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To cite this article: Elizabeth S M Dukes *et al* 2020 *Environ. Res. Lett.* **15** 075007

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Environmental Research Letters



LETTER

OPEN ACCESS

RECEIVED
27 February 2019

REVISED
14 February 2020

ACCEPTED FOR PUBLICATION
17 February 2020

PUBLISHED
2 July 2020

A community nitrogen footprint analysis of Baltimore City, Maryland

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Keywords: nitrogen, nitrogen footprints, sustainability, diet, community

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Abstract

The nitrogen footprint tool (NFT) provides a novel way for communities to understand the environmental impacts of their collective activities and consumption. Reactive nitrogen (Nr; all N species except N₂) is created by the Haber–Bosch process for food production and as a by-product of fossil fuel combustion and two natural processes, biological nitrogen fixation and lightning. While it is a vital input for food production, too much Nr has a negative effect on the environment. Calculating the amount of Nr released to the environment as a result of an entity's resource consumption is the first step in reducing those Nr losses. The nitrogen (N) footprint method has previously taken this approach at the personal and institution scale. In this study, the approach is extended, for the first time, to the spatial patterns of the community nitrogen footprint within a large city, through the integration of diverse geographic information to calculate the N footprint distribution within the City of Baltimore, Maryland, USA. The total N footprint of Baltimore City was ~19 000 MT N or 30 kg N per capita in 2016, dominated by the food production sector (73%), followed by the energy and transportation sectors (15% combined). There was geographic variability among census block groups' per capita N footprint within Baltimore City; driven primarily by economic and development factors. Several management scenarios were assessed to better understand what actions may reduce the Baltimore N footprint at the city and community scale over time. The study explored the effect and efficacy of reducing meat consumption based on differences in city consumption patterns, increasing the use of renewable energy sources, and reducing electricity consumption on the city's total N footprint. The model for the Baltimore City N footprint calculation can be applied to other communities in the United States at the spatial grain of the census block group or any country with this level of data to provide an indicator of nitrogen sustainability.

Introduction

Nitrogen (N) is essential for all life. While it is abundant in the atmosphere as unreactive N₂, for most biological species it must first be converted to reactive nitrogen (Nr) (e.g. NH₃) to be used. In the natural environment, the conversion of N₂ to Nr is done by microbes that perform biological Nr fixation (BNF) and by lightning. Humans create Nr in three ways: as synthetic fertilizer and as an industrial feedstock via the Haber–Bosch process, fossil fuel combustion, and

cultivation induced BNF (i.e. legumes). Thus, humans add to the global Nr pool primarily through food and energy production. Excess Nr additions can have detrimental effects to the environment including smog and haze, forest die-back, acidification of waterways, eutrophication, climate change, and ozone depletion. These effects are manifested as Nr molecules move through and between earth systems in a nitrogen 'cascade' (Galloway *et al* 2003).

An N footprint is the amount of Nr released to the environment as a result of an entity's resource use

(Leach *et al* 2012). These resource uses include food, energy, transportation, and fertilizer. The entity could be a person, institution, or—as in this case—a community. The N footprint includes all Nr losses related to an entity's resource consumption, regardless of where those losses occur (e.g. upstream or downstream of the entity). The footprint model differs from other indicators such as input output models (Hobbie *et al* 2017) and Nr spatial indicators (NrSI) which estimate Nr losses from food production and energy use on a per area basis (Liang *et al* 2018). Nitrogen footprint tools (NFTs) have been developed at personal (Leach *et al* 2012) and institutional (Leach *et al* 2013, Castner *et al* 2017, Galloway *et al* 2014) scales and are used for both tracking N footprints and setting reduction goals. The community NFT broadens the scope of these existing tools to address the nitrogen dilemma on a larger scale by developing methods adapting spatial data processing to estimate geographic patterns of both N footprint drivers and outcomes. A community refers to a collection of people living in a certain region and governed under a particular municipality. This can include cities, counties, or other groups under a common jurisdiction. The community NFT could be used for the same objectives as the individual and institution level footprints but needs to be modified as a city or geographic region is a heterogeneous aggregation of individuals, neighborhoods, and public/private institutions, and not a single entity as a person or individual institution. A community N footprint shows the spatial distribution of the N footprints which allows stakeholders to use the tool to estimate current patterns and target specific neighborhoods within a community for reductions.

NFTs should be used in conjunction with other sustainability and socio-economic indicators to provide a wholistic view of the community. Using the N footprint as a metric for sustainability expands the focus from energy initiatives and gives a quantitative method to assess the impacts of food choices and energy decisions on the environment (Pierer *et al* 2014, Castner *et al* 2017, Hayashi *et al* 2018, Oita *et al* 2018). In communities, the NFT can be used as a method alongside other sustainability assessments (e.g. greenhouse gas inventories, N budget approaches, carbon footprint assessments, neighborhood indicators, food desert maps) to comprehensively assess spatial patterns of community environmental sustainability and socioeconomic wellbeing. Using multiple metrics to assess community sustainability and resilience identifies any potential tradeoffs across metrics and gives a more complete picture of the best ways differently to address issues at spatial scales that are sensitive to local demography, behavior and built environment. The intended users of this tool are city/county government agencies, non-governmental organizations (NGOs), community and local research groups and non-profit organizations interested in promoting community sustainability and benefits.

Baltimore City was chosen as the study site for the first community NFT because it is connected to a set of rich databases through the Baltimore Ecosystem Study (<http://beslter.org>) and because there are documented direct consequences of excess Nr on the local environment. Baltimore City drains into the Chesapeake Bay, an important natural resource for ecosystem services related to water filtration, climate stability, recreation, and fisheries, producing an estimated \$22.5 billion in benefits each year (Phillips and McGee 2016). The eutrophication caused by excess nutrients (predominantly nitrogen and phosphorous) reduces the capacity for the Chesapeake Bay to provide these ecosystem services. Reducing the detrimental effects of eutrophication improves the capacity of the bay to provide ecosystem services (EPA 2002). Excess Nr in Baltimore also contributes to tropospheric ozone and smog in the Baltimore area, which is detrimental to the environment and can cause respiratory illnesses in humans (Birch *et al* 2011). In 2011, Baltimore City ranked higher than 90% of cities in the US in NO_x concentrations (a by-product of fossil fuel combustion and local air quality pollutant) over the year (EPA 2015).

Baltimore, similar to many other cities, has no agricultural land (USGS 2018) meaning much if not all of the N losses attributed to food production occur outside of the city limits. Food production is a large contributor to individual and institution N footprints (Leach *et al* 2012, Leach *et al* 2016, Castner *et al* 2017) which also occur outside of system bounds. Analyzing losses occurring inside and outside of city limits is important in order to inform and engage local stakeholders (Gu *et al* 2017). For Baltimore, the local N losses would occur from the following sectors: wastewater, pet waste, natural gas use, transportation, and fertilizer used for lawns. Losses outside of the city would occur from the following sectors: electricity generation, food production, and pet food production. It is important to note that some of the electricity (~0.5% of usage) (EIA 2019) and some food (produced in home gardens) would be local losses. For the purposes of this study, these categories are considered to be non-local losses as the majority of the losses occur outside of the city. Though these Nr losses occur outside of the city, it is the consumption and purchasing decisions of residents and businesses within the city that generate these losses. Therefore, these non-local losses contribute to the city's total N footprint. Communities interested in measuring and reducing the local and nonlocal impacts of excess Nr can benefit from using the community N footprint analysis. The Baltimore City N footprint provides stakeholders information to evaluate strategies to mitigate these impacts and improve local water quality and human health.

The objectives of this study were to: (1) calculate and map the N footprint of Baltimore City, (2) present potential reduction scenarios to reduce this

footprint, (3) determine the impact of income on N footprints in Baltimore City, and (4) provide a methodology for additional communities to calculate their N footprints.

