Assessing the Geographical Variability and Reduction Potential of the Nitrogen Footprint of a Community: A Case Study in Charlottesville, Virginia

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Abstract

Nitrogen (N) is imperative for life on earth, but excess reactive nitrogen can have harmful effects on marine and terrestrial environments, the atmosphere, and human health. Anthropogenic creation of reactive N (Nr; all N species but N_2) and subsequent inputs to the environment are largely associated with agricultural production and fossil fuel combustion. While many efforts have been made to decrease N losses to the environment at the production end in both the food and energy sectors, fewer efforts focus on the impacts of consumer choices. This study focuses on how a consumer can impact their community's contributions to N pollution, and provides a tool to manage that pollution. The community nitrogen footprint tool (NFT) is a metric created to track the impact of a community on excess Nr released to the environment. Applying the community NFT to Charlottesville City for 2017, the total N footprint, local N footprint, and per capita N footprint, were estimated to be 1,400 metric tons (MT) N, 114 MT N, and 30.0 kg N, lower than the US average, respectively. Great geographical variability in the per capita N footprint within Charlottesville City was found, which correlated positively with median household income ($p = 0.01$) and the proportion of the population that is white ($p = 0.01$). This result adds evidence from a local context to support the theory that socioeconomically advantaged populations contribute more to local and global environmental change. Census block groups within Charlottesville City which have a higher N footprint have greater opportunities for reduction, and potential changes in consumer choices, influenced by government planning decisions, were examined. It was found that reductions in beef and overall protein consumption could lead to the greatest reduction in total N footprint, and changes in personal transportation could lead to the greatest reduction in the local N footprint.

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Introduction

Nitrogen and the Environment

Nitrogen (N) is essential to life on earth, but anthropogenic sources can introduce large, harmful amounts of reactive N (Nr) to the environment. These Nr species, which are essential to both terrestrial and marine ecosystems, are in limited supply (Gruber & Galloway 2008). While N is the most abundant element on earth and in the atmosphere, 99% of this N is in the form of unreactive molecular nitrogen, N_2, and is unavailable for use by most living organisms. Nr encompasses all other compounds of N in the biosphere and atmosphere, such as nitrous oxide (N_2O), nitrate (NO_3^-), ammonium (NH_4^+) and ammonia (NH_3). Prior to human influence, there were two main ways in which Nr was created: lightning and biological nitrogen fixation (Galloway et al. 2003).

Human activities introduce large amounts of Nr into the environment. As the human population increases, so does the amount of Nr that is created and lost to the environment. Total anthropogenic Nr creation in 1860, prior to the industrial revolution, only amounted to about 15 Tg N/year (Galloway et al. 2008). In 2010, annual anthropogenic inputs of Nr amounted to 210 Tg N/year, roughly equal to the amount of Nr that is naturally fixed in the biosphere (Fowler et al. 2013). Most of this Nr is added via agricultural production, through fertilizers created using the Haber-Bosch process to convert N_2 to reactive NH_3 (Galloway et al. 2004). Additionally, the increasing production of crops which convert N_2 to Nr through biological nitrogen fixation, such as rice and legumes, has contributed to the global increase in Nr (Galloway et al. 2003). The third largest contributor to global increases in Nr is the combustion of fossil fuels, which releases NO_x (nitrogen oxides) into the atmosphere (Galloway et al. 2003).

Effects of Anthropogenic Increases in Nr

Anthropogenic inputs of Nr have both beneficial as well as detrimental effects on the environment. In terms of its benefits, the current population of the earth could not be sustained without increases in agricultural production made possible by Nr created from the Haber-Bosch process (Erisman et al. 2013). However, the additional Nr lost to the environment can be detrimental to both human and environmental health. NO_x can have adverse impacts on human and environmental health when released into the atmosphere from both fossil fuel combustion and agriculture. It can lead to the formation of tropospheric ozone (O_3), smog, and aerosols. This decrease in air quality leads to a whole suite of direct and indirect effects on human health, such as increases in instances of asthma and lung cancer, as well as reductions in crop yields because of O_3 damages to crops (Erisman et al. 2013). Atmospheric N_2O (nitrous oxide) is another species of Nr released to the environment as a result of human activity (i.e. burning fossil fuels). This is a greenhouse gas and thus contributes to climate change (Galloway et al. 2003). Once in the stratosphere, N_2O contributes to stratospheric ozone depletion, and is currently the leading factor in doing so (Erisman et al. 2013).

