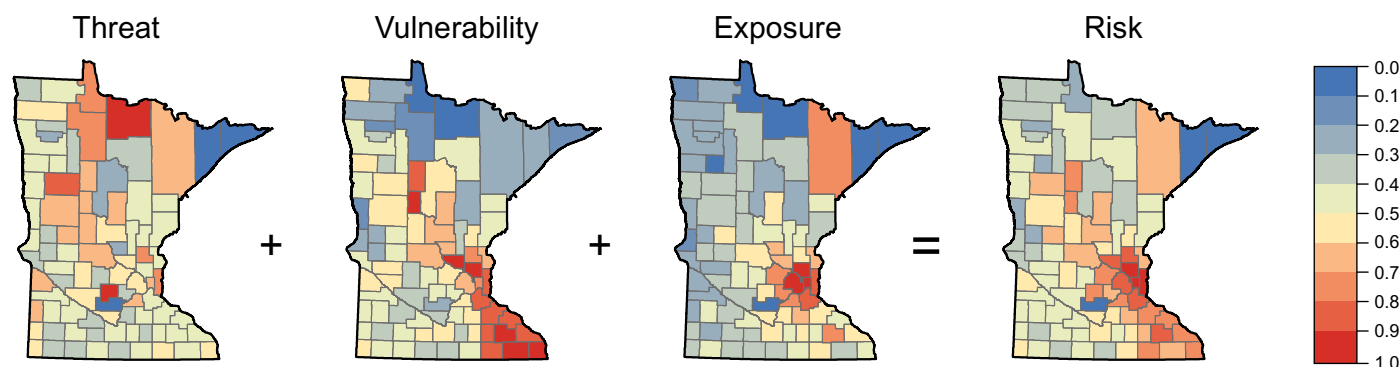
Fig. 2. Spatial heterogeneity in N-related damages. Damages are associated with groundwater NO_3^- contamination where the risk of damages is estimated as the sum of NO_3^- threats, vulnerability, and exposure. Threat is represented here as the risk of row crop expansion, calculated as the percent change in fertilized acres of cropland between 2007 and 2012 (60). Vulnerability is estimated from soil and geologic characteristics that facilitate the transport of NO_3^--enriched runoff and increase the susceptibility of aquifers to contamination (51). Exposure is quantified as the number of households in each county that rely on self-supplied groundwater, normalized by county area and log-transformed (48). All indices were normalized on a 0-to-1 scale.

costs of an additional unit of N_2O that contributes to damages from climate change are constant throughout the state because we assume a constant emission factor for N_2O and global damages that are not spatially dependent on where the N was applied (Fig. 1).

The SCN framework can also be useful where mechanistic models for each step in the causal chain linking N losses to damages are not available or the data required to parameterize these models prevent full quantification of all N-related costs. In these cases, risk mapping or multicriteria analyses allow decision-makers to visualize the spatial heterogeneity of changes in N and the differential exposure and sensitivity of specific populations to N-related impacts and future threats. We mapped potential risks to groundwater NO_3^- contamination using many of the same data inputs outlined in the approach above (form, transport, and exposure at specified end points) to illustrate how these elements of the SCN can be useful to decision-making even in the absence of well-parameterized mechanistic models. For every county in Minnesota, we combined data on drivers of N-related threats (agricultural expansion risk), with geologic, soil, and aquifer characteristics that affect the transport of N into groundwater (51), and potential damages to households as estimated by the population in each county served by groundwater (Fig. 2). The resulting map illustrates the added value of considering the spatial distribution of factors that affect where N will likely increase in the future, where it travels, and the potential exposure of different populations. Even without monetized benefits or process-based models for all N-related damage pathways, spatial risk mapping can identify areas where N interventions are most likely to minimize the SCN now and in the future (Fig. 2). This approach could be adapted to other damage pathways for N, such as degraded surface water quality or hypoxia, where data on the supply and demand for N-related impacts can be captured spatially.

DISCUSSION

The social costs of N pollution are highly dependent on where N enters the environment, where it travels, and the damages that occur along the transformation of N through different forms and across space. Unlike the SCC, there is no spatially constant value for the SCN. Although this fact places greater data and modeling complexities on analysts estimating the SCN, we argue that it is possible to generate marginal N costs at an appropriate scale for use in policy analyses and

in improved spatial targeting of N-related interventions. By tracking the transport and transformation of N from source to end points, our approach can identify how N management in different places will likely affect different groups of beneficiaries.

