Air quality–related health damages of food

Nina G. G. Domingo[a], Srinidhi Balasubramanian[a,1], Sumil K. Thakrar[a,1], Michael A. Clark[b], Peter J. Adams[c], Julian D. Marshall[d], Nicholas Z. Muller[e], Spyros N. Pandis[f], Stephen Polasky[g], Allen L. Robinson[h], Christopher W. Tessum[i], David Tilman[j], Peter Tschofen[e], and Jason D. Hill[a,2]

[a]Department of Bioproducts and Biosystems Engineering, University of Minnesota, St. Paul, MN 55108; [b]Oxford Martin School, Nuffield Department of Population Health, University of Oxford, Oxford OX3 7DQ, United Kingdom; [c]Department of Civil and Environmental Engineering, Carnegie Mellon University, Pittsburgh, PA 15213; [d]Department of Civil & Environmental Engineering, University of Washington, Seattle, WA 98195; [e]Department of Engineering and Public Policy, Tepper School of Business, Carnegie Mellon University, Pittsburgh, PA 15213; [f]Department of Chemical Engineering, Carnegie Mellon University, Pittsburgh, PA 15213; [g]Department of Applied Economics, University of Minnesota, St. Paul, MN 55108; [h]Department of Mechanical Engineering, Carnegie Mellon University, Pittsburgh, PA 15213; [i]Department of Civil and Environmental Engineering, University of Illinois, Urbana, IL 61801; and [j]Department of Ecology, Evolution, and Behavior, University of Minnesota, St. Paul, MN 55108

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Agriculture is a major contributor to air pollution, the largest environmental risk factor for mortality in the United States and worldwide. It is largely unknown, however, how individual foods or entire diets affect human health via poor air quality. We show how food production negatively impacts human health by increasing atmospheric fine particulate matter ($PM_{2.5}$), and we identify ways to reduce these negative impacts of agriculture. We quantify the air quality–related health damages attributable to 95 agricultural commodities and 67 final food products, which encompass >99% of agricultural production in the United States. Agricultural production in the United States results in 17,900 annual air quality–related deaths, 15,900 of which are from food production. Of those, 80% are attributable to animal-based foods, both directly from animal production and indirectly from growing animal feed. On-farm interventions can reduce $PM_{2.5}$-related mortality by 50%, including improved livestock waste management and fertilizer application practices that reduce emissions of ammonia, a secondary $PM_{2.5}$ precursor, and improved crop and animal production practices that reduce primary $PM_{2.5}$ emissions from tillage, field burning, livestock dust, and machinery. Dietary shifts toward more plant-based foods that maintain protein intake and other nutritional needs could reduce agricultural air quality–related mortality by 68 to 83%. In sum, improved livestock and fertilization practices, and dietary shifts could greatly decrease the health impacts of agriculture caused by its contribution to reduced air quality.

air quality | agriculture | fine particulate matter | food | pollution

The health and environmental consequences of feeding the increasingly large and affluent global population are becoming increasingly apparent. These consequences have spurred interest in identifying food production practices and diets that improve human health and reduce environmental harm. Recent work has demonstrated that many of the opportunities for food producers and consumers to improve nutritional outcomes also have environmental benefits, such as reducing greenhouse gas emissions, land and water use, and eutrophication (1–6). It is largely unknown, however, how individual foods and diets affect air quality, even though air pollution is the largest environmental mortality risk factor in the United States and globally (7, 8), and agriculture is itself known to be a major contributor to reduced air quality (8, 9). In the United States alone, atmospheric fine particulate matter ($PM_{2.5}$) from anthropogenic sources is responsible for about 100,000 premature deaths each year, one-fifth of which are linked to agriculture (10, 11).

Here, we show how different foods affect human health by reducing air quality. We consider the emission of pollutants that contribute to atmospheric $PM_{2.5}$, the chronic exposure to which increases the incidence of premature mortality from cardiovascular disease, cancer, and stroke (12, 13). These pollutants include directly emitted $PM_{2.5}$ (primary $PM_{2.5}$) and $PM_{2.5}$ formed in the atmosphere (secondary $PM_{2.5}$) from the precursors ammonia (NH_3), nitrogen oxides (NO_x), sulfur dioxide (SO_2), and nonmethane volatile organic compounds (NMVOCs). From a spatially explicit inventory of emissions of primary $PM_{2.5}$ and secondary $PM_{2.5}$ precursors from agricultural supply chain activities for commodities in the contiguous United States (*SI Appendix*, Figs. S1 and S2) (14, 15) (*Materials and Methods*), we estimate increases in atmospheric concentrations of total (primary + secondary) $PM_{2.5}$ attributable to agricultural emissions; total $PM_{2.5}$ transport, chemistry, and removal; and exposure of populations to total $PM_{2.5}$ using an ensemble of three independent air quality models (16–19). We describe damages attributable to 95 agricultural commodities and 67 final food products (full list in *SI Appendix*, Table S1), which cover >99% of US agricultural production (20).