In addition to contributing to air pollution and the acceleration of the greenhouse effect, Nr can also greatly enhance water pollution, particularly through eutrophication of estuaries. Excess nitrate from agricultural fertilizer runoff and wastewater can accumulate in waterways, making its way to estuaries where it leads to excessive algal growth. This can result in decreases in aquatic light availability as well as hypoxia as the algae die and decompose (Howarth & Marino 2006). This process, known as eutrophication, is a major issue in many estuaries, such as the Chesapeake Bay, and a main focus of water quality monitoring and conservation. All of these negative effects of anthropogenic contributions to Nr in the environment can be linked by the nitrogen cascade. The N cascade is defined by the cascading nature of excess Nr in the environment, as one atom of N can have all of the above effects as it is converted to different species of Nr (Galloway et al. 2003).

Management of Reactive Nitrogen

Strategies for managing and reducing the amount of Nr lost to the environment have been established and used in many different aspects of food and energy production. Interventions in the energy sector include controlling NO_x emissions from power plants and vehicles using fossil fuel combustion (Galloway et al. 2008), and increasing the use of renewable energy in place of fossil fuels (Leach et al. 2013). In the agricultural sector, management of excess fertilizer inputs to the soil is a way to reduce N inputs and subsequent Nr losses. Additionally, engineering crops to increase their N-uptake, as well as improving the management of livestock can greatly curb N lost to the environment (Galloway et al. 2008).

In all of these interventions, the opportunity for reduction comes at the producer level. Often in the implementation of N reduction strategies, the role of the consumer is left out, downplayed, or underutilized. The consumer, however, can have a large impact in the role that they play in N reduction by way of their choices. The nitrogen footprint tool (NFT) is one way for consumers to begin to understand the negative and positive impacts of the choices that they make on N pollution.

Nitrogen Footprint Tools

An NFT is a way to measure the amount of reactive nitrogen released to the environment as a consequence of someone or something's resource use. There are currently three existing variations of the NFT: The personal NFT (Leach et al. 2012; 2020), the institutional NFT (Leach et al. 2013; Castner et al. 2017), and the community NFT (Dukes et al. 2020). The personal NFT calculates an individual's nitrogen footprint based on their consumption choices, including food purchased, goods and services, transportation, sewage treatment, and housing and electricity use. Using the calculator, an individual can compare their nitrogen footprint to the US and other countries' average N footprints (Leach et al. 2012; 2020). The purpose of this tool is for a person to evaluate how their lifestyle and consumer choices are affecting their impact on Nr in the environment.

The institutional NFT has been used by universities and research organizations to track their cumulative impact on Nr in the environment, based on institutional energy use, transportation, sewage treatment, food purchased, and fertilizer use (Leach et al. 2013; Castner et al. 2017). This tool can be used to track and reduce an institution's N footprint. For example, the University of Virginia (UVA) released its first Nitrogen Action Plan in May 2019, based on the findings of the institutional NFT, defining actions towards the reduction goal of 25% below 2010 levels by 2025 (UVA Nitrogen Working Group 2019).

Most recently, the community NFT was developed for use for the City of Baltimore (Milo 2018). The goal of the study was to encapsulate the consumption choices of a community as a whole by calculating the total N footprint of census block groups within the city, determine correlation with income, and develop feasible reduction strategies. Areas incorporated are food purchased, pet food and waste, fertilizer use on home lawns, wastewater treatment, transportation, electricity, and natural gas. Following the initial use of the tool (Milo 2018), the community NFT was updated for the final version of the Baltimore City NFT (Dukes et al. 2020). In the present study, the methods used in Dukes et al. (2020) were used with various updates for the Charlottesville City N footprint. These changes include area-specific adjustments, such as emissions and wastewater treatment factors, adjustments in the methodology of the tool, such as food categorization and vehicle classification, and adjustments in the format of the tool itself. These changes are further explained under the methods section below.

Charlottesville Context

Charlottesville City is concerned with reducing its greenhouse gas emissions and limiting its impact on the local environment (i.e., air and water pollution). Charlottesville City has established a greenhouse gas inventory, estimating that in 2016, community-wide greenhouse gas emissions totaled 362,192 $MTCO_2e$. Charlottesville City has set goals for reducing its impact, such as switching to more renewable energy and increasing energy efficiency (Charlottesville Department of Public Works 2019). The addition of the N footprint to this context could improve public knowledge about the issues surrounding Nr in the environment, as well as catalyze and inform reduction efforts. Additionally, this research adds to the collaboration between Charlottesville City, Albemarle County, and UVA in the Climate Action Together program, to work cohesively on climate initiatives (Turner 2019).