Earlier studies assumed static partitioning of N fluxes into different pools and then relied on constant per-unit N damage costs, regardless of where the N entered the environment or where it moved (10, 11). These damage costs were not specific to the location or preferences of affected populations. In some cases, values were based on surveys from far-removed locations with only indirect association with N pollution [for example, surveys of Baltic residents on their willingness to pay (WTP) for a cleaner Baltic Sea were applied to estimate N-related damages in the United States (52)]. We recommend the use of spatially explicit damage functions that incorporate social and economic data to better capture distributional benefits and costs of N. There are ample research opportunities in expanding and improving damage functions for various N forms and loss pathways. In particular, more investment is needed to develop damage functions for hypoxia and stratospheric ozone depletion, to better understand residence times in various pools, to identify thresholds that drive nonlinear responses, and to improve both localized and generalizable nonmarket valuation approaches (53).

A further challenge related to the valuation of N pollution is how to aggregate costs and evaluate trade-offs among different end points (for example, health, treatment costs, and climate impacts). By valuing different damage costs in monetary terms, as we did for the state of Minnesota, analysts can aggregate all damages into a single number. However, aggregation can mask underlying assumptions that drive the variation and magnitudes of costs. For example, both air pollution and water pollution are associated with negative health impacts. However, the cost of air pollution is modeled using estimates of premature deaths and associated values of statistical life, whereas N-related water costs are estimated on the basis of the treatment costs incurred to avoid exposure to contaminated water. Not surprisingly, our SCN estimates found that air pollution health costs dwarfed water quality treatment costs by orders of magnitude (Fig. 1).

Previous N damage assessments have estimated higher costs for degraded water quality by assuming a relationship between nitrate exposure and increased incidence of cancer, even below the drinking water standard (9, 52). These approaches yield large numbers, but the public health and epidemiological research linking nitrate in drinking

water and cancer is inconclusive (*54*). Monetary valuation can also mask equity and distributional impacts, such as disproportionate effects of degraded water quality on low-income, rural, and minority households (*55*). Our monetary estimates for Minnesota suggest that the air pollution costs of N greatly exceed the costs of degraded water quality, but this interpretation assumes that treatment costs are reflective of the full societal costs of polluted water. More comprehensive estimates of the true value of clean water, inclusive of potential health, recreational, or aesthetic values, may change the ratio between air- and water-related N costs and assist policy-makers to better evaluate trade-offs associated with alternative strategies for N management.

The need for spatially explicit tracking of the impacts and distribution of SCN differs from the SCC, where spatial targeting of interventions is not needed. A central goal of climate mitigation is to find the most cost-effective ways to reduce global emissions, regardless of the location of the source. In contrast, questions related to efficient N management are highly contextual and spatially heterogeneous. There is no single estimate for the SCN that applies to all places. Instead, there will be an SCN for each place at each time depending on the form, transport, and distribution of damages for each N-related change. For example, in China, a rise in N associated with food and energy production has led to eutrophication of highly valued coastal areas and has degraded air and water quality in nearby population centers (*12*). Benefits of policies designed to reduce N pollution targeted to these areas in China are estimated to far exceed the economic costs to farmers (*56*). The health and well-being benefits of N reductions in China are likely to be different from the potential benefits of N reductions in Iowa (*57*) or elsewhere. The most efficient N solutions will account for the spatial variability of N use, the magnitude of N-related costs, and the distribution of costs among different groups.

Increasing demand for food and energy will continue to result in the long-term accumulation of N in the environment. Having better estimates of the SCN will allow for more informed assessments of the complex food, energy, and environmental trade-offs associated with this growing application of N. There is no one-size-fits-all approach to estimating the SCN, but there is now sufficient information to begin using simple models and spatial data on N loss, transport, affected populations, and damages to estimate the SCN in ways that greatly improve upon earlier estimates. As investments continue in the science, modeling, and data needed to globally improve SCN accounting, the SCN framework presented here is a step toward mainstreaming N-related costs into cost-benefit studies, policy analyses, and ecosystem services assessments. Further work on SCN will also advance full cost accounting for other constituents (such as phosphorus or sediment) that incur damages through diverse pathways over heterogeneous spatial and temporal scales. The end goal for all pollutants of concern is to better provide decision-makers with efficient and robust estimates of externalities that capture the true costs and benefits of alternative activities or interventions.