Methods

System bounds

The system bound of this community-level N footprint calculation is the city limits of Baltimore. Food includes food purchased by individuals living in Baltimore City, wastewater includes all wastewater generated in Baltimore City, pet food and waste includes all pet food bought in the city and all pet waste released in the city, electricity and natural gas includes all usage within the city limits, transportation includes all miles (kilometers) traveled within city limits. This system bound was chosen for three reasons: the intended use of the N footprint calculation, the scale of aggregated data available, and the jurisdictional level of agencies intended to use the tool. The N footprint calculations were performed at the census block group scale. Census block groups are the smallest scale that the United States Census Bureau publishes data and is an area which has a population of 600–3000 individuals (CEX 2016). This resolution made it possible to differentiate N footprints at the ‘neighborhood scale,’ which was particularly relevant for whole-city analyses (Boone *et al* 2012). The existence of census block group data across the US allows this methodology to be used at a wide range of scales, e.g. census tracts, counties, watersheds, cities.

Food purchase data was available at a census block group scale from the 2016 Consumer Expenditure Report (CEX 2016), Supplemental Nutrition Assistance Program data (American FactFinder 2018). Data such as the electricity, natural gas use, vehicle miles traveled, and wastewater volume were available at a city and county scale and scaled to census block groups on a per capita basis using scaling. Using data specific to Baltimore at the census block group level allows the estimation of the spatial distribution of N footprint drivers and outcomes, and sets the community N footprint apart from other national or regional calculation methods which use national or regional averages to determine a per capita footprint (Leach *et al* 2012, Gu *et al* 2013, Shibata *et al* 2014).

The US Census Bureau’s Consumer Expenditure Report (CEX 2016) contains information on the purchases made by individuals in each census block group. The Consumer Expenditure Report is a biannual survey which asks households to record purchases at grocery stores, retail stores and other expenditures (e.g. rent, electricity, car titles) for two weeks for residents in all 50 US states. These survey results from 2016 were aggregated to represent the entire census block group’s annual expenditures (CEX 2016).

Building the tool

The N footprint calculations were performed in Microsoft Excel (modified from Leach *et al* 2013), and ArcGIS was used to map those N footprint results. ArcGIS was also used to transform data sets from the Consumer Expenditure Report for analysis in the Excel NFT. A brief description of the calculations is given below for the following sectors: Food, wastewater, fertilizer use for home lawns, electricity use, natural gas, pet food, pet waste, and transportation. All footprint results were calculated in kilograms of nitrogen (kg N) and summed to determine the nitrogen footprint of the census block group. The sum of the 646 census block groups N footprints in Baltimore City was the city’s N footprint. More information on the detailed calculations are listed in the supplementary material parts 1 and 2 is available online at stacks.iop.org/ERL/15/075007/mmedia.

Food

For a specific food product, the dollars spent on food (USD) in each census block group from the United States Consumer Expenditure Report (CEX 2016) was converted to kilograms using average price per kilogram (USD/kg) datasets (BLS 2016 and USDA 2016):

$$F = (D_f / C_f) \times N_c \times VNF, \quad (1)$$

where F is the product food production N footprint (kg N), D_f is the dollars spent on food (USD) (CEX 2016), C_f (USD) is the cost of food per kilogram (BLS 2016 and USDA 2016), N_c (%) is the nitrogen content of the food product (USDA 2018); and VNF (kg N lost/kg N consumed) is the nitrogen used in the food production process but not in the consumed product (Leach *et al* 2020).

The other components of the N footprint include food waste and transport. The summary equation in calculating the N footprint of one food product category is:

$$N_{\text{food}} = F + W + T, \quad (2)$$

where N_{food} is the total N footprint of the food product (kg N), F is the product food production N footprint (kg N), W is food waste (virtual N and food waste N) at the consumer level (kg N), and T is transport N losses (kg N).

This calculation was completed for all food product categories (18 total) (Leach *et al* 2012) in each census block group. More details on data sources and complete calculations can be found in the supplementary material parts 1a and part 2.

Wastewater treatment

Wastewater refers to the N released following wastewater treatment of sanitary effluent from Baltimore City residents. Wastewater generated in Baltimore is treated at the Patapsco and Back River treatment plants (Baltimore City Department of Public Works 2019). The total gallons of wastewater treated from Baltimore City residents and businesses,

subtracting wastewater usage from Baltimore County which is also treated at these plants, in 2016 was 31 298 million gallons (118 476 million liters) (K Grove, Baltimore Department of Public Works, personal communication, March 2018). The total gallons treated were divided among census block groups on a per capita basis (CEX 2016). This was then converted into kg N lost to the environment through the treatment process as:

$$N_{\text{wastewater}} = G_{\text{cbg}} \times N_w \times (1 - R), \quad (3)$$

where $N_{\text{wastewater}}$ is the wastewater footprint of the census block group (kg N), G_{cbg} is the amount of wastewater treated from the census block group (gal), N_w is the nitrogen content of wastewater (kg N), and R is the removal factor at the sewage treatment plant (%).

More details and complete calculations can be found in the supplementary material part 1b.

Fertilizer application for home lawns

The total lawn area in each census block group was determined (USGS 2018), the average amount of N fertilizer applied per m^2 of lawn and the percentage of households applying fertilizer (Fraser *et al* 2012), and the average N uptake by turfgrass (55%) (Hermanson *et al* 1994) was used to determine the N footprint from fertilizer in each census block group as:

$$N_{\text{fertilizer}} = L_s \times H \times F_n \times (1 - U), \quad (4)$$

where $N_{\text{fertilizer}}$ is the fertilizer N footprint of the census block group (kg N), L_s is the amount of lawn in the census block group (m^2), H is the percentage of households applying fertilizer (%), F_n is the amount of nitrogen fertilizer applied (kg N m^{-2}), and U is the fertilizer uptake factor of turfgrass (%).

More details and complete calculations can be found in the supplementary material part 1c.

Electricity use

The total kilowatt hours of electricity used at businesses and residences in Baltimore City was collected (M Straub, Baltimore Gas and Electric, personal communication February 2018) and split into census block groups based on dollars spent on electricity (CEX 2016 and American FactFinder 2018). The NO_x and N_2O emissions for the region (EPA 2016) and atomic weight conversions were used to determine the N emissions from electricity in each census block group:

$$N_{\text{electricity}} = (E \times EF_{\text{NO}_x}) + (E \times EF_{\text{N}_2\text{O}}), \quad (5)$$

Where $N_{\text{electricity}}$ (kg N) is the electricity N footprint for the census block group, E is the kilowatt hours used in each census block group (kwh), EF_{NO_x} (2.72E-04 kg NO_x -N/kwh) is the amount of NO_x -N per kilowatt hour, and $EF_{\text{N}_2\text{O}}$ (4.08E-06 kg N_2O -N/kwh) is the amount of N_2O -N per kilowatt hour.

More details and complete calculations can be found in the supplementary material part 1d.

Natural gas

The total therms (10 000 British Thermal Units) of natural gas used at businesses and residences in Baltimore City was collected (M Straub, personal communication February 2018) and split into census block groups based on dollars spent on natural gas (American FactFinder 2018, CEX 2016). The NO_x (3.42E-04 kg NO_x /therm) and N_2O (1.06E-05 kg N_2O /therm) emissions for natural gas (EPA 2017) and atomic weight conversions were used to determine the N footprint from natural gas in each census block group:

$$N_{\text{naturalgas}} = (N_g \times EF_x) + (NON_g \times EF_{\text{N}_2\text{O}}), \quad (6)$$

where $N_{\text{naturalgas}}$ is the natural gas N footprint for the census block group N_g is the therms used in each census block group (therms), EF_{NO_x} (kg NO_x -N/therm) is the amount of NO_x -N per therm, and $EF_{\text{N}_2\text{O}}$ (kg N_2O -N/therm) is the amount of N_2O -N per therm.

More details and complete calculations can be found in the supplementary material part 1e.