Environmental Justice Framework

Environmental injustice or environmental inequality refers to reality that certain groups of people may be disproportionately vulnerable to or impacted by environmental disasters and phenomena than other groups (Brulle & Pellow 2006). In past decades, studies have shown that certain groups of people, namely people of color, have been more vulnerable than the general population to negative environmental health impacts, due to proximity to waste sites, landfills, and above average water and air pollution (Walker 2009). The understanding of environmental justice has been expanding to include a broader set of environmental concerns, as well as affected populations. Environmental justice more generally includes populations that are socioeconomically disadvantaged for a variety of reasons, and may be unequally vulnerable to food insecurity, access to transportation, exposure to flood risk, the effects of climate change, and more. For example, multiple studies have shown negative correlations between household income and the likelihood of living in a flood-prone area (Walker & Burningham 2011; Brouwer et al. 2007). Additionally, it has been shown that lower income and more racially diverse populations can be subject to greater levels of air pollution than the general population (Houston et al. 2016; Gwynn & Thurston 2001). One preliminary study conducted in Charlottesville City may provide local evidence to this, finding presumably greater NO_2 concentrations in neighborhoods that were predominantly lower income and African American when compared to those of higher income white neighborhoods (Knowles 2019).

Additionally, it is known that it is wealthier segments of the population that are contributing more to worldwide climate change and pollution that are disproportionately affecting poorer and more vulnerable populations (Preston et al. 2014). Thus, while wealthier people are contributing more to global climate change, poorer communities and minorities are bearing more of the burden.

Research Questions

This research aimed to apply the community NFT to Charlottesville City, explore patterns in the N footprint within a framework of environmental justice, and look for opportunities for footprint reduction in this context. The research questions are: (1) how does the

Charlottesville N footprint compare to that of other locations? (2) What is the geospatial variability of the N footprint within Charlottesville City, and (3) how does it relate to socio-economic patterns? Additionally, (4) where in Charlottesville City are the greatest opportunities for reduction in the N footprint, and (5) how might certain changes in consumer choices offer strategies for reduction?

Methods

System Bounds

The system bounds of this N footprint calculation are the city limits of Charlottesville City (Figure 1). UVA, which lies both within Charlottesville City and Albemarle County, was excluded from the bounds of this study. This was due to the difficulty of including a large research institution like UVA in a calculation that is meant for a community and the complications presented by the city/county overlap of UVA. In addition to these reasons, excluding UVA helped align the system bounds of this study to the boundaries of Charlottesville City's 2016 greenhouse gas inventory, which also excluded the institution.

Figure 1: System bounds dictated by Charlottesville City limits.

Community NFT Methodology

The community NFT was used to calculate the N footprint of Charlottesville City which is the second city to use the community NFT methodology to assess its N footprint, following the Baltimore City case study (Milo 2018; Dukes et al. 2020). The community NFT estimates the total and per capita N footprint of census block groups within a community, based on the Nr released to the environment from food purchases, wastewater generation, fertilizer use on home lawns, electricity use, natural gas use, pet food and waste, and transportation. The community

NFT estimates the kg of N produced by a given sector from the dollars spent on that given commodity (e.g., food item), or from other collected data on that given commodity. For example, for energy use (e.g., electricity use), the total kilowatt hours (kWh) used by residents, as well as the dollars spent on electricity, are used to calculate the kg of N produced. For wastewater, the gallons of wastewater treated by the wastewater treatment plants are used to calculate the kg of N produced. Figure 2 below illustrates the steps taken to calculate the N footprint of one food product (Milo 2018). For further detail on the calculations involved in converting dollars spent on each commodity to kg of N, see Dukes et al. (2020).