MATERIALS AND METHODS
Estimating costs associated with domestic groundwater NO3⁻ contamination
We estimated the damage costs of NO_3^- groundwater contamination caused by N fertilizer application for Minnesota households that rely on private drinking water wells. We obtained domestic well data from the County Well Index (CWI), a spatially explicit database of wells drilled in Minnesota since 1974. We combined the CWI database with a Minnesota Pollution Control Agency well database that was volun-

tarily collected from 11 counties in southeastern Minnesota. The resulting database contained 76,589 wells with known NO_3^- concentrations, known locations, and information on well characteristics, depth, and aquifer tapped. Similar well databases exist in other states and are collected nationally by government agencies, such as the U.S. Geological Survey (*58*).

Using this database of wells with known NO_3^- concentrations, we developed a logistic regression model to predict NO_3^- contamination for wells with unknown NO_3^- concentrations following methods described and applied in southeastern Minnesota by Keeler and Polasky (*50*). In brief, we estimated a model based on a training set of wells with known NO_3^- concentrations and known locations and spatially heterogeneous source, transport, and attenuation factors that affect the probability that applied N will contaminate domestic wells. Best-fit explanatory variables and estimated parameters are shown in table S2.

Using the resulting model, we estimated the total costs of N fertilizer application in each county as the product of the model-predicted percentage of contaminated wells in each county, the total number of households that rely on self-served groundwater in each county (*48*), and the average annualized cost of well contamination per household (*50*). Costs of well contamination were estimated on the basis of surveyed behaviors of well owners in Minnesota responding to increased levels of N in their drinking water (*50*). Costs include the weighted average annualized costs of well owners that opted to construct a new well, purchase bottled water, or invest in a point-of-use nitrate removal system (*50*). We converted the total costs in each county into per-unit costs by dividing the total costs in each county by reported on-farm N inputs in each county using fertilizer data for 2006 (*59*). We assumed that groundwater contamination by nitrate did not extend beyond the boundaries of the county where the pollution originated; therefore, the water quality damages only reflect costs to households in Minnesota.

To present the groundwater-related N costs as a spatial map of N-related risks (Fig. 2), we combined three spatial data sets representing threats, vulnerability, and exposure to drinking water nitrate contamination. To represent drivers of N-related change (threats), we calculated the percent change in fertilized acres of cropland between 2007 and 2012 in each county using the Cropland Data Layer (*60*). Counties with greater rates of agricultural expansion were assumed to be more at risk to increases in N loading. To estimate the likelihood that this N would reach groundwater aquifers in each county, we used a groundwater contamination susceptibility layer created by the Minnesota Pollution Control Agency that represents soil and geologic characteristics that facilitate the transport of NO_3^--enriched runoff into groundwater (*51*). To quantify exposure, we mapped the number of households in each county that rely on self-supplied groundwater using data from the U.S. Geological Survey (*48*). All three factors were weighted equally and summed to present risk as a normalized scale from 0 to 1, with higher-value counties representing locations with the greatest potential return on investment in reducing future N loss.

Estimating costs associated with groundwater NO3⁻ contamination of public water supplies
To estimate the total costs associated with NO_3^- contamination in public water supplies, we obtained lists of all community and noncommunity public water suppliers currently treating or monitoring for NO_3^- in Minnesota (table S3). All public water suppliers are required to monitor and treat for nitrate if they have recorded nitrate levels at or exceeding the federal drinking water standard of 10 parts per million (ppm) nitrate-N. We assembled cost for treatment, monitoring, and wellhead protection from survey data collected by the Minnesota