Pet food

The average number of cats and dogs per person in the USA (Okin 2017) and the population of the census block groups (CEX 2016) were used to estimate the number of cats and dogs in each census block group. From this, the average amount per year (kg) and ingredients of food products in dog and cat food (e.g. chicken, beef, grains, and vegetables) was gathered (Baldwin *et al* 2010) to determine the amount of pet food in each census block group. The food production N footprint of pet food was treated the same as human food. The final step of the pet food N footprint is computed as:

$$N_{\text{petfood}} = F_p + W_p + T_p, \quad (7)$$

where and N_{petfood} is the total N footprint of the food product (kg N), F_p is the product food production N footprint (see equation (1); kg N), W_p is food waste at the consumer level (kg N), and T_p is transport N losses (kg N),

This calculation was done for each ingredient of the pet food for each census block group. More information is available in the supplementary material part 1f.

Pet waste

Pet waste was treated differently than human waste. It was assumed that all pet waste (urine and feces) is deposited to the land surface since most excreted N is contained in urine (Allard 1981). The N content of the pet food (all assumed to be excreted; USDA 2018) and the N uptake factor of turfgrass (55%) (Hermanson *et al* 1994) were used to determine the N footprint of pet waste:

$$N_{\text{petwaste}} = N_{\text{cp}} \times (1 - U), \quad (8)$$

where N_{petwaste} (kg N) is the N footprint of pet waste in the census block group, N_{cp} is the nitrogen content of the pet food (kg N), and U is the uptake factor of turfgrass (%).

More information is available in the supplementary material part 1g.

Transportation

The transportation N footprint of Baltimore City included all miles traveled within census block group limits. The total miles traveled by vehicle type (light trucks, motorcycles, cars, buses, single unit, and combination unit trucks) within city limits was obtained (MDOT 2016) and divided based on the total dollars spent on each transport type in a census block group (CEX 2016). The NO_x and N_2O emissions for each transport type (EPA 2017) (additional information on emissions factors in supplementary material) and atomic weight conversions were used to determine the N footprint from transportation in each census block group as:

$$N_{\text{transport}} = (M_t \times EF_{\text{NO}_x}) + (M_t \times EF_{\text{N}_2\text{O}}), \quad (9)$$

where $N_{\text{transport}}$ is the transport N footprint for a vehicle type in that census block group (kg N), M_t is the miles traveled by a vehicle type in each census block group (miles), EF_{NO_x} (kg NO_x -N/mile) is the amount of NO_x -N per mile, and $EF_{\text{N}_2\text{O}}$ (kg N_2O -N/mile) is the amount of N_2O -N per mile.

This was done for each vehicle type in each census block group. More information and full equations are in the supplementary material part 1h.

Comparison between income and nitrogen footprint

To evaluate the relationship between income and the nitrogen footprint of census block groups within Baltimore City, the average income of households in each census block group was collected from the American FactFinder database (American FactFinder 2018). Linear regression analysis was used to examine the relationship between the average income and average per capita N footprint of census block groups. Census block groups without complete data sets were removed from this analysis.

Scenarios

The Baltimore City results were used to investigate N footprint spatial patterns, and the differential impacts of N management scenarios on the N footprint. Management scenarios were modeled to determine the potential scale of impact for individual and combined cases. The energy reduction scenarios followed the reduction strategies suggested in the 2015 Maryland Climate Action Plan (Hogan *et al* 2015). The food scenarios focused on reducing consumption of high N-footprint food products primarily beef and other animal products.

The following scenarios were analyzed:

1. Energy scenarios: Maryland Climate Action Plan
 - a. Reduce energy consumption in residential and business locations by 10%
 - b. Decrease single passenger car travel by 10% by increasing public transportation by 10%
 - c. Increase renewables by 20% (assuming a conversion from coal to renewable)
2. Food scenarios: proposed for Baltimore City
 - d. Convert 15% of fast food restaurants to vegetarian restaurants
 - e. Cutting beef consumption by 50% by weight (grams) in census block groups consuming excessive amounts (over 80 g of protein per capita per day)
 - f. Switch 25% of beef purchases to beans by weight (grams)

The food scenarios were run by replacing and reducing food category purchases input to the community footprint tool. For example, food scenario (e), cutting beef consumption by 50% (weight) for census block groups consuming protein in excess (80 g per capita per day which is well above the required daily protein in the US of 46 g for women and 56 g for men) WHO 2007. The 80 g N per person per day was used as the cut off for this scenario to ensure that consumers still would consume the required protein level. For these over-consuming census block groups, beef consumption was cut in half and the impact on the total N footprint was assessed.

All scenario strategies were evaluated relative to a baseline year of 2016 and do not include growth projections or changes in emissions factors for any future year. Details are provided in supplementary material part 3.

Results

Baltimore city total nitrogen (N) footprint results and per capita results

The total N footprint of Baltimore City was 19 000 MT N and 30 kg N per capita in 2016. Note the per capita N footprint is an estimate including all activities occurring in the area including businesses and commuter contributions. The largest contributor to the N footprint of Baltimore City was food production sector (meat, dairy/egg, and crops) at 73%, with meat products being the most important (figure 1). Energy use sectors (electricity, natural gas, and transportation) were the next largest contributor, making up 15% of the city's footprint. Pet food and waste was the third largest contributor, at 10% of the total N footprint. Other categories making up smaller portions of the footprint included wastewater (1%) and fertilizer use for home lawns (<1%).

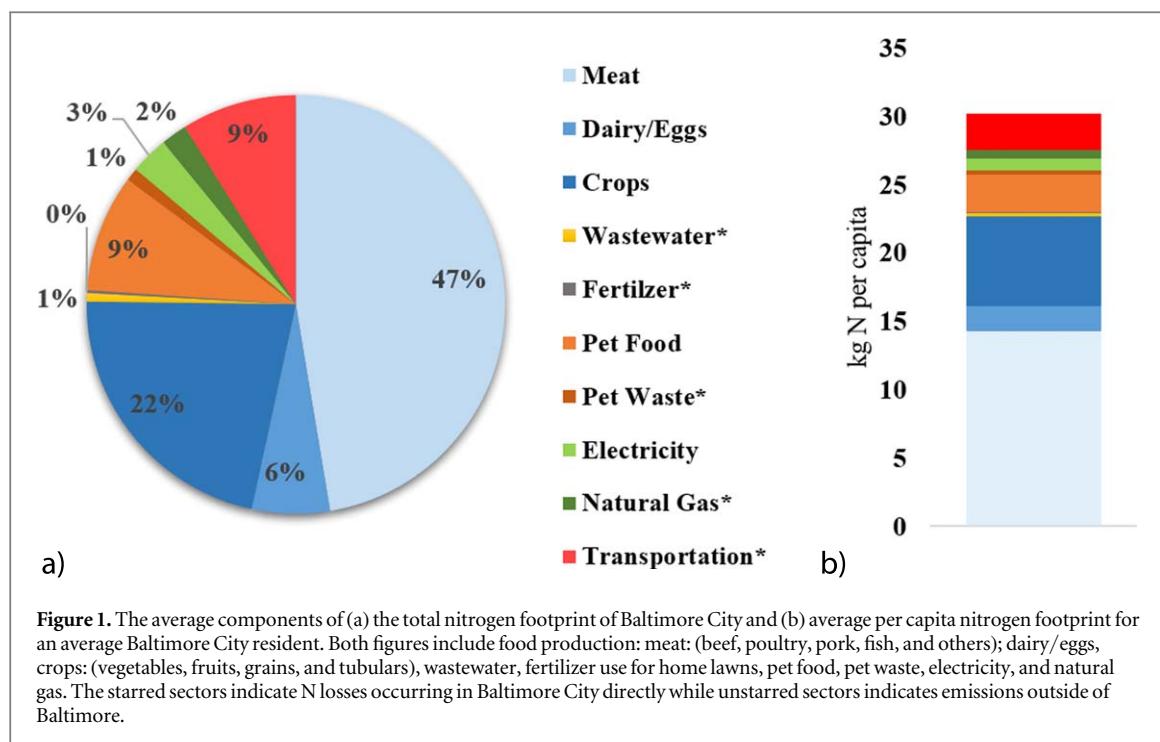


Figure 1. The average components of (a) the total nitrogen footprint of Baltimore City and (b) average per capita nitrogen footprint for an average Baltimore City resident. Both figures include food production: meat (beef, poultry, pork, fish, and others); dairy/eggs, crops: (vegetables, fruits, grains, and tubulars), wastewater, fertilizer use for home lawns, pet food, pet waste, electricity, and natural gas. The starred sectors indicate N losses occurring in Baltimore City directly while unstarred sectors indicates emissions outside of Baltimore.