Results

We find that US agriculture results in 17,900 deaths (range across models: 15,600 to 20,300) per year via reduced air quality (Fig. 1 and *SI Appendix*, Figs. S3–S7). Damages are driven by NH_3 emissions (Fig. 1; "Pollutant"; 12,400 deaths; 69% of total) mainly from livestock waste and fertilizer application (Fig. 1; "Process").

Significance

Poor air quality is the largest environmental health risk in the United States and worldwide, and agriculture is a major source of air pollution. Nevertheless, air quality has been largely absent from discussions about the health and environmental impacts of food. We estimate the air quality–related health impacts of agriculture in the United States, finding that 80% of the 15,900 annual deaths that result from food-related fine particulate matter ($PM_{2.5}$) pollution are attributable to animal-based foods. By estimating these impacts and exploring how to reduce them, this work fills a critical knowledge gap. Our results are relevant to food producers, processors, and distributors, and to policymakers and members of the public interested in minimizing the negative consequences of food.

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[1]S.B. and S.K.T. contributed equally to this work.

[2]To whom correspondence may be addressed. Email: hill0408@umn.edu.

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Primary $PM_{2.5}$ is also a major contributor (4,800 deaths, 27% of total), largely from dust from tillage, livestock dust, field burning, and fuel combustion in agricultural equipment use. NO_x, SO_2, and NMVOCs are minor contributors (collective total: 700 deaths; 4% of total). Areas causing the greatest damages are spatially concentrated, with the top 10% of the most damaging counties (308 counties) together responsible for 8,400 deaths per year (47% of total deaths). These counties are mainly located in California, Pennsylvania, North Carolina, and along the Upper Midwest Corn Belt (Fig. 2 and *SI Appendix*, Fig. S4 and Table S2).

We also attribute total deaths from agricultural supply chain emissions to the production of specific commodities, which we combine into 16 groups (Fig. 1; "Commodity"). This analysis shows that 57% of deaths are from crops and 43% from livestock. However, a substantial portion of crops is used as animal feed and nonfood products (Fig. 1; "Product"). In attributing direct damages to final products, we find that 89% (15,900 deaths) of the total deaths caused by agriculture are linked to food production, with the remaining 11% (2,000 deaths) linked to biofuels and other nonfood products (e.g., plant and animal fibers) (Fig. 1; "Source"). Of food-related damages, 80% (12,700 deaths) are attributable to animal-based foods (when impacts of animal feed production are included) and 20% (3,200) to plant-based foods.

Next, we consider the per-unit damages of 11 food groups (Fig. 3 and *SI Appendix*, Table S1), taken as the production-weighted average of the foods in each group, and using four metrics suited to meet different nutritional needs (per 10^9 kg, 10^9 serving, 10^9 g protein, and 10^9 kcal, each measured as raw edible portion). We find that red meat dominates in air quality–related health damages, whether normalized by total mass, serving, protein mass, or caloric value. Per serving, production-weighted averages of red meat are 2× greater than those of eggs, 3× greater than those of dairy products, 7× greater than those of poultry, 10× greater than those of nuts and seeds, and at least 15× greater than the production-weighted average of any other plant-based food. Similar trends hold when these food groups are compared using the other three metrics. The lowest-impact production of red meat has a greater impact than the highest-impact production of any other food, absent the dietarily insignificant comparison of red meat to fruit as measured on a per-protein content basis. We observe a wide range of spatial variation in per-unit damages of major crops and livestock commodities (*SI Appendix*, Fig. S8). Damages vary spatially because of site-specific production practices, atmospheric chemistry and transport, and population density (Fig. 2 and *SI Appendix*, Fig. S4), consistent with prior studies focused on maize (21) and switchgrass (22). Limitations of supply chain information (e.g., where the crops that are fed to animals in a given location are grown) restrict our understanding of the spatial variation in per-unit damages for animal-based foods as final products.

We also estimate the air quality–related health benefits that can be achieved through the actions of food producers and consumers. We identify interventions that reduce $PM_{2.5}$-related emissions, focusing on interventions that target the most harmful agricultural processes, promote dietary shifts, reduce food loss and waste, and encourage healthy per capita consumption levels (*Materials and Methods*). We generate spatially explicit inventories for each intervention scenario and compare them to a baseline scenario for current production practices and diets (*SI Appendix*, Fig. S9 and Table S3), modeling the resulting changes in $PM_{2.5}$ concentrations and annual deaths.