Department of Health (MDH) and conducted our own surveys of community and noncommunity water suppliers, MDH compliance officers in charge of monitoring water suppliers, and vendors that sell or rent NO_3^- treatment systems (61). We combined this information with data from previous surveys in Minnesota (61) and national assessments of NO_3^- treatment and costs (61–64). We estimated the net present value of NO_3^- treatment costs over a 20-year time horizon assuming a 3% discount rate. We used estimates from Minnesota in this application, but treatment costs for NO_3^- can be generalized to other places as the methodologies and technologies represent industry standards applied globally [see cost tables from previous studies (61–64)]. Similar to private well costs, we estimated the per-unit costs of N fertilizer application in each county by dividing the total cost of treatment by reported on-farm N inputs in each county using data from 2006 (59). The costs in Fig. 1 are the sum of private domestic well contamination and public water supplier costs per county. For both private and public water quality sources, we only valued N-related damages due to water treatment needed to comply with federal drinking water standards. There may be public health costs of N exposure to contaminated drinking water below regulatory levels. Some public health and epidemiological studies have estimated elevated risks for subpopulations exposed to chronic levels of nitrate below the regulatory standard of 10 ppm nitrate-N, including increased risks of cancer and birth defects (54, 65). There remains uncertainty in the generalizability of these findings, and recent reviews have suggested that the public health data on the relationship between nitrate and health risks are inconclusive (54). For these reasons, we elected not to assign a monetary value to N exposure via drinking water for levels below the drinking water standard.

Estimating costs associated with N_2O, NO_x, and NH_3 air emissions

We evaluated climate-related damage costs for N_2O emissions from N fertilizer application by converting N_2O into CO_2 equivalent emissions and applying the SCC (38, 42, 66). We estimated environmental health damages associated with NH_3 and NO_x emissions based on their contribution to premature deaths caused by formation and exposure to $PM_{2.5}$. For all forms of atmospheric N, we used survey data from farmers in Minnesota on average fertilizer application rate and percentages of forms of N fertilizer applied to corn (67). On the basis of fertilizer rate and form, we applied constant emission factors for NO_x (0.005) (38), NH_3 (0.08) (40, 43, 68), and N_2O (0.01) (38, 42, 43) from N fertilizer application. Total emissions in each county in Minnesota were calculated by multiplying the emission factors by the reported on-farm N inputs in each county (59).

To translate N_2O emissions associated with N fertilizer application in each county to climate-related damage costs, we applied an approach for estimating the social cost of non-CO_2 greenhouse gases developed by Marten and Newbold (66). The authors developed social cost ratios for N_2O relative to CO_2 by estimating N_2O-specific damages using integrated assessment models. These models account for differences in the long-term radiative forcings of CO_2 and N_2O and provide a more accurate assessment of social costs versus approaches that use a constant global warming potential (66). Using this approach, we estimated the social cost of N_2O as 395 times that of CO_2 and scaled the SCC as defined by the U.S. Government Interagency Working Group (16) relative to N_2O. The U.S. federal government standard for the SCC is $0.038/kg CO_2 emitted under a 3% discount rate. To estimate the social cost of N_2O, we applied a social cost of N_2O value of $15.01/kg N_2O assuming a 3% discount rate.

To estimate the number of premature deaths associated with air pollution emissions from each county, we used the Intervention Model for Air Pollution (InMAP), an emissions-to-health impact model for $PM_{2.5}$ (69). InMAP simulates the transport, transformation, and removal of emissions and then calculates mortalities based on resulting $PM_{2.5}$ concentrations, epidemiological information (70), and U.S. Census data. InMAP is spatially explicit in terms of both where pollutants are emitted and where damages in the form of premature deaths occur across the United States. Damage costs presented in Fig. 1 represent damages that occur downwind of N emissions, even beyond the borders of Minnesota. These damage costs are then allocated back to the county where the N entered the environment. InMAP offers usability advantages over more computationally intensive chemical transportation models in that InMAP only requires the input of a shapefile with locations of total annual emissions (69). This spatially explicit approach allowed us to estimate N-related damages for N applied in different locations where damages were reported in terms of the total number of deaths associated with N-related emissions from each county where N was applied. The cost of premature death reflects the WTP of people in the United States for reductions in their risk of mortality. We used a baseline value of statistical life in 2006 of $7.4 million (44).