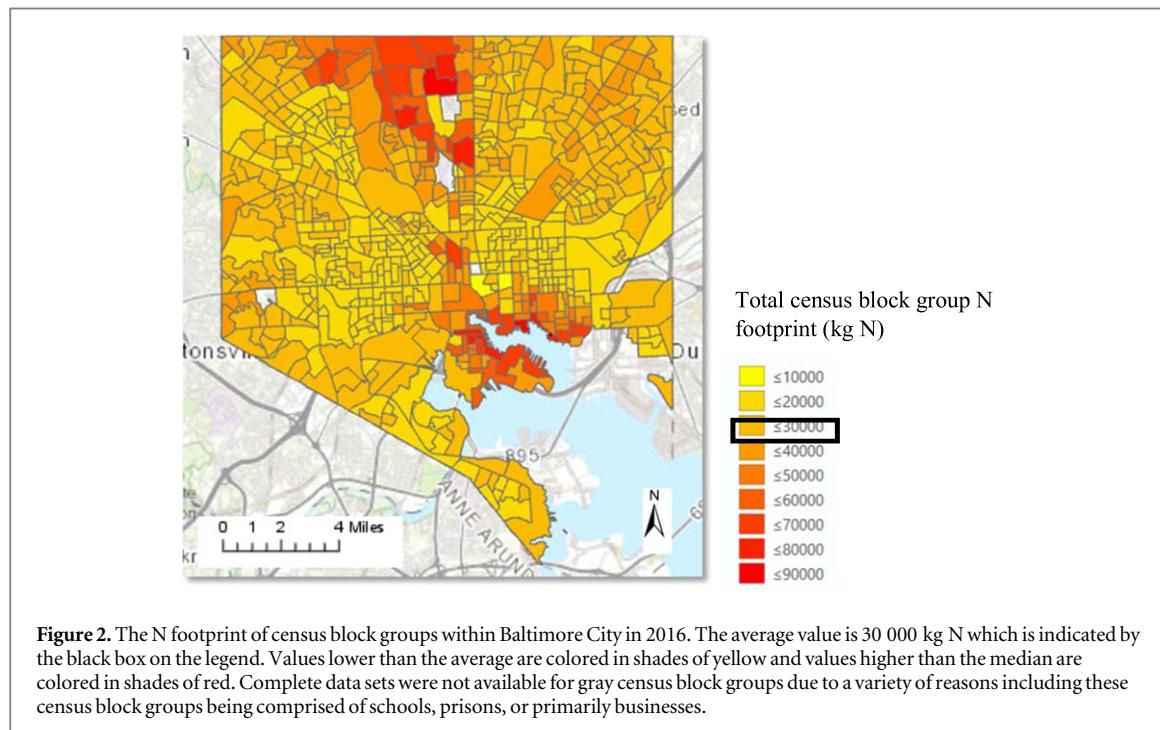


Figure 2. The N footprint of census block groups within Baltimore City in 2016. The average value is 30 000 kg N which is indicated by the black box on the legend. Values lower than the average are colored in shades of yellow and values higher than the median are colored in shades of red. Complete data sets were not available for gray census block groups due to a variety of reasons including these census block groups being comprised of schools, prisons, or primarily businesses.

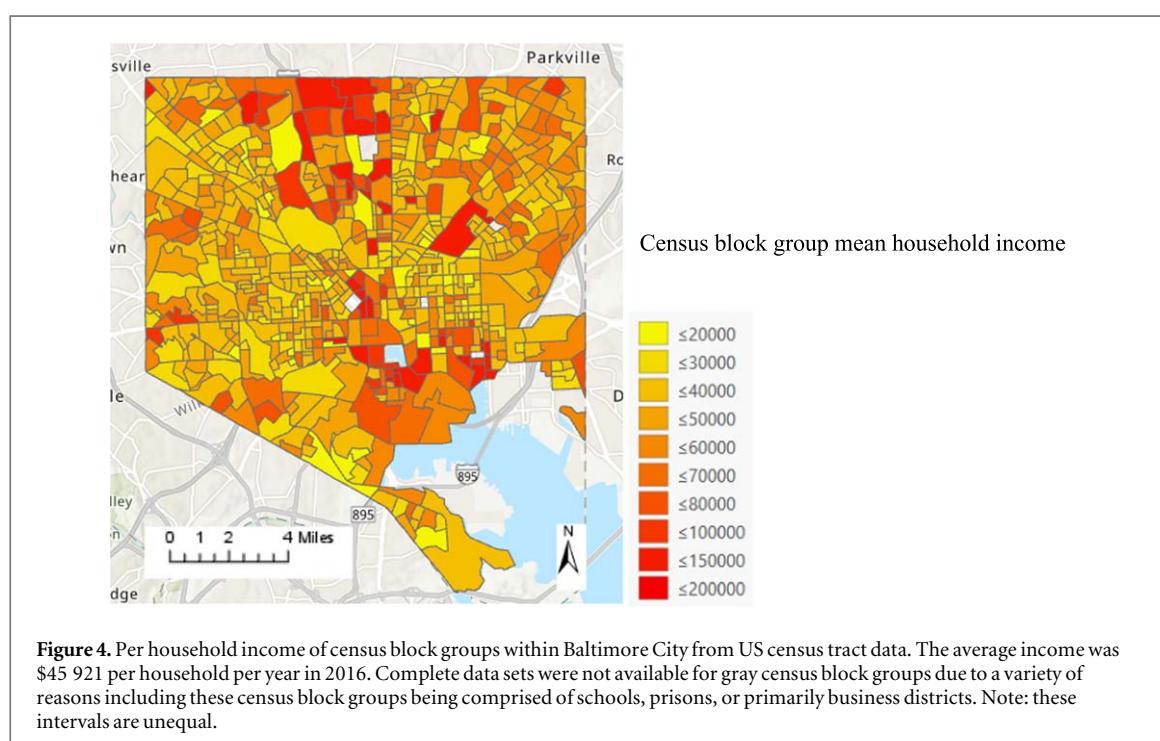
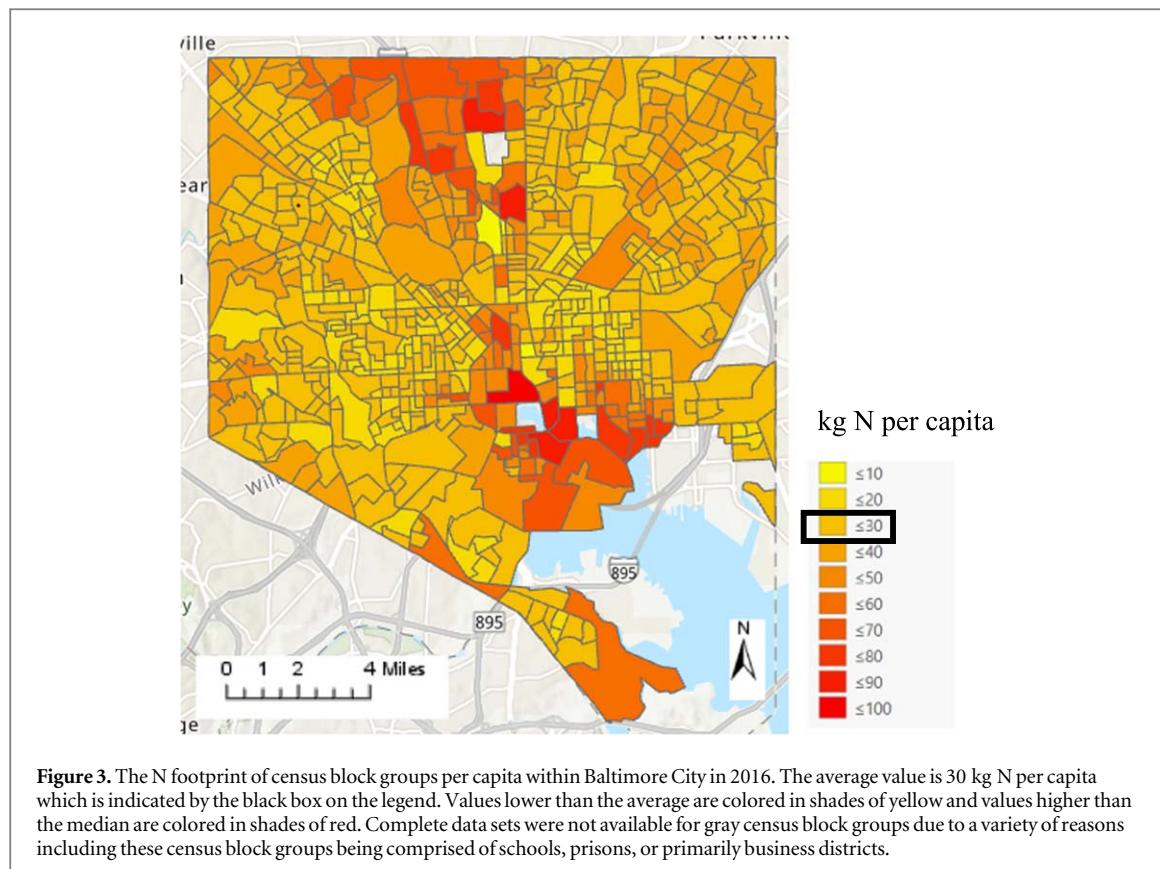
Distribution of the N footprint among census block groups