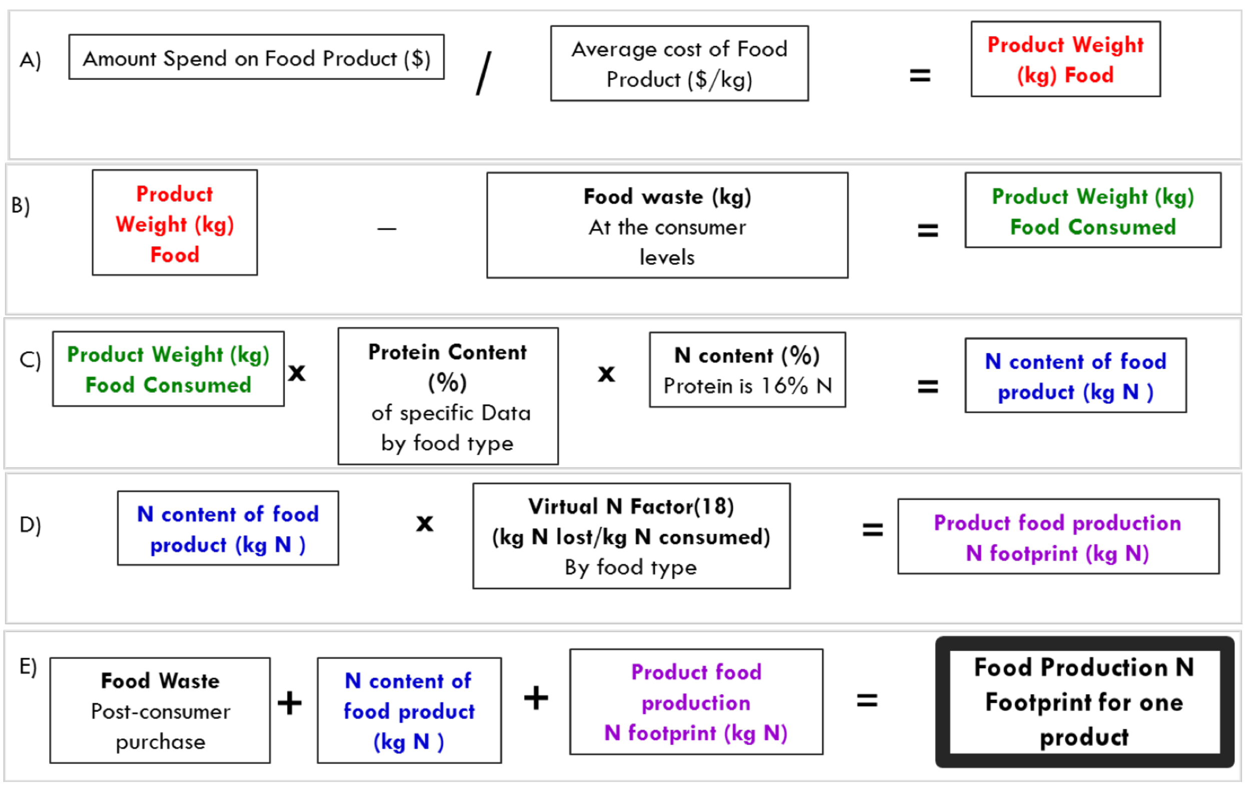


Figure 2: Pathway from dollars spent on a given food product to the N footprint from food production of that product (Milo 2018).

Since the creation of the community NFT for use in Baltimore City (Milo 2018), the tool has been updated. First, dollars spent through the Supplemental Nutrition Assistance Program (SNAP) on food products were added, in order to more fully capture the impact of food purchasing on a community's N footprint (Dukes et al. 2020). Further, the methodology used to calculate many of the average prices of Consumer Expenditure Report (CEX) food items was updated from Milo (2018) to Dukes et al. (2020) to more accurately estimate the price of the items (Dukes et al. 2020).

In the present Charlottesville City study, further adjustments were made. Specifically, the changes made are:

- Adapting location-specific factors to the Charlottesville City context (eGRID emissions factor, wastewater treatment plant N removal factor, home lawn fertilizer use estimate),
- Adjusting food categorizations to more accurately capture food products purchased (see below for details),
- Adjusting food weight calculations for restaurant meals (see below for details),
- Streamlining data entry, with entry for each sector separated from constants used and calculations.

In addition, an instruction manual outlining the data required to calculate a complete community N footprint, how to enter the data, and the methodology behind the tool has been compiled. The version of the community NFT used in this study and the instruction manual are available by request. For access, please contact Julia Stanganelli (jas7ua@virginia.edu) or Elizabeth Dukes (esm9gq@virginia.edu).

Data Collection and Community NFT Updates

The N-related data used in this calculation include food purchases, wastewater generation, transportation, electricity, natural gas, pets and pet waste, and home lawn fertilizer application.

For food purchased, the Consumer Expenditure Report (CEX) from the Bureau of Labor Statistics (BLS) was used for the dollars spent on each food item, broken down by census block group (Bureau of Labor Statistics 2017). These data were converted from dollars spent, to kg of food and then kg of N using the methodology outlined above (Figure 2). Following the methodology shown in Figure 2 above, once the average price of a food item is used to calculate its total weight, the N footprint of that food product is calculated using the Virtual N Factor (VNFs) associated with its food type or category (Leach et al 2012; 2020). For the Charlottesville City N footprint, some changes were made in the categorization of certain food products into food types in order to more accurately calculate the N footprint (Table 1).

Table 1: Changes made in food categorization from Dukes et al. (2020) to the current study.

CEX Food Item	Previous Assigned Food Type(s)	New Assigned Food Type(s)
Other Meat	Beef, Pork	Beef, Pork, Chicken
Other Lunchmeat	Beef, Pork	Beef, Pork, Chicken
Dried Beans & Peas	Beans	Beans, Vegetables
Nondairy Cream & Milk	Oils	Liquids, Nuts, Beans
Frozen Meals	Meal percentages based on Baltimore City total food purchased	Average meal percentages (Table 2)
Other Frozen Prep. Food	Meal percentages based on Baltimore City total food purchased	Average meal percentages (Table 2)
Misc. Prepared Food	Meal percentages based on Baltimore City total food purchased	Average meal percentages (Table 2)

Additionally, the methodology used to calculate the weight of meals purchased at restaurants or “away from home” was adjusted. Previously, the components of a meal were quantified based on the percentages of dollars spent in each food category for food at home in Baltimore. For the Charlottesville City N footprint calculations, an average meal was computed using the US average percentages of food groups consumed (Leach et al. 2020) (Table 2).