For all three atmospheric forms of N, we calculated per-unit costs of N fertilizer application above baseline by dividing total costs in each county, estimated as described above, by the on-farm N inputs in each county (59).

SUPPLEMENTARY MATERIALS

REFERENCES AND NOTES

1. J. N. Galloway, A. R. Townsend, J. W. Erisman, M. Bekunda, Z. Cai, J. R. Freney, L. A. Martinelli, S. P. Seitzinger, M. A. Sutton, Transformation of the nitrogen cycle: Recent trends, questions, and potential solutions. *Science* **320**, 889–892 (2008).

2. T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, P. M. Midgley, *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge Univ. Press, 2013), 1535 pp.

3. N. Gruber, J. N. Galloway, An Earth-system perspective of the global nitrogen cycle. *Nature* **451**, 293–296 (2008).

4. A. W. Rea, C. Davis, D. A. Evans, B. T. Heninger, G. Van Houtven, Using ecosystem services to inform decisions on U.S. air quality standards. *Environ. Sci. Technol.* **46**, 6481–6488 (2012).

5. A. R. Townsend, R. W. Howarth, F. A. Bazzaz, M. S. Booth, C. C. Cleveland, S. K. Collinge, A. P. Dobson, P. R. Epstein, E. A. Holland, D. R. Keeney, M. A. Mallin, C. A. Rogers, P. Wayne, A. H. Wolfe, Human health effects of a changing global nitrogen cycle. *Front. Ecol. Environ.* **1**, 240–246 (2003).

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

7. A. R. Townsend, R. W. Howarth, Fixing the global nitrogen problem. *Sci. Am.* **302**, 64–71 (2010).

8. C. Brink, H. van Grinsven, B. H. Jacobsen, G. Velthof, Costs and benefits of nitrogen in the environment, in *The European Nitrogen Assessment*, M. A. Sutton, C. M. Howard, J. W. Erisman, G. Billen, A. Bleeker, P. Grennfelt, H. van Grinsven, B. Grizzetti, Eds. (Cambridge Univ. Press, 2011).

9. M. A. Sutton, A. Bleeker, C. M. Howard, M. Bekunda, B. Grizzetti, W. d. Vries, H. J. M. van Grinsven, Y. P. Abrol, T. K. Adhya, G. Billen, E. A. Davidson, A. Datta, R. Diaz, J. W. Erisman, X. J. Liu, O. Oenema, C. Palm, N. Raghuram, S. Reis. R. W. Scholz, T. Sims, H. Westhoek, F. S. Zhang, *Our Nutrient World: The Challenge to Produce More Food and Energy with Less Pollution* (Centre for Ecology and Hydrology, 2013), 114 pp.

10. J. E. Compton, J. A. Harrison, R. L. Dennis, T. L. Greaver, B. H. Hill, S. J. Jordan, H. Walker, H. V. Campbell, Ecosystem services altered by human changes in the nitrogen cycle: A new perspective for US decision making. *Ecol. Lett.* **14**, 804–815 (2011).

11. D. J. Sobota, J. E. Compton, M. L. McCrackin, S. Singh, Cost of reactive nitrogen release from human activities to the environment in the United States. *Environ. Res. Lett.* **10**, 25006–25018 (2015).

12. B. Gu, X. Ju, J. Chang, Y. Ge, P. M. Vitousek, Integrated reactive nitrogen budgets and future trends in China. *Proc. Natl. Acad. Sci. U.S.A.* **112**, 8792–8797 (2015).

13. B. Gu, Y. Zhu, J. Chang, C. Peng, D. Liu, Y. Min, W. Luo, R. W. Howarth, Y. Ge, The role of technology and policy in mitigating regional nitrogen pollution. *Environ. Res. Lett.* **6**, 14011–14019 (2011).

14. F. Eigenbrod, P. R. Armsworth, B. J. Anderson, A. Heinemeyer, S. Gillings, D. B. Roy, C. D. Thomas, K. J. Gaston, The impact of proxy-based methods on mapping the distribution of ecosystem services. *J. Appl. Ecol.* **47**, 377–385 (2010).

15. M. Greenstone, E. Kopits, A. Wolverton, Developing a social cost of carbon for US regulatory analysis: A methodology and interpretation. *Rev. Environ. Econ. Policy* **7**, 23–46 (2013).