The total N footprint varied among census blocks due to multiple factors such as the number of businesses, population distribution (see supplementary figures 2 and 3), and varying lifestyles of residents. The range was 2600–171 000 kg N with an average of about 30 000 kg N (figure 2).

In addition to total N footprint, we analyzed variation in the per capita N footprint among census block groups. The average N footprint per capita in Baltimore City was 30 kg N per year in 2016, with variation

among census block groups ranging from 8 to 103 kg N per capita (figure 3). There was also variation in the distribution among sectors within block groups. For example, the footprint for the census block group with the lowest footprint was derived 53% from food, 12% from fossil fuels, and 35% from pets and fertilizer use for home lawns. The footprint of the census block group with 103 kg N per capita was derived 83% from food, 15% from fossil fuels, and 2% fertilizer and pets.

The spatial variation in N footprints among census block groups was related to spatial variation in income (figures 4, 5). There was a significant



correlation ($p < 0.01$, $R^2 = 0.43$) between the N footprint and annual household income (figure 5). The average annual income per household in Baltimore City was \$45,921 (American Factfinder Database 2018).

Local and non-local N footprints of Baltimore city
The local N footprint refers to the Nr lost within city limits while the non-local N footprint refers to the N lost outside of the city boundaries. For this analysis, the sectors assumed to impact local losses were:

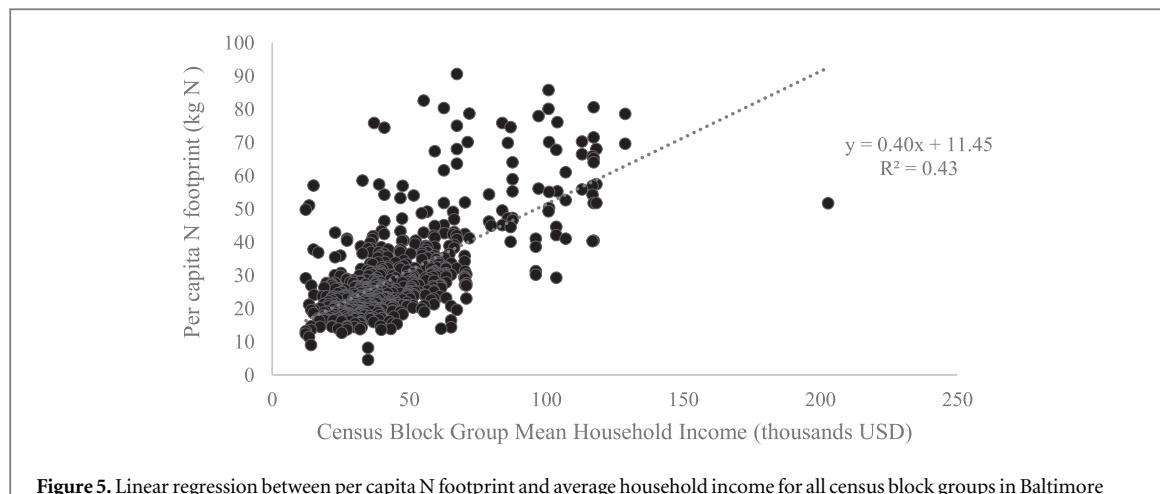


Figure 5. Linear regression between per capita N footprint and average household income for all census block groups in Baltimore City. This shows a significant correlation between income and per capita N footprint ($P < 0.01$).

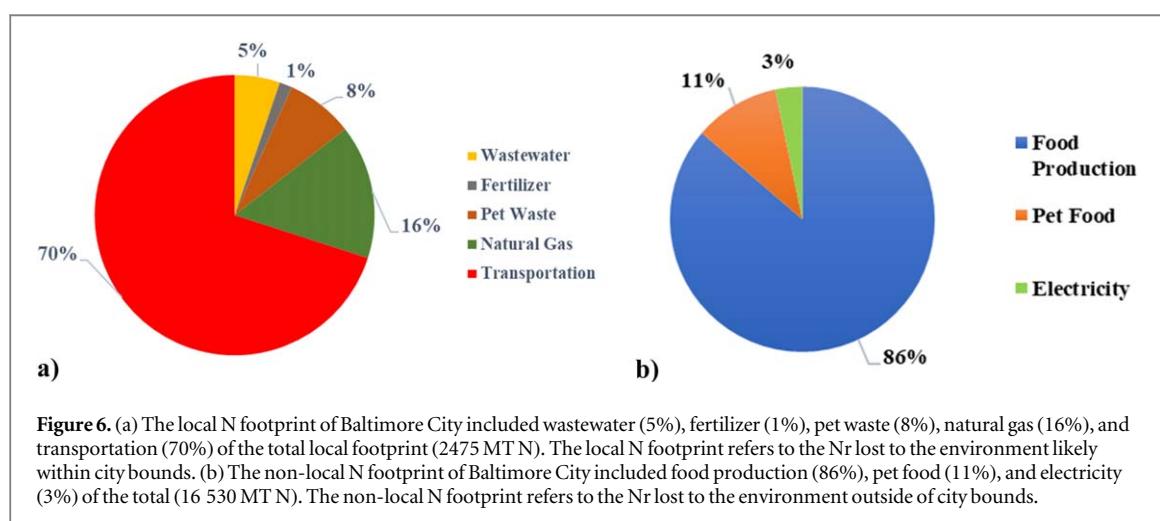


Figure 6. (a) The local N footprint of Baltimore City included wastewater (5%), fertilizer (1%), pet waste (8%), natural gas (16%), and transportation (70%) of the total local footprint (2475 MT N). The local N footprint refers to the Nr lost to the environment likely within city bounds. (b) The non-local N footprint of Baltimore City included food production (86%), pet food (11%), and electricity (3%) of the total (16 530 MT N). The non-local N footprint refers to the Nr lost to the environment outside of city bounds.

wastewater (excluding sludge), pet waste, fertilizer use on home lawns, natural gas, and transportation. The remaining sectors (food production, pet food, and electricity) were assumed to be non-local losses as the majority of the Nr lost from these activities is outside of the city bounds. Of the total N footprint of Baltimore City, ~13% (2475 MT N) were local losses while the remaining 87% (16 530 MT N) were non-local. The largest contributor to the local N footprint was transportation (70%) followed by natural gas (16%), pet waste (8%), wastewater (5%), and fertilizer (1%) (figure 6(a)). The largest contributor to the non-local footprint was food production (86%) followed by pet food (11%) and electricity (3%) (figure 6(b)).