We find that improvements in agricultural production, such as changing livestock feed practices to reduce the amount of excess protein ingested and therefore excreted as nitrogen, or using fertilizer amendments and inhibitors, can greatly reduce air quality–related health damages (Fig. 4). Implementing measures to reduce agricultural emissions across all producers could prevent 7,900 deaths per year (50% of total deaths from food production). The greatest benefits are from changes in livestock waste management and fertilizer application practices. Producer-side interventions in the 10% of counties with the highest mitigation potential alone could prevent 3,600 deaths per year (22% of total deaths from food production). Expanding such interventions to the top 50% of counties would prevent 41% of total $PM_{2.5}$-related deaths linked to food production.

Our findings suggest that the monetized $PM_{2.5}$-related health benefits of such interventions could greatly exceed implementation costs. For example, using a Value of Statistical Life of $10 million (23, 24), we find that the annual monetized damage cost of

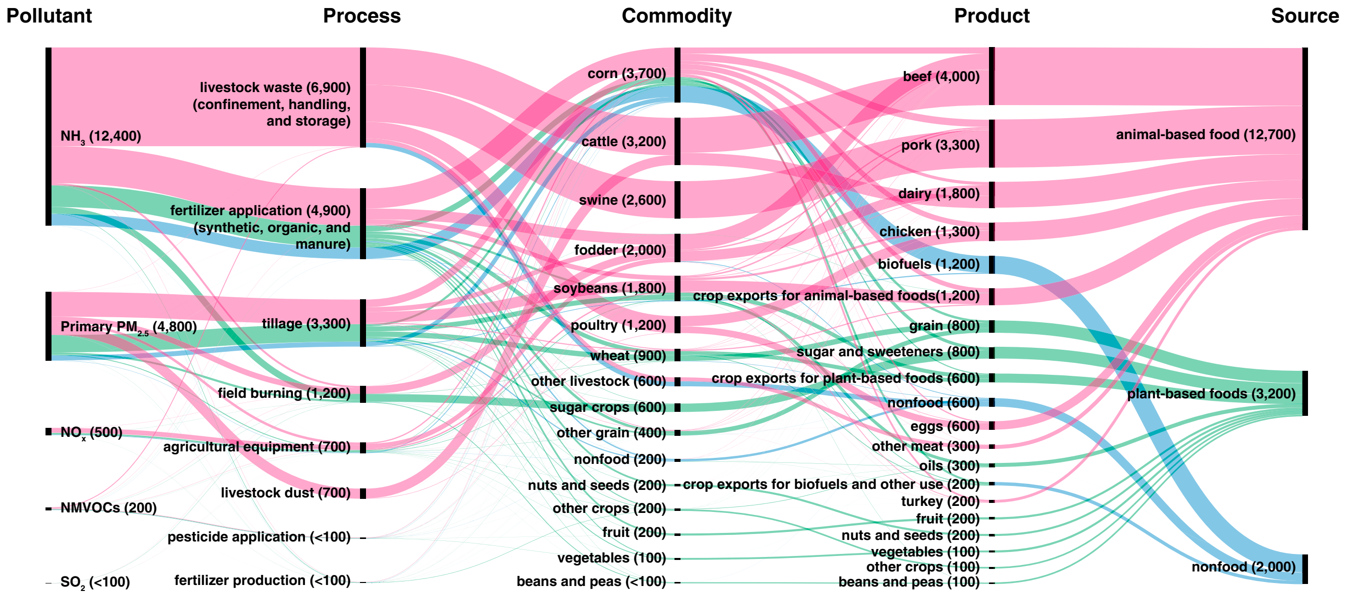

Fig. 1. Annual premature deaths attributed to increased atmospheric $PM_{2.5}$ from agriculture. Five alternate categorizations (columns) are shown: pollutant, process, commodity, product, and source. Pollutants include primary $PM_{2.5}$ and secondary $PM_{2.5}$ formed from precursor gases (NH_3, NO_x, NMVOCs, and SO_2). The height of each black bar within each column corresponds to the number of attributed deaths; deaths within each column sum to 17,900.