16. US Interagency Working Group on Social Cost of Carbon, *Technical Support Document: Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866* (U.S. Government, 2015).

17. N. Z. Muller, R. Mendelsohn, Measuring the damages of air pollution in the United States. *J. Environ. Econ. Manage.* **54**, 1–14 (2007).

18. R. B. Alexander, J. K. Böhlke, E. W. Boyer, M. B. David, J. W. Harvey, P. J. Mulholland, S. P. Seitzinger, C. R. Tobias, C. Tonitto, W. M. Wollheim, Dynamic modeling of nitrogen losses in river networks unravels the coupled effects of hydrological and biogeochemical processes. *Biogeochemistry* **93**, 91–116 (2009).

19. D. K. Borah, M. Bera, Watershed-scale hydrologic and nonpoint-source pollution models: Review of mathematical bases. *Trans. ASAE* **46**, 1553–1566 (2003).

20. A. J. Guswa, K. A. Brauman, C. Brown, P. Hamel, B. L. Keeler, S. S. Sayre, Ecosystem services: Challenges and opportunities for hydrologic modeling to support decision making. *Water Resour. Res.* **50**, 4535–4544 (2014).

21. B. L. Keeler, S. Polasky, K. A. Brauman, K. A. Johnson, J. C. Finlay, A. O'Neill, K. Kovacs, B. Dalzell, Linking water quality and well-being for improved assessment and valuation of ecosystem services. *Proc. Natl. Acad. Sci. U.S.A.* **109**, 18619–18624 (2012).

22. W. Nordhaus, Estimates of the social cost of carbon: Concepts and results from the DICE-2013R model and alternative approaches. *J. Assoc. Environ. Res. Econ.* **1**, 273–312 (2014).

23. W. Nordhaus, J. Boyer, *Roll the Dice Again: Economic Modeling of Climate Change* (MIT Press, 2000).

24. S. T. Waldhoff, D. Anthoff, S. Rose, R. S. J. Tol, The marginal damage costs of different greenhouse gases: An application of FUND. *Econ. Discuss. Pap.* **2011**, 2011–2043 (2011).

25. C. W. Hope, The marginal impacts of CO_2, CH_4 and SF_6 emissions. *Clim. Policy* **6**, 537–544 (2006).

26. F. C. Moore, D. B. Diaz, Temperature impacts on economic growth warrant stringent mitigation policy. *Nat. Clim. Change* **5**, 127–131 (2015).

27. R. S. Pindyck, Climate change policy: What do the models tell us? *J. Econ. Lit.* **51**, 860–872 (2013).

28. W. Pizer, M. Adler, J. Aldy, D. Anthoff, M. Cropper, K. Gillingham, M. Greenstone, B. Murray, R. Newell, R. Richels, A. Rowell, S. Waldhoff, J. Wiener, Using and improving the social cost of carbon. *Science* **346**, 1189–1190 (2014).

29. L. T. Johnson, C. Hope, The social cost of carbon in US regulatory impact analyses: An introduction and critique. *J. Environ. Stud. Sci.* **2**, 205–221 (2012).

30. R. L. Revesz, P. H. Howard, K. Arrow, L. H. Goulder, R. E. Kopp, M. A. Livermore, M. Oppenheimer, T. Sterner, Global warming: Improve economic models of climate change. *Nature* **508**, 173–175 (2014).

31. E. Nelson, G. Mendoza, J. Regetz, S. Polasky, H. Tallis, D. Cameron, K. M. Chan, G. C. Daily, J. Goldstein, P. M. Kareiva, E. Lonsdorf, R. Naidoo, T. H. Ricketts, M. Shaw, Modeling multiple ecosystem services, biodiversity conservation, commodity production, and tradeoffs at landscape scales. *Front. Ecol. Environ.* **7**, 4–11 (2009).

32. S. Polasky, E. Nelson, D. Pennington, K. A. Johnson, The impact of land-use change on ecosystem services, biodiversity and returns to landowners: A case study in the State of Minnesota. *Environ. Resour. Econ.* **48**, 219–242 (2011).