There was spatial variation in the local and non-local per capita N footprints (figures 7(a), (b)), similar to the total N footprints (figure 3).

Calculation reduction strategies and scenarios

The scenario analysis suggested that strategies to reduce N footprints in Baltimore City should, unsurprisingly, focus on food (figure 8), which makes up 73% of the City's footprint (figure 1). The most effective scenario was to reduce the amount

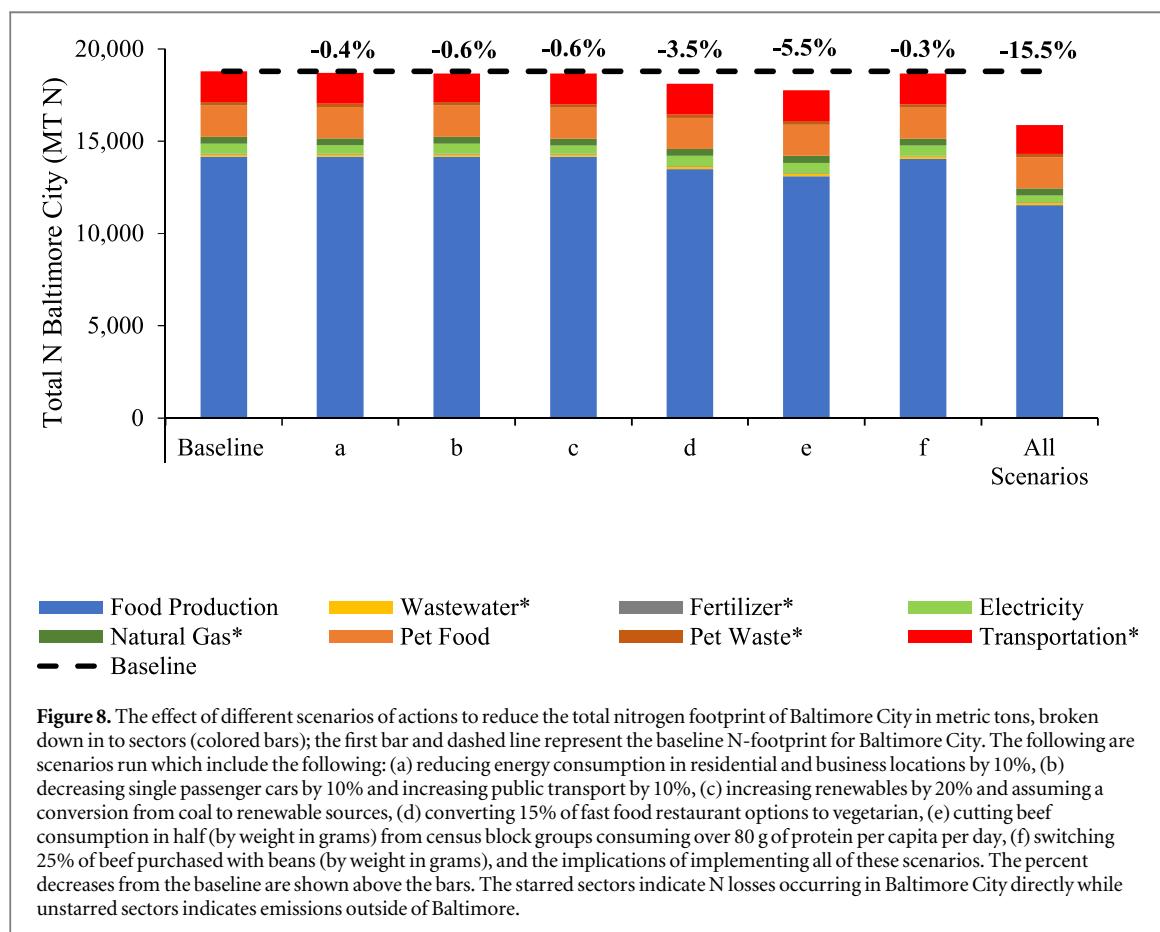
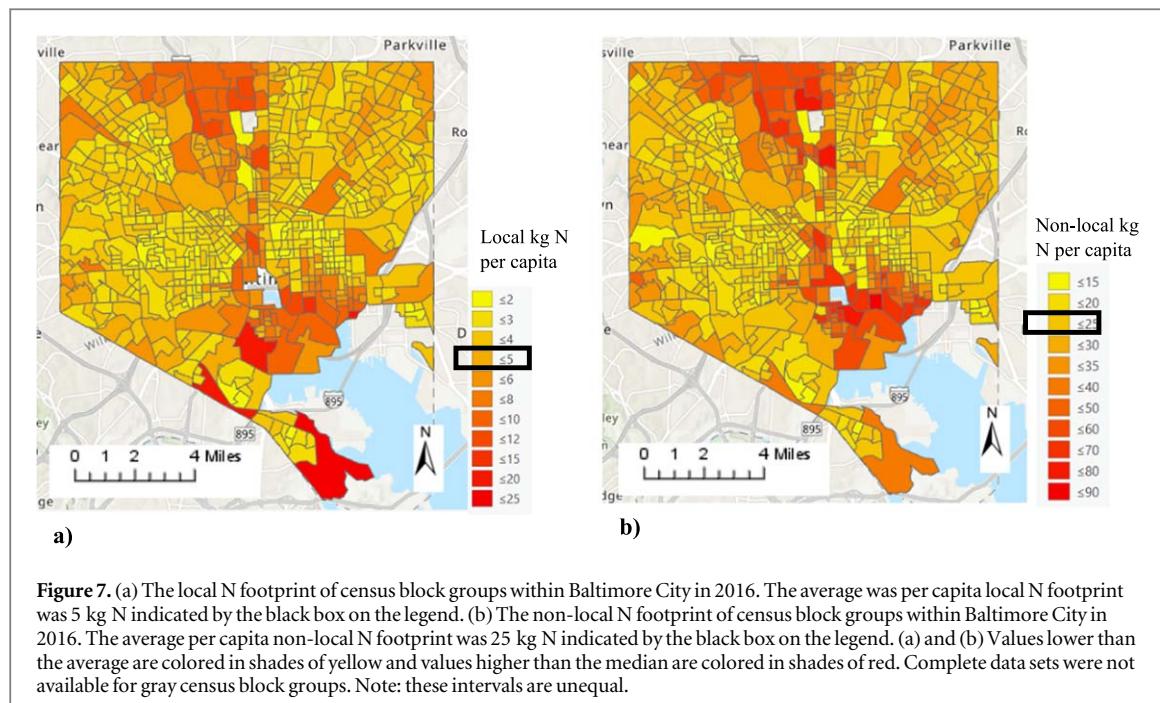
of beef purchased in census block groups over-consuming protein (more than 80 g of protein per person per day) by 50% (in weight), which reduced the total footprint of the city by 5.5% (Scenario (e) in figure 8). Implementing all food scenarios together produced a total footprint reduction of 14% (data not shown). Energy and transportation scenarios reduced the footprint by 1.9%. (data not shown). Combining all scenarios (food and energy) reduced the city's footprint by 16% (Scenario (all scenarios) in figure 8).

Some of the scenarios: (a) reducing energy consumption in residential and business locations by 10%, (b) decreasing single passenger cars by 10% and increasing public transport by 10%, would affect the local N footprint specifically (figure 9).