Categories included in food at home categorizations but excluded here are spices, sugars, and oils. This is because spices and sugars were not explicitly categorized in Leach et al. (2020), and oils seemed to distort the composition of a typical meal.

Table 2: US yearly food consumption per capita (Leach et al. 2020) and associated meal component percentages.

Food Category	kg /person/year	% of Total Food Weight (% of Average Meal)
Coffee and Tea	5	0.75%
Wheat	71	10.61%
Rice	5	0.75%
Fruit	66	9.87%
Beans	4	0.60%
Potatoes	35	5.23%
Vegetables	72	10.76%
Nuts	5	0.75%
Liquids	68	10.16%
Chicken	43	6.43%
Pork	23	3.44%
Beef	31	4.63%
Milk	203	30.34%
Cheese	13	1.94%
Eggs	12	1.79%
Fish	13	1.94%

The percentage of households receiving SNAP by census block group was also needed, as it was not included in the CEX data on dollars spent on food products. The number of households receiving SNAP benefits in each census tract in Charlottesville was downloaded from Social Explorer, and used as an average for the number of households on SNAP in each census block group within each tract (ACS 2017a). By multiplying the percent of households on SNAP by the average SNAP dollars given to households in a city, the total SNAP dollars spent per census block group was calculated. Then, the total dollars spent is multiplied by the percentage of total dollars that a given food product group is said to occupy, and divided by the average price of that food product. The percentage of total dollars for each food product group was calculated using a 2011 USDA study on foods typically purchased with SNAP (Food and Nutrition Office 2016). The SNAP food categories were then assigned to the food categories used in the NFT, and the total food weights in each were added to the total weights from food purchased through CEX data to get the total food weights for each census block group. These categories are shown in Table 6 of the Dukes et al. (2020) supplementary material.

For wastewater, the gallons of wastewater treated at the Moore's Creek Treatment Plant and the treatment N removal factor (79%), at this plant, were used (Rivanna Water and Sewer Authority 2017).

For transportation, the daily vehicle miles traveled within the city in 2017, broken down by type of vehicle (e.g., car, truck, etc.), were obtained from the Virginia Department of Transportation (VDOT 2017). The majority of vehicle miles traveled in Charlottesville (86%) were by passenger cars. Emissions factors for NO_x and N_2O for each vehicle type from the National Emissions Inventory were used (EPA 2017) (Table 3).

Table 3: Emissions factors for NO_x and N_2O by vehicle type (National Emissions Inventory (EPA 2017)).

	kg NO_x/mile	**kg N_2O/mile**
Motorcycles	0.000256	0.0000036
Passenger Cars	0.000593	0.0000036
Light Duty Trucks	0.000593	0.0000036
Buses	0.00175	0.00000068
Medium-Heavy Duty Trucks	0.00175	0.000001

Data from the CEX were also used to separate vehicle miles traveled by census block groups based on dollars spent on gasoline, diesel, and bus fares.

A few changes were made from the methodology used in Dukes et al. (2020) to calculate the N footprint from transportation. First, the vehicle types from the VDOT database were classified into motorcycles, passenger cars, buses, light duty trucks, and medium-heavy duty trucks according to FHWA (Federal Highway Administration) class groups (Federal Highway Administration 2014) (Appendix A). These classes were chosen to correspond to the available emissions factors for vehicle types. Additionally, the proportion of gas and diesel vehicles for each of these vehicle types was estimated based on percentages from the National Emissions Inventory (EPA 2017) (Table 4).

Table 4: Percent of gasoline and diesel vehicles (National Emissions Inventory (EPA 2017)).

	% Gasoline	% Diesel
Motorcycles	100%	0%
Passenger Cars	99%	1%
Light Duty Trucks	97%	3%
Medium-Heavy Duty Trucks	17%	83%

For electricity use, the kWh used for residences and businesses were obtained from Dominion Energy (Dominion Energy 2017). Since part of UVA lies within Charlottesville City, but is excluded by the bounds of this study, the substations supplying electricity to UVA within Charlottesville City were removed from the total kWh. EGRID emissions factors for NOx and N_2O for the SRVC region were obtained from the EPA Emissions and Generation Resource Integrated Database. The SRVC emissions factor for NO_x is $2.64*10^4$ kg/kWh, and the emissions factor for N_2O is $6.25*10^6$ kg/kWh (EPA 2018). For natural gas use, the therms used for residents and businesses were obtained from the local utility (Charlottesville Gas 2017). For both electricity and natural gas, in order to divide the business energy use geographically, the number of businesses in each census block group was obtained using ArcGIS Business Analyst data (ESRI 2018).