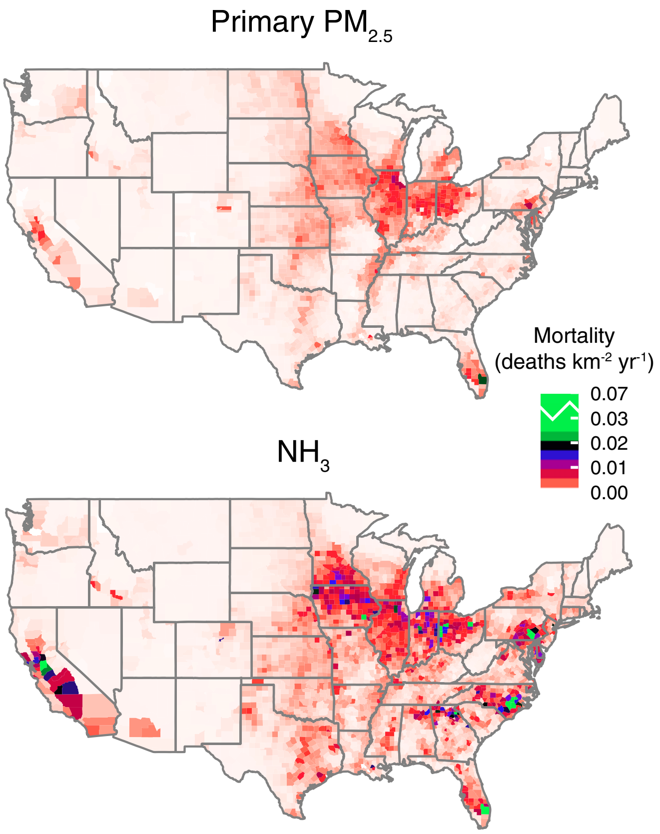

Fig. 2. Spatial distribution of $PM_{2.5}$-related mortality attributed to US agricultural production. Shown are annual premature deaths per square kilometer attributed to primary $PM_{2.5}$ (*Top*) and secondary $PM_{2.5}$ from NH_3 (*Bottom*), which together comprise 97% of agricultural $PM_{2.5}$-related deaths. Maps for the other 3% of deaths (i.e., from NO_x, NMVOCs, and SO_2) are shown in *SI Appendix*, Fig. S4. For each county, the mortality shown is that which occurs somewhere in the United States as a result of emissions from that county; that is, these maps show where the impact originates, not necessarily where it is experienced.

$PM_{2.5}$-related deaths from US food production are \$159 billion. The benefits of many of the explored interventions are 1.3 to 14.7× greater than the highest estimated implementation costs, consistent with the results of coarser resolution global analyses (25). For instance, the $PM_{2.5}$-related health benefits (range: 33.4 to 42.4 $\$ \cdot \mathrm{kg}^{-1}$ of NH_3) of interventions for nonorganic fertilizer application, such as improvements in timing, method of application, use of amendments and inhibitors, and a shift to less emissive fertilizer types, greatly exceed the implementation costs (range: –0.8 to 3.2 $\$ \cdot \mathrm{kg}^{-1}$ of NH_3).

We also find that nationwide dietary shifts that decrease consumption of animal-based foods can lead to large decreases in agricultural $PM_{2.5}$-related death rates, simultaneously reducing direct damages from livestock waste management and indirect damages from feed production (Fig. 4). Substituting poultry for red meat could prevent 6,300 annual deaths (40% of total deaths from food production). Even greater benefits of 10,700 to 13,100 deaths prevented per year (68 to 83%) could be achieved from more ambitious shifts to vegetarian, vegan, or flexitarian diets such as the planetary health diet of the EAT-Lancet Commission (2). Other demand-side mitigation strategies, such as decreasing caloric intake proportionally across all food groups to be in line with metabolic requirements and decreasing household food loss and waste levels, could lead to more modest reductions in agricultural $PM_{2.5}$-related death rates (range: 700 to 1,200 avoided deaths per year).

Many of the food production solutions that could reduce air quality–related health damages, such as improving nitrogen use efficiency in crop and livestock production, or decreasing food