Discussion

Baltimore city's total and per capita N footprint

The largest sector in the Baltimore City total (~13 800 MT yr⁻¹) and per capita (23 kg N/capita/yr) N footprints was food production. This was consistent with the US average N footprint (24 kg N/capita/yr)



(Leach *et al* 2020) and average institution footprints (Castner *et al* 2017). The average per capita N footprint in Baltimore City (30 kg N/cap/yr) was lower than the average US resident's N footprints (42 kg N/cap/yr) (Leach *et al* 2020) (figure 10).

The average N footprint of food in the US (24 kg N) was slightly higher than a Baltimore City residents' (19 kg N). Leach *et al* 2020 The weight of food consumed by Baltimore City residents is on average 15% less than the average US. The US average N

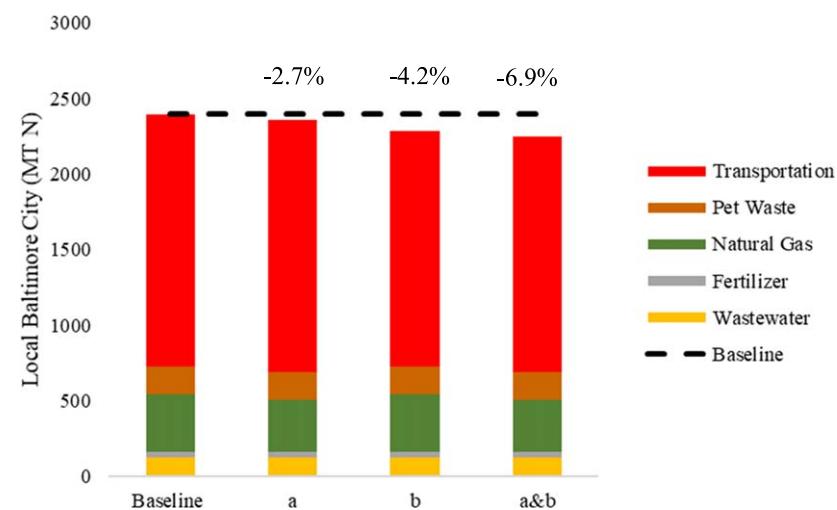


Figure 9. The effect of different scenarios of actions to reduce the local nitrogen footprint of Baltimore City in metric tons, broken down in to sectors (colored bars); The first bar and dashed line represent the baseline N-footprint for Baltimore City. The following are scenarios run which include the following: (a) reducing energy consumption in residential and business locations by 10%, (b) decreasing single passenger cars by 10% and increasing public transport by 10%, and a&b which is a combination of those two scenarios.

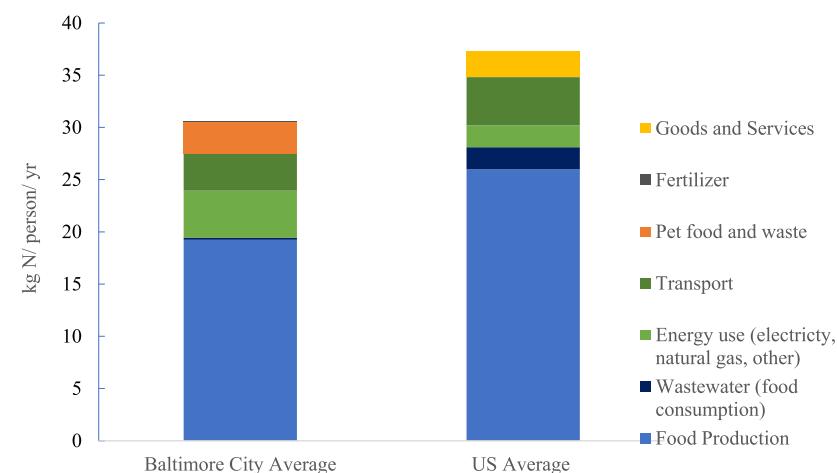


Figure 10. The average per capita N footprint for Baltimore City residents (30 kg N/cap/yr) and for the US (37 kg N/cap/yr) (Leach *et al* submitted). The Baltimore City average includes pets and fertilizer while the US average does not. The US average includes goods and services while the Baltimore City average does not.

footprint looks at an average US citizen's food consumption and energy use while the Baltimore City N footprint looks more closely at a citizen's actual purchases and usage to make recommendations specific to the community. There are sources of uncertainty that should be considered for this calculation.

The Baltimore N footprint considers N losses to the environment from businesses electricity, natural gas, wastewater, food, and fertilizer use, but does not consider losses to the environment from the industrial feedstock of goods purchased by city residents, which may be a significant portion of the footprint (Gu *et al* 2013). For example, N losses to the environment from residents purchasing clothing in 2016 are not included in this analysis. These are potential additions to be made in future studies.

Another source of uncertainty is within the CEX dataset. The CEX report collects data which is through two-week surveys of a sample population in each census block group. Cook *et al* (2000) evaluated the accuracy of a dietary survey given to individuals in comparison to actual consumption and found that people are notoriously bad at reporting food consumption data and tend to under report by 29%–46% of their daily intake. The reporting frame was only for two-weeks out of the year which is used to estimate a year's worth of food purchasing. Using a longer time-frame and tracking receipt data may be ways to remedy this uncertainty however, the CEX survey is the only federal household survey to provide information on consumer expenditures (CEX 2016). The datasets used to convert dollars to kilograms were both based on US

averages which may not have held true for Baltimore City prices.

The N footprint of electricity and natural gas in Baltimore City was approximately twice as large as the US average. However, the calculation for Baltimore includes businesses, while the US average only includes households. The N footprint of transportation in Baltimore was one third less than the US average, likely because the calculation for Baltimore only included travel within census block group limits. However, this would include transportation of non-residents commuting to the city for work. This is especially pertinent for Baltimore City as the commuters increase the weekday, daytime population of Baltimore City by about ~37% (American Community Data 2015).

Wastewater made up a smaller percentage of the N footprint in Baltimore City than the US average due to the presence of sewage treatment facilities with higher N removal than the US average in Baltimore City. In addition, there were sectors included in the Baltimore City N footprint (e.g. pet food, pet waste, fertilizer use on home lawns) that were not in the personal N footprint and vice versa (e.g. goods and services).

It is important to note that the N footprint model does not indicate where N losses occur. The calculation was driven by resources used within each census block group. As mentioned earlier, the N footprint is tied to the consumption of residents within each census block group which is influenced by policy, infrastructure, and individual behavior. The actual losses to the environment can occur either outside of Baltimore as non-local losses or within as local losses (or proximal to) the city of the location where the resources were used. Sectors affecting local N pollution were fertilizer use on home lawns, pet waste, natural gas use, transportation, and wastewater. Sectors affecting non-local pollution include electricity use, food production, and pet food.

More information on data quality and uncertainty is provided in the supplementary material part 4.

Spatial distribution of the N footprint and relationship to income

In this study, the N footprint was compared with one socio-economic data set: household income (figure 3). There was a significant positive relationship between income and per capita N footprints in Baltimore City. This relationship was driven by differences in food and transportation, i.e. higher income areas purchased more food (primarily meat products) and drove personal-use vehicles for longer distances than those in lower income areas. Establishing the relationship between N footprints and income is helpful for targeting reduction strategies to specific areas. For example, strategies in the higher income areas could be focused on reducing food waste, eliminating unnecessary protein heavy diets, and encouraging use of public

transportation. Strategies in lower income areas may need to focus less on reducing food purchases as some residents may not have their nutritional needs met (Drewnowski and Eichelsdoerfer 2011). Strategies in this area could focus on a combination of meeting nutritional needs sustainable (Gephart *et al* 2016) as well as focusing on sustainable business practices such as reducing electricity and natural gas use and using renewables for on-site energy generation. Further investigation of the spatial variability of the N footprint among census blocks alongside other environmental and socio-economic indicators should be used to evaluate best practices in particular areas.