33. W. D. Nordhaus, *The Climate Casino: Risk, Uncertainty, and Economics for a Warming World* (Yale Univ. Press, 2013), 392 pp.

34. M. L. Weitzman, What is the "damages function" for global warming—And what difference might it make? *Clim. Change Econ.* **1**, 57–69 (2010).

35. M. L. Weitzman, Tail-hedge discounting and the social cost of carbon. *J. Econ. Lit.* **51**, 873–882 (2013).

36. J. Sawyer, E. Nafziger, G. Randall, L. Bundy, G. Rehm, B. Joern, *Concepts and Rationale for Regional Nitrogen Rate Guidelines for Corn* (Iowa State Univ. Extension, 2006).

37. I. Shcherbak, N. Millar, G. P. Robertson, Global metaanalysis of the nonlinear response of soil nitrous oxide (N_2O) emissions to fertilizer nitrogen. *Proc. Natl. Acad. Sci. U.S.A.* **111**, 9199–9204 (2014).

38. E. Stehfest, L. Bouwman, N_2O and NO emission from agricultural fields and soils under natural vegetation: Summarizing available measurement data and modeling of global annual emissions. *Nutr. Cycl. Agroecosyst.* **74**, 207–228 (2006).

39. W. H. Schlesinger, On the fate of anthropogenic nitrogen. *Proc. Natl. Acad. Sci. U.S.A.* **106**, 203–208 (2009).

40. A. Bouwman, T. Kram, K. Klein Goldewijk, *Integrated Modelling of Global Environmental Change. An Overview of IMAGE 2.4* (Netherlands Environmental Assessment Agency, 2006).

41. B. Z. Houlton, E. Boyer, A. Finzi, J. Galloway, A. Leach, D. Liptzin, J. Melillo, T. S. Rosenstock, D. Sobota, A. R. Townsend, Intentional versus unintentional nitrogen use in the United States: Trends, efficiency and implications. *Biogeochemistry* **114**, 11–23 (2013).

42. Intergovernmental Panel on Climate Change (IPCC), *IPCC Guidelines for National Greenhouse Gas Inventories* (Cambridge Univ. Press, 2006).

43. J. M. Kusiima, S. E. Powers, Monetary value of the environmental and health externalities associated with production of ethanol from biomass feedstocks. *Energy Policy* **38**, 2785–2796 (2010).

44. U.S. Environmental Protection Agency (EPA), *Technical Support Document: Estimating the Benefit per Ton of Reducing PM2.5 Precursors from 17 Sectors* (EPA, 2013).

45. N. Fann, K. R. Baker, C. M. Fulcher, Characterizing the $PM_{2.5}$-related health benefits of emission reductions for 17 industrial, area and mobile emission sectors across the U.S.. *Environ. Int.* **49**, 141–151 (2012).

46. C. W. Tessum, J. D. Hill, J. D. Marshall, Life cycle air quality impacts of conventional and alternative light-duty transportation in the United States. *Proc. Natl. Acad. Sci. U.S.A.* **111**, 18490–18495 (2014).

47. M. L. McCrackin, J. A. Harrison, J. E. Compton, A comparison of NEWS and SPARROW models to understand sources of nitrogen delivered to US coastal areas. *Biogeochemistry* **114**, 281–297 (2013).

48. M. A. Maupin, J. F. Kenny, S. S. Hutson, J. K. Lovelace, N. L. Barber, K. S. Linsey, *Estimated Use of Water in the United States in 2010* (U.S. Geological Survey Circular, 2014), 56 pp.

49. S. S. Rabotyagov, C. L. Kling, P. W. Gassman, N. N. Rabalais, R. E. Turner, The economics of dead zones: Causes, impacts, policy challenges, and a model of the Gulf of Mexico hypoxic zone. *Rev. Environ. Econ. Policy* **8**, 58–79 (2014).

50. B. L. Keeler, S. Polasky, Land-use change and costs to rural households: A case study in groundwater nitrate contamination. *Environ. Res. Lett.* **9**, 074002 (2014).

51. E. Porcher, *Groundwater Contamination Susceptibility* (Minnesota Pollution Control Agency, 1989).

52. H. J. M. Van Grinsven, M. Holland, B. H. Jacobsen, Z. Klimont, M. a. Sutton, W. Jaap Willems, Costs and benefits of nitrogen for Europe and implications for mitigation. *Environ. Sci. Technol.* **47**, 3571–3579 (2013).