For pets and pet waste, the number of cats and dogs owned per census block group was estimated using the average number per household within the US (Okin 2017). The option of using dog licenses in Charlottesville City as a measure of the number of dogs owned was explored. However, after communicating with the local SPCA and the City Treasurer, it was determined that the US average number of dogs and cats per household would likely be a more accurate estimation, due to the lack of certainty in what proportion of dogs are actually licensed.

For fertilizer application, the total area of turfgrass per census block group in Charlottesville City was calculated using land cover data at a 1 meter resolution from the Chesapeake Bay Conservancy's Land Cover Data Project in ArcGIS Pro (Chesapeake Conservancy 2014). The land cover classes "Turfgrass" and "Tree Canopy over Turf" were used. The classes of "Fractional Turf (Small)" and "Fractional Turf (Medium)" were excluded, as it appeared that these classes, which represented a relatively small area, encompassed small parks and a golf course, and this study aimed to include only home lawns as much as possible. The methodology from Dukes et al. (2020) was used to estimate fertilizer use from the total area of turfgrass, with the exception of a change in the factor used for average household fertilizer application rate. The present study used an estimate from Fraser et al. (2013) of median household fertilizer application rate of 28.5 kg N/hectare/year, for those households using fertilizer. This was estimated by Fraser et al. (2013) using household surveys of Baltimore, Maryland. Additionally, the percentage of households using fertilizer was estimated to be 54.5%, from Fraser et al. (2013), as there was no local data available. It is important to note that fertilizer application here refers only to home lawn fertilizer use and not fertilizer used for agricultural purposes. Nr losses due to fertilizer used in food production is captured in the "food" sector of the N footprint.

In addition to the N-related data, socioeconomic data were collected from the US Census Bureau via Social Explorer, using the 2017 American Community Survey 5-Year Estimates. Data included total population per census block group (ACS 2017b), number of households per census block group (ACS 2017c), median household income (ACS 2017d), and the percent of the population that is white (ACS 2017e).

ArcGIS Methods and Statistical Analyses

ArcGIS Pro was used to map the N footprint of Charlottesville City by census block group, as well as contributions to the N footprint of each of the sectors. The geospatial variability of median household income and the proportion of each census block group that is white was also examined in ArcGIS Pro. In addition to visually comparing these distributions using choropleth maps, regression analyses were performed in Microsoft Excel to test for a significant geographical correlation between the N footprint and median household income, as well as with the proportion of the population that is white.

N Footprint Reduction Strategies

Census block groups with the highest N footprints, and thus the highest reduction potential were identified. Particularly for these areas, reduction strategies were identified and quantified, as to how community members could theoretically alter their choices and cause a reduction in the overall N footprint of their census block group and their community. These strategies focused on sectors and choices that the individual consumer can play a large role in, such as choice of food consumption, choice of mode of transportation, choice of electricity and natural gas, and lawn fertilization rates. There are, however, some aspects of the community N footprint that the consumer does not have a direct role in influencing, such as the treatment of wastewater at the facility level, and the composition of their electricity grid.

The methods used to compute each reduction scenario are found in Table 5.

Table 5: Calculation methods for the reduction scenarios used for the Charlottesville City N footprint.

Reduction Scenario	Calculation Method
Food: Replace 10% of Beef with Chicken	Reduce the kg of beef purchased per census block group by 10%, increase the kg of chicken purchased per census block group by an equivalent weight
Food: Replace 10% of Beef with Beans	Reduce the kg of beef purchased per census block group by 10%, increase the kg of beans purchased per census block group by an equivalent weight
Food: Residents consume closer to Recommended Daily Allowance (RDA) for protein	Calculate the difference from the average kg protein per capita consumed per census block group to 75g/person/day, an estimate based on the Recommended Daily Allowance (RDA) for protein (Pendick 2015). For census block groups that are currently consuming over this amount, subtract protein by food category based on the percent that a given category is contributing to the overall protein consumption for that census block group
Transportation: Replace 10% of Car Use with Bus Use	Reduce the passenger car miles driven per census block group by 10%, increase the bus miles ridden per census block group by an equivalent number of miles divided by 40 (estimating 40 passengers/bus)
Transportation: Replace 10% of Fossil Fuel-Powered Cars with Electric Cars	Reduce the fossil fuel-powered passenger car miles driven per census block group by 10%, increase the kWh of electricity used per census block group by 1 kWh for every 3 miles that were reduced (using EPA fuel economy estimates that the best electric vehicles drive 3 miles/kWh (EPA 2020))
Transportation: Replace 10% of Car Use with Biking	Reduce the passenger car miles traveled per census block group by 10%
Transportation: Decrease Car Use by 10% with Carpooling	Reduce the passenger car miles traveled per census block group by 10%
Energy: Replace 10% of Electricity Use with Renewables	Reduce the kWh of electricity used per census block group by 10%
Energy: Replace 10% of Natural Gas Use with Renewables	Reduce the therms of natural gas used per census block group by 10%
Fertilizer: Decrease lawn fertilizer application rate by 25%	Reduce the estimated lawn fertilizer application rate by 25%