More broadly, it will be important to determine if the relationship between per capita N footprint and income holds outside of Baltimore City in future studies. Income, alongside other factors, have been shown to be a general driver of human impact on the environment in analyses. For example, in short term studies carbon emission increases with an increase in income but ultimately leads to a decrease in emissions over time in the US (Liu *et al* 2019). This study on carbon footprints follows the Kuznets Curve which identifies that in most situations, the environment degradation will increase with income until a certain point where money begins being invested back into the environment and restoration begins (Dinda 2004 and Zhang *et al* 2015). Tracking the N footprint in Baltimore City and other communities across the US could determine if similar trends are visible with regards to the N footprint.

Effectiveness and efficacy of local and non-local N footprint scenarios

The scenario analysis suggested that dietary changes are the most effective way to reduce the total N footprint of Baltimore City. Changes in energy and transportation had a much smaller impact. However, changes in food consumption may be harder to achieve than changes in the energy related sectors. In addition, changes in the food sector impact emissions outside of the city rather than within the city, meaning that dietary changes would not directly reduce N losses within Baltimore. The energy scenarios listed align with goals and initiatives already in place with the Maryland Climate Action Plan. Assuming the goals of this action plan are achieved, the N footprint co-benefits shown in this study would also be achieved.

Only some of the N footprint strategies presented in this paper would reduce local N losses. For example, food related scenarios would primarily reduce N losses outside of the city (i.e. where the food was produced) while natural gas related scenarios will reduce local N pollution. Depending on the community's goals, differentiating strategies impacting the local and non-local environments could determine the strategies implemented. Stakeholders concerned with local air

and water quality would be more inclined to push for strategies focusing on transportation, fertilizer use on lawns, pet waste, wastewater, natural gas, and transportation. Additional improvements to the local Baltimore City N footprint could include continuing to upkeep and improve the wastewater treatment plant as this plant uses some of the most advanced technology available to treat waste and remove Nr. The Baltimore City's wastewater treatment plants have advanced treatment processes that remove significant amounts of nitrogen, particularly compared to other treatment plants in the United States (see EPA 2016). There are potentially small efficiency gains possible depending on the technology used and upkeep at the plant (Tchobanoglou and Burton 1991, Gu *et al* 2013), though Baltimore is a clear example for other cities. Development of a city-wide reduction goal could focus on reducing the local N footprint while the total N footprint could be used for educational purposes. For example, future strategies and scenarios could look at the impact of pet waste pick-up laws on the local N losses in Baltimore City. The total N footprint (local and non-local sectors) could be used to educated residents on their impact on the environment on both a local and global scale.

Stakeholders concerned with Baltimore's global impact on the environment would be more inclined to push for both local and non-local strategies focusing on food production and electricity use.

Co-benefits of reducing Baltimore city's nitrogen footprint

Reducing Baltimore City's N footprint will reduce nitrogen pollution within and outside of Baltimore. There is a potential for these strategies focused on local nitrogen emissions to positively impact other city goals for human health and the environment. For example, changes in energy and transportation will reduce the N footprint, improve the health of Baltimore residents, and increase the resilience of the electricity grid. NO_x is a contributor to the formation of tropospheric ozone, which can cause respiratory health issues and vehicle emissions include a range of other pollutants with negative human health consequences (e.g. PM, CO, etc). Studies in the Chesapeake Bay region evaluated the economic and social impact of reducing specific Nr species. One study indicated focusing on NO_x pollutant reduction is one of the most effective and economically savvy way to improve human and environmental health (Birch *et al* 2011). The resilience of the power system is increased by integrating more renewables into the fuel mix, decreasing the city's reliance on finite fossil fuel resources. The resilience of the electricity system could also be improved by implementing policies that reduce overall electricity usage at peak times, preventing power surges and outages.

There are also ancillary benefits from reducing Baltimore's food production N footprint, including improving the health of Baltimore City residents and reducing waste loads. Promoting a reduction in the consumption of red meat with initiatives such as vegetarian fast food options, decreasing beef purchased in high income areas, and encouraging switching from beef to beans will reduce the amount of red meat consumed. Overconsumption of red meat has been tied to multiple health effects such as increased risk for cancer, diabetes, and heart disease (Godfray *et al* 2018). In large cities, finding areas to dispose of waste becomes an issue as the city grows. Reducing the waste load at local landfills can be accomplished by providing a composting service for food scraps for the city. Composting increases the decomposition rate of waste and reduces the need for landfill space.

Reducing the N footprint of the city can also improve the economic resilience of the city. Decreasing Nr loads to the Chesapeake Bay is a priority in the region for sustaining both fisheries and tourism. These fisheries are a source of income for fishers and restaurants in the surrounding harbor area. Improving the health of the Chesapeake Bay improves the experience of tourists enjoying the beauty of Baltimore City's Inner Harbor district.

Applicability to other communities and environmental and socio-economic indicators

The community NFT is the first in the suite of NFTs to evaluate city spatial patterns of N footprints with a census block group scale resolution. Using the community as the system bounds, the tool gives insight on what the patterns of residential and commercial impacts are of the N footprint. The community system bounds also allows for local issues regarding N pollution to be the focus for reduction.

This analysis can be applied to other communities within the US and beyond. The majority of the data used was gathered from publicly available databases; in particular the United States Census Consumer Expenditure Report. The data gathered from the Consumer Expenditure Report are available for communities across the United States. The spatial grain of the community NFT allows stakeholders to objectively quantify and evaluate the N footprints of specific sectors and locations within the community. With knowledge of the wholistic picture of sustainability and demographics within the area, this can be used to determine appropriate measures to take to reduce the N footprint.

A future goal of this study is to use the community NFT to calculate the N footprint of other communities. Work that entails comparing different communities' (i.e. urban versus rural, east versus west coast, or wealthy versus poor) N footprints would be useful in evaluating drivers of the N footprint unique to certain community types and general trends across

communities. Another future goal would be to distinguish between business and residential N footprints which was not possible in this study due to lack of available data. Determining the contribution of each entity within the community would allow for specific recommendations to be made to each group.

The community NFT's spatial scale would also be useful to use in conjunction with other environmental indicators such as carbon, water, or phosphorus footprints to provide an expanded view of environmental sustainability. Adding socio-economic indicators to this tool could further expand the scope of the tool to evaluate social equality and equity with respect to environmental indicators and changes. Factors could include ethnicity, age groups, food availability, and average education of residents within each block group. An inclusion of this lens can broaden the scope of environmental sustainability to city resilience.

Summary

This study presents the first-ever community-level NFT, which allows users to examine N footprint patterns of a community on a fine spatial scale, examine relationships of the N footprint to socio-economic factors (e.g. income), and create targeted reduction strategies to mitigate and prevent excess N losses. The community NFT uses publicly available datasets to analyze the N footprint of a community. In the Baltimore City study, the relationship of the N footprint and household income was found to be significant. Some reduction strategies were based on the spatial nature of these findings while others focused on city-wide reductions.

With collaboration from multiple groups within a community, this NFT tool can be used to effectively assess the scope of N emissions associated with the community and determine how sustainability actions could reduce those emissions. When used alongside other sustainability and socio-economic metrics, an N footprint calculation can provide a broader view of the overall sustainability and resiliency of a community. If multiple stakeholders within a community are able to collaborate on feasible reduction strategies, the NFT can educate communities and reduce nitrogen pollution as a result of a community's resource use and benefit sustainability and resiliency goals of the community.

Acknowledgments

This study would not have been possible without the support and guidance of many others. We thank Julia Stanganelli (University of Virginia) for her assistance with analyzing the food and SNAP data, Chris Gist and Drew MacQueen (University of Virginia) for their assistance with mapping in ArcGIS Pro, and Dexter Locke (US Forest Service) for his contribution of Consumer Expenditure Report Data. The work of the

Nitrogen Footprint Tool Network was supported by Cooperative Agreement No. 83563201 awarded by the US Environmental Protection Agency.

Data availability statement

Any data that supports the findings of this study are included within the article.

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