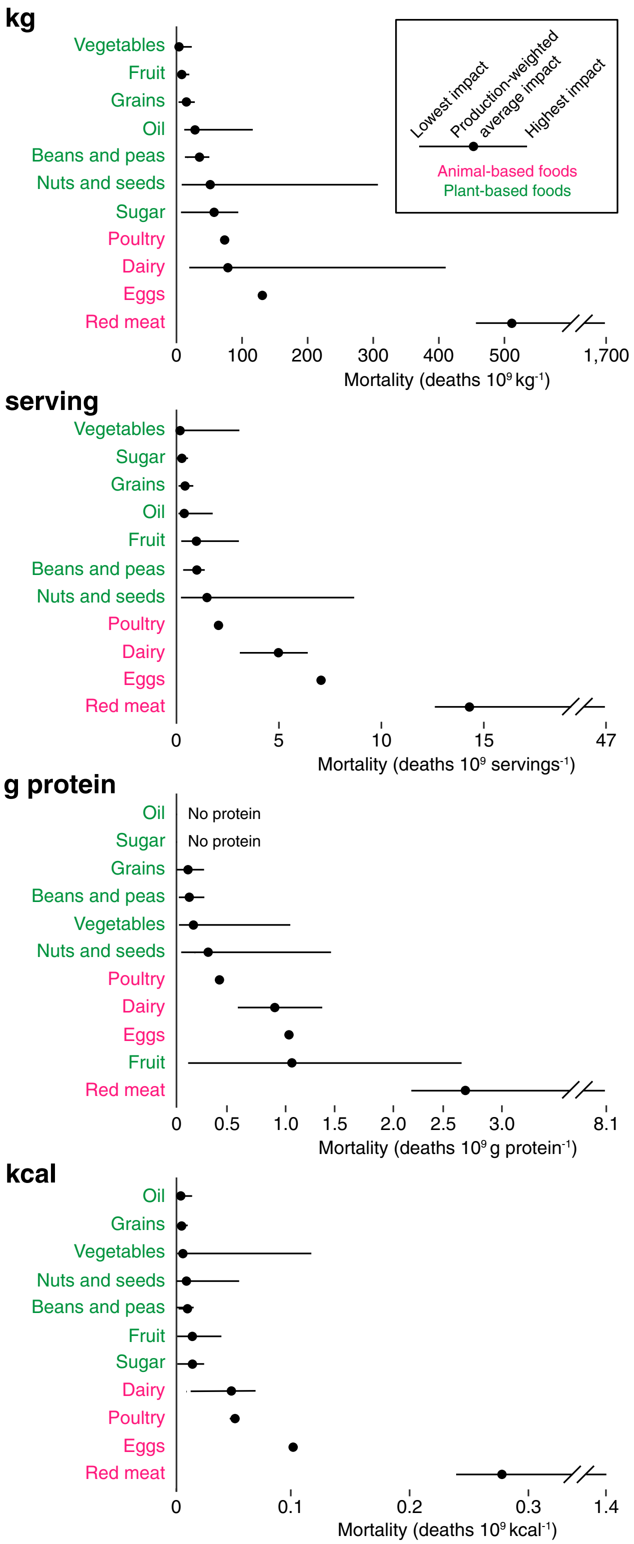

Fig. 3. Annual premature deaths attributed to total $PM_{2.5}$ per unit of food production. Annual premature mortality attributed to total $PM_{2.5}$ per 10^9 kg, 10^9 serving, 10^9 g protein, and 10^9 kcal, each measured as raw edible portion. Horizontal lines indicate the range of per-unit damages within the food group. Food groups are ordered lowest to highest within each panel.

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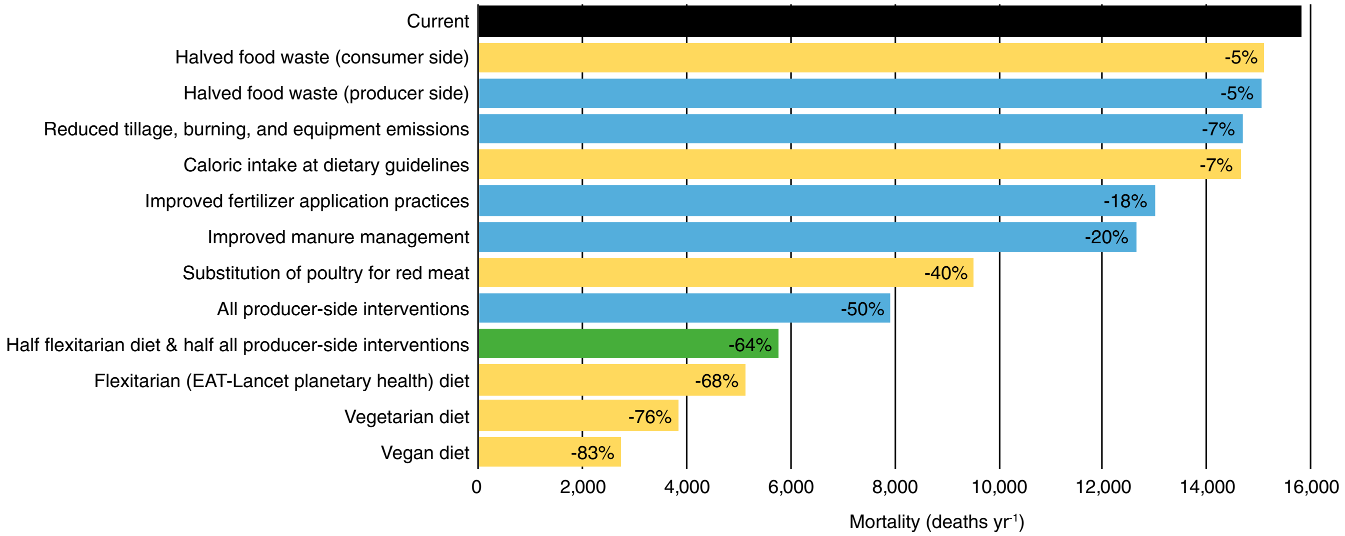