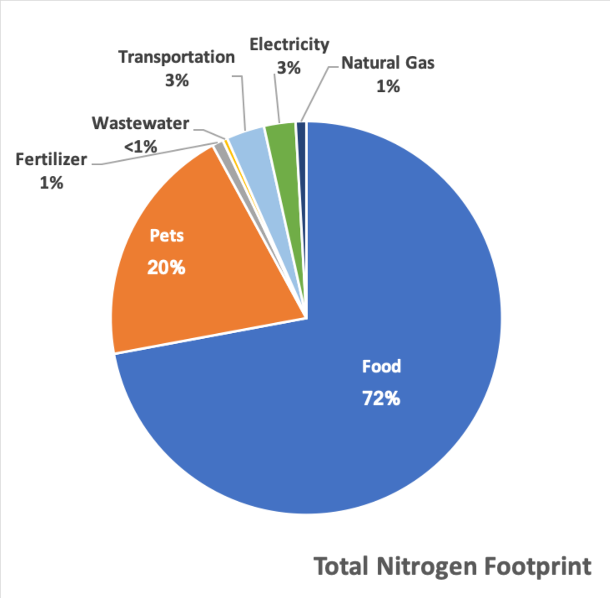
Results

Total and Local N Footprints

The total N footprint of Charlottesville City in 2017 was estimated to be 1,400 MT N. The total N footprint encompasses all Nr lost to the environment as a result of the resource use and consumption of the residents and businesses within the city. This includes "upstream" losses, such as Nr lost to the environment due to the production of food consumed in the city, and electricity used in the city, but generated elsewhere. Food makes up the largest portion of the total N footprint, at 72%. Pet food and pet waste makes up the second largest portion, at 20%. Electricity and transportation each make up 3%, fertilizer and natural gas each make up 1%, and wastewater makes up less than 1% (Figure 3a).

The local N footprint of Charlottesville City in 2017 was estimated to be 114 MT N. The local N footprint includes only Nr losses that occur locally. This excludes Nr losses "upstream", due to the production of human food and pet food and electricity generation. Food waste and pet waste are still included in the local N footprint. Transportation contributes the most to the local N footprint, at 39%. Pet waste makes up the second largest portion, at 24%. Fertilizer and natural gas each make up 11%, and food waste and wastewater make up 10% and 5%, respectively (Figure 3b).

The average per capita N footprint for Charlottesville City is 30.0 kg N per person (Figure 4). This can be compared to the average per capita N footprint for Baltimore, 33.6 kg N per person, and for the US, 40 kg N per person. Charlottesville City has a comparable food footprint to the US overall, but a lower wastewater, transportation, natural gas, and electricity footprint.



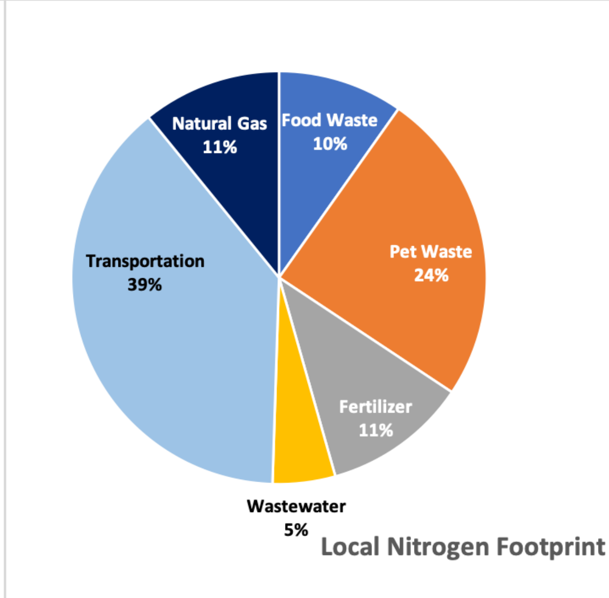


Figure 3a (left): The total N footprint of Charlottesville City by sector. Food constitutes the largest sector, contributing to 72% of the total nitrogen footprint. Pets (pet food and pet waste), follows, at 20%. Transportation and electricity each make up 3%, natural gas and fertilizer use each makeup 1%, and wastewater contributes to <1%.

Figure 3b (right): The local N footprint of Charlottesville City by sector. Transportation constitutes 39% of the local NFT. Pet waste follows, making up 24%. Natural gas, fertilizer, food waste, and wastewater make up the remaining 11%, 11%, 10% and 5%, respectively.