53. S. M. Olmstead, The economics of water quality. *Rev. Environ. Econ. Policy* **4**, 44–62 (2010).

54. M. Ward, T. deKok, P. Levallois, J. Brender, G. Gulis, B. Nolan, J. VanDerslice; International Society for Environmental Epidemiology, Workgroup report: Drinking-water nitrate and health—Recent findings and research needs. *Environ. Health Perspect.* **113**, 1607–1614 (2005).

55. E. Moore, E. Matalon, C. Balazs, C. J. Firestone, S. De Anda, M. Guzman, N. Ross, P. Luu, *The Human Costs of Nitrate-Contaminated Drinking Water* (The Pacific Institute, 2011).

56. X.-T. Ju, G.-X. Xing, X.-P. Chen, S.-L. Zhang, L.-J. Zhang, X.-J. Liu, Z.-L. Cui, B. Yin, P. Christie, Z.-L. Zhu, F.-S. Zhang, Reducing environmental risk by improving N management in intensive Chinese agricultural systems. *Proc. Natl. Acad. Sci. U.S.A.* **106**, 3041–3046 (2009).

57. D. R. Kanter, X. Zhang, D. L. Mauzerall, Reducing nitrogen pollution while decreasing farmers' costs and increasing fertilizer industry profits. *J. Environ. Qual.* **44**, 325–335 (2015).

58. B. T. Nolan, K. J. Hitt, Vulnerability of shallow groundwater and drinking-water wells to nitrate in the United States. *Environ. Sci. Technol.* **40**, 7834–7840 (2006).

59. J. A. M. Gronberg, N. E. Spahr, *County-Level Estimates of Nitrogen and Phosphorus from Commercial Fertilizer for the Conterminous United States, 1987–2006* (U.S. Geological Survey Scientific Investigations Report, 2012), 20 pp.

60. U.S. Department of Agriculture, National Agricultural Statistics Service, Quick Stats 2.0 (2015); www.nass.usda.gov/Quick_Stats/.

61. University of Minnesota Department of Soil, Water, and Climate, *Cost of Nitrate Contamination of Public Water Supplies: A Report of Interviews with Water Suppliers* (Legislative Commission on Minnesota Resources, 2007).

62. K. L. Honeycutt, *Alternative Water Supply Options for Nitrate Contamination in California's Tulare and Salinas Groundwater Basins* (University of California Davis, Department of Civil and Environmental Engineering, 2011).

63. V. Jensen, J. Darby, C. Seidel, C. Gorman, *Drinking Water Treatment for nitrate. Centre for Watershed Sciences* (University of California, Davis, 2012).

64. C. Seidel, C. Gorman, J. Darby, V. Jensen, *An Assessment of the State of Nitrate Treatment Alternatives. Final Report of the American Water Works Association, Inorganic Contaminant Research & Inorganic Water Quality Joint Project Committees* (University of California, Davis, 2011), pp. 118–121.

65. J. Brender, P. Weyer, Agricultural compounds in water and birth defects. *Curr. Environ. Health Rep.* **3**, 144–152 (2016).

66. A. L. Marten, S. C. Newbold, Estimating the social cost of non-CO_2 GHG emissions: Methane and nitrous oxide. *Energy Policy* **51**, 957–972 (2012).

67. P. M. Bierman, C. J. Rosen, R. T. Venterea, J. A. Lamb, Survey of nitrogen fertilizer use on corn in Minnesota. *Agr. Syst.* **109**, 43–52 (2012).

68. U.S. Environmental Protection Agency (EPA), *2011 National Emissions Inventory, Technical Support Document* (EPA, 2015).

69. C. W. Tessum, J. D. Hill, J. D. Marshall, InMAP: A new model for air pollution interventions. *Geosci. Model Dev.* **8**, 9281–9321 (2015).

70. D. Krewski, M. E. Andersen, E. Mantus, L. Zeise, Toxicity testing in the 21st century: Implications for human health risk assessment. *Risk Anal.* **29**, 474–479 (2009).

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The social costs of nitrogen

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