Fig. 4. Annual premature deaths attributed to total $PM_{2.5}$ from food production that could be mitigated by a given intervention or suite of interventions. Yellow bars correspond to consumer-side interventions, blue bars to producer-side interventions, and green to a combination of the two. Values for percent decrease in mortality from current mortality are shown.

loss and waste, are likely accompanied by other environmental benefits, such as decreasing greenhouse gas emissions, nutrient pollution, and undesirable land-use change (26–28). Further, dietary shifts that increase the fraction of kilocalories from plant-based foods can improve diet-related health outcomes by reducing the incidence of chronic noncommunicable diseases, such as type 2 diabetes, coronary heart disease, and cancer (29, 30).

This work contributes to a more comprehensive understanding of the air quality–related health damages of food and identifies solutions for reducing the negative impacts of food across a diverse range of diets, production practices, and other site-specific factors. Current diets and food production practices cause substantial damages to human health via reduced air quality; however, their corresponding emissions sources, particularly ammonia, are lightly regulated compared to other sources of air pollution, such as motor vehicles and electricity production. This is true despite agriculture having comparable health damages to these other sources of pollution (10, 31). Meaningful reductions in air quality–related health damages will likely require simultaneous interventions, such as dietary shifts and changes in how we manage livestock waste and apply fertilizer. Although our results are for the United States, our approach can be applied globally, with mitigation efforts anticipated to reduce premature deaths substantially. Reductions should be especially large in regions where $PM_{2.5}$ concentrations are sensitive to ammonia emissions, where agricultural burning is commonly practiced, and in densely populated regions with high $PM_{2.5}$ exposure levels (25).

Materials and Methods

We estimated the air quality–related annual deaths attributable to the US agricultural sector, which includes annual deaths attributable to 95 agricultural commodities that span the entirety of animal production, and cropland and grassland pastures captured in the 2014 US Department of Agriculture (USDA) Cropland Data Layer (CDL) (32). We then computed the per-unit annual impacts of 67 final products from 11 food groups. Finally, we estimated the air quality–related health benefits that could be achieved through producer- and consumer-side interventions.

Extraction of Agricultural Emissions. County-level air pollution impacts from the agricultural sector were estimated by identifying and extracting emissions data linked to crop and livestock production from the US Environmental Protection Agency (EPA)'s 2014 National Emissions Inventory v2 (NEI2014) (14). Emissions from the contiguous 48 states were included, covering >99% of US agricultural production. We identified agricultural processes from source classification codes (SCCs), with the seven agricultural processes listed as follows: 1) livestock waste (confinement, handling, and storage), 2) tillage, 3) fertilizer application (synthetic, organic, and manure), 4) field burning, 5) agricultural equipment fuel combustion, 6) livestock dust, and 7) pesticide application (15). As 88% of all ammonia, ammonium nitrate, urea, and other nitrogen compounds produced in the United States are used as fertilizer, the same fraction was used to allocate emissions from the production of these chemicals to a "fertilizer production" category (33). All emissions were used as published by the NEI2014, with two exceptions. First, NEI2014 estimates of primary $PM_{2.5}$ from tillage and livestock dust do not account for differences in fugitive dust emissions by land cover, as they depend on dry deposition rates and wind speeds (15). As a result, county-level transport fractions were applied to account for local effects (34). Second, we adjusted the estimates of tillage emissions in NEI2014 using data collected by the USDA in the Agricultural Resource Management Survey to better reflect the current number of tillage passes associated with individual crops (35).

Allocation of Emissions. We categorized emissions by pollutant type (i.e., primary $PM_{2.5}$, NH_3, NO_x, SO_2, and NMVOCs), agricultural process (e.g., livestock waste and fertilizer application), commodity that is the onsite emissions source (e.g., livestock types such as beef cattle, and crop types such as corn), and final product (e.g., beef).

Livestock production. Emissions from livestock production come from either livestock waste management or ancillary livestock dust. These emissions were attributed to specific animal types using SCCs within the NEI2014 (15). Livestock waste emissions of 10 major livestock types (beef cattle, dairy cattle, broilers, layers, swine, turkeys, goats, lambs, horses, and other livestock) were estimated separately by different management stages (confinement, handling and storage, and land application of manure) using the Carnegie Mellon University (CMU) Farm Emissions Model (36) but were aggregated into a livestock-specific emissions category in the NEI2014 (15). To allocate emissions by management stage, we derived the state-level distribution of emissions by management stage by first running the CMU Ammonia Model on which the Farm Emissions Model is based (36). Next, we applied that distribution to emissions published in the NEI2014. All emissions associated with confinement, handling, and storage were attributed to the livestock commodity. Emissions associated with land application of manure were attributed to crop production and further allocated to a specific crop commodity using crop production practices data from the USDA Economic Research Service (ERS) (35).

Crop production. In terms of emissions, crop production processes of interest included fertilizer production, fertilizer application, tillage, agricultural equipment use, field burning, and pesticide application. For fertilizer production and pesticide application, national-level emissions were distributed according to crop fertilizer and pesticide use data published by the USDA ERS (37, 38). For tillage and field burning, SCCs within the NEI2014 were used to allocate emissions to a specific crop type (15). Because the NEI2014 only includes tillage emissions for 21 crops, we introduced tillage emissions from an additional 71 crops available in the 2014 CDL by averaging county-level average emissions factors for annual or perennial crops in the NEI2014; we then applied the appropriate emission factor (annual or perennial) to county-level crop acreage (32).

Emissions from agricultural equipment use and fertilizer application are not preallocated to crops in the NEI2014 and therefore required additional allocation. For agricultural equipment use, we allocated county-level emissions to crop commodities using the county-level crop acreage of 92 crops (including grassland pasture) in the CDL (32). In the case of fertilizer application (for synthetic and organic fertilizers but not manure), we allocated county-level NH_3 emissions to specific crops, in proportion to crop acreages from the CDL (32) paired with crop-specific nitrogen volatilization rates and irrigation rates obtained from the Environmental Policy Integrated Climate (EPIC) model (39). However, the EPIC model only includes crop-specific data for 20 crops, with all other emissions aggregated into an "other_crops" category. As preliminary results suggested that the total emissions of the other_crops category were comparable to those of major crops such as corn and soybean, further resolution in the other_crops category was achieved by allocating emissions in proportion to the county-level distribution of crop acreage from the CDL. Emissions from the roughly 1% of counties listed in the NEI2014 but not included in the EPIC model were conserved and allocated according to the state-level distribution of emissions.

We then allocated emissions from crops to final products (e.g., crop products, animal products, exports, and biofuel) using production data from annual Yearbook Data Tables and the 2015 Agricultural Statistics Report (20, 40). This allowed us to estimate the total annual deaths associated with the production of 95 agricultural commodities as well as the per-unit annual deaths associated with the production of 67 food products (*SI Appendix*, Table S2).

Annual Deaths. We input spatially explicit emissions inventory data into three reduced-complexity chemical transport models (RCMs): Air Pollution Emission Experiments and Policy v3 (16), EASIUR (Estimating Air pollution Social Impact Using Regression) (17), and Intervention Model for Air Pollution (18). All three models include simplified representations of atmospheric chemistry and physics, which reduce computational demands relative to traditional chemical transport models, including linearization that omits meteorological coupling. This enabled us to evaluate a broad range of emissions scenarios. At the same time, each of the models has a different structure and makes different simplifying assumptions, which reduces the likelihood that all three models would make the same type of error. We chose these RCMs as they allow users to distinguish the $PM_{2.5}$-related mortality by emissions source locations and provide higher resolution than other national-scale RCMs, such as the US EPA Response Surface Model (19). The RCMs are described in the *SI Appendix*.

Because the RCMs only cover counties in the contiguous United States, we excluded NEI2014 emissions in noncontiguous states from the analysis. The RCMs are customized to estimate annual deaths according to the American Cancer Society's concentration-response function, which averages a 6% increase in annual deaths per 10 $\mu g \cdot m^{-3}$ in $PM_{2.5}$ concentration. Although NO_x and volatile organic compounds can react to form tropospheric ozone (O_3), which can also result in premature mortality, we excluded O_3 from this analysis because the resulting air quality–related health impacts are overall greatly exceeded by those of $PM_{2.5}$ (8).

Despite key differences between the formulation of the three RCMs, estimated marginal social costs per tonne of primary $PM_{2.5}$, NH_3, NO_x, and SO_2 generally fall within a factor of 2–3 for all US counties (19). The agreement of RCM model predictions is greatest for primary $PM_{2.5}$ (Pearson correlation coefficient = 0.73 to 0.81) for which the atmospheric chemistry that translates pollutant emissions to changes in $PM_{2.5}$ concentrations is relatively straightforward. It is weakest for NO_x and SO_2 (Pearson correlation coefficients of 0.35 to 0.49 and 0.07 to 0.54, respectively) for which the atmospheric chemistry is more complex. Overall, total emission-weighted annual deaths in the United States vary between 12 to 33% for ground-level sources (19).

Sensitivity Analysis. We evaluated the seasonal sensitivity of annual deaths using the seasonal social costs per tonne estimated by the EASIUR model. Specifically, we tested the seasonal sensitivity of NH_3 from livestock waste management and fertilizer application: NH_3 is the primary driver of agricultural emissions, and social costs per tonne of NH_3 are highest (roughly 2.5× greater) when seasonal emissions are relatively low (41). The NEI2014 estimates annual emissions. We obtained monthly NH_3 emissions from livestock waste management and fertilizer application by applying the monthly distribution of emissions from Pinder et al. and Goebes et al., respectively (41, 42). Damages using the seasonal option in EASIUR were comparable to those using the annual average option (*SI Appendix*, Fig. S6).

Mitigation Interventions. We estimated the air quality–related health benefits that can be achieved through interventions by producers and consumers, largely targeting NH_3 as it is a major driver of $PM_{2.5}$-related deaths attributable to food production in the agricultural sector (43). Specifically, we focused on intervention scenarios that could reduce emissions linked to livestock waste management, fertilizer application, tillage, field burning, fuel combustion, dietary shifts, food loss and waste, and per capita consumption levels.

We estimated the air quality–related health benefits of interventions by comparing health outcomes for an intervention scenario with those for a baseline scenario in which food producers and consumers behave according to business as usual. To measure the health outcomes linked to an intervention scenario, we first estimated the emissions reductions that can be achieved from a specific intervention and used that information to create a spatially explicit inventory of reduced emissions. Using the emissions inventory as input for the RCMs, we then modeled the resulting health outcomes.

We estimated emissions reductions of producer-side intervention scenarios by averaging emissions reductions linked to existing interventions as found in a survey of the literature (*SI Appendix*, Table S4). Identified interventions were grouped by agricultural process such as livestock waste management and fertilizer application. When possible, they were further grouped into subcategories such as livestock housing type or fertilizer type. For instance, emissions reductions for interventions targeting dairy cattle at the confinement stage are estimated by averaging emissions reductions for individual interventions, such as installing grooved floor systems with tooth scrapers in the confinement facilities or establishing a tree shelterbelt surrounding confinement facilities.

With regard to consumer-side interventions, we examined two caloric scenarios: 1) caloric intake is at current US levels (average of 2,590 kilocalories per capita per day), and (2) caloric intake is reduced to a level that would maintain a body mass index between 20 and 25 for an average person (average of 2,400 kilocalories per capita per day) (44). In the second scenario, we assumed that caloric intake was reduced proportionally across all food groups to achieve the target caloric level. Six isocaloric dietary scenarios from the EAT-Lancet Commission were considered: 1) business as usual in the United States, 2) the planetary health diet, 3) the planetary health diet with high milk consumption, 4) planetary health diet with high red meat consumption, 5) vegetarian, and 6) vegan (2, 3). In modeling alternative diets, the EAT-Lancet Commission considers national preferences of different food groups. Because foods can be imported or exported, the composition and volume of foods produced in the United States do not exactly match those of foods consumed in the United States, though 87% of food and beverages purchased in the United States are domestically produced (45).

We considered two options for estimating annual deaths linked to diets and food production in the United States for the business-as-usual dietary scenario: 1) we assumed annual deaths in the business-as-usual dietary scenario are equal to annual deaths from the US agricultural sector minus annual deaths from nonfood production, and 2) we assumed that annual deaths in the business-as-usual dietary scenario can be computed by matching the per-kilocalorie annual deaths associated with food groups with the caloric composition of the average United States diet from the EAT-Lancet Commission (2). The EAT-Lancet Commission estimates caloric composition of the baseline US diet using country-specific food availability data and model equations from the International Model for Policy Analysis of Agricultural Commodities and Trade. We found that the estimated annual deaths from both options differed by 8% (option one: 15,900 deaths per year and option two: 17,200 deaths per year). We used the results of the first option to analyze mitigation interventions because that option more closely represents current US food production. We estimated annual deaths linked to alternative scenarios by matching the per-kilocalorie annual deaths associated with food groups with the caloric composition of the diet being examined (assuming all food consumed in the United States is produced domestically). We assumed that the average damage of food groups remained constant with changes in production. More information on the per-kilocalorie annual deaths attributable to food groups and the caloric composition of the diets are in *SI Appendix*, Tables S2 and S3, respectively.

We considered two food loss and waste scenarios: food loss and waste at current US levels (46), and food loss and waste reduced by 50%. We distinguish food loss and waste by food type and by food supply chain stage (agricultural production, postharvest handling and storage, processing and packaging, distribution, and consumption) using estimates for the North America and Oceana region (46). We also assumed that reductions occur proportionally across both food loss and waste.

Finally, we explored the cost effectiveness of selected NH_3 mitigation interventions, including changes in practices related to livestock feed, animal housing, manure storage, manure application, and synthetic fertilizer application.

Data Availability. All study data are included in the article and/or *SI Appendix*.

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