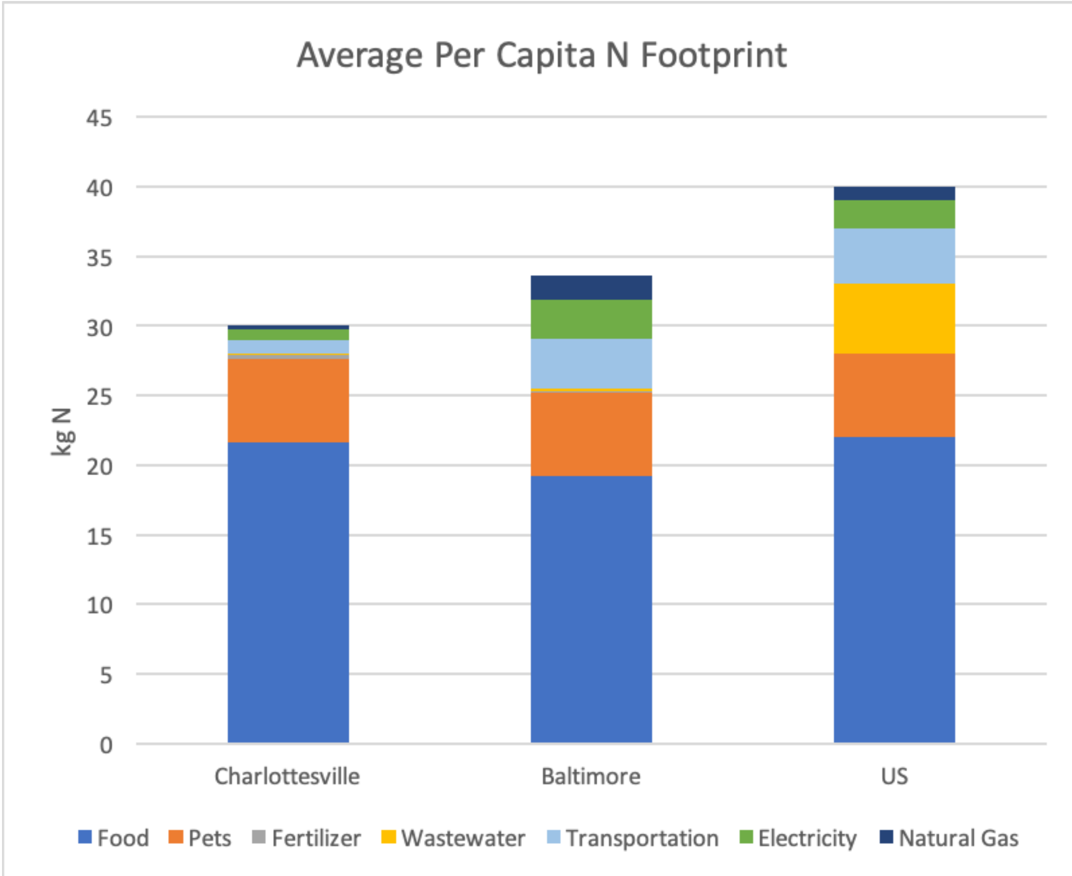


Figure 4: Comparison of the average per capita N footprint of Charlottesville City, Baltimore City, and the US. The average per capita N footprints are 30.0 kg N, 33.6 kg N, and 40 kg N, respectively.

Geographical Distribution of the N Footprint

Both the total per capita N footprint and local per capita N footprints have some of their highest values in the downtown area, and just north of downtown (Figure 5). Other relatively high values can also be seen in mostly the north/northeast areas of the city. The food N footprint per capita (Figure 6) and the transportation N footprint per capita (Figure 7), both follow this pattern as well, with the highest values being concentrated near downtown and in the north/north east areas of the city. It is important to note that when considering the transportation N footprint, Figure 7 represents the N footprint contributions made by the transportation of the residents within each census block group, not necessarily by the vehicles that have traveled through a given block group.

Looking at the N footprint of energy use, electricity and natural gas can be broken down by the residential and business footprints. Residential electricity use per capita follows a similar geographical pattern to the overall N footprint, being the most heavily concentrated near downtown and in the north/northeast sections of the city. The business electricity use is heavily concentrated downtown (Figure 8). Note that the assumption was made that all businesses use the same amount of electricity regardless of size, due to the lack of publicly available data on individual business energy consumption. The N footprints for both residential and business natural gas use follow very similar geographical patterns to that for electricity (Figure 9).

The N footprint of home lawn fertilizer use is larger in the north/northeast areas of Charlottesville City, both overall and per capita (Figure 10). The N footprints of wastewater and pet food and waste are larger in the southern areas of Charlottesville City (Figure 11; Figure 12). Since the N footprint for these two sectors was estimated based on population data and did not vary per capita by census block group, their concentration reflects the population density of Charlottesville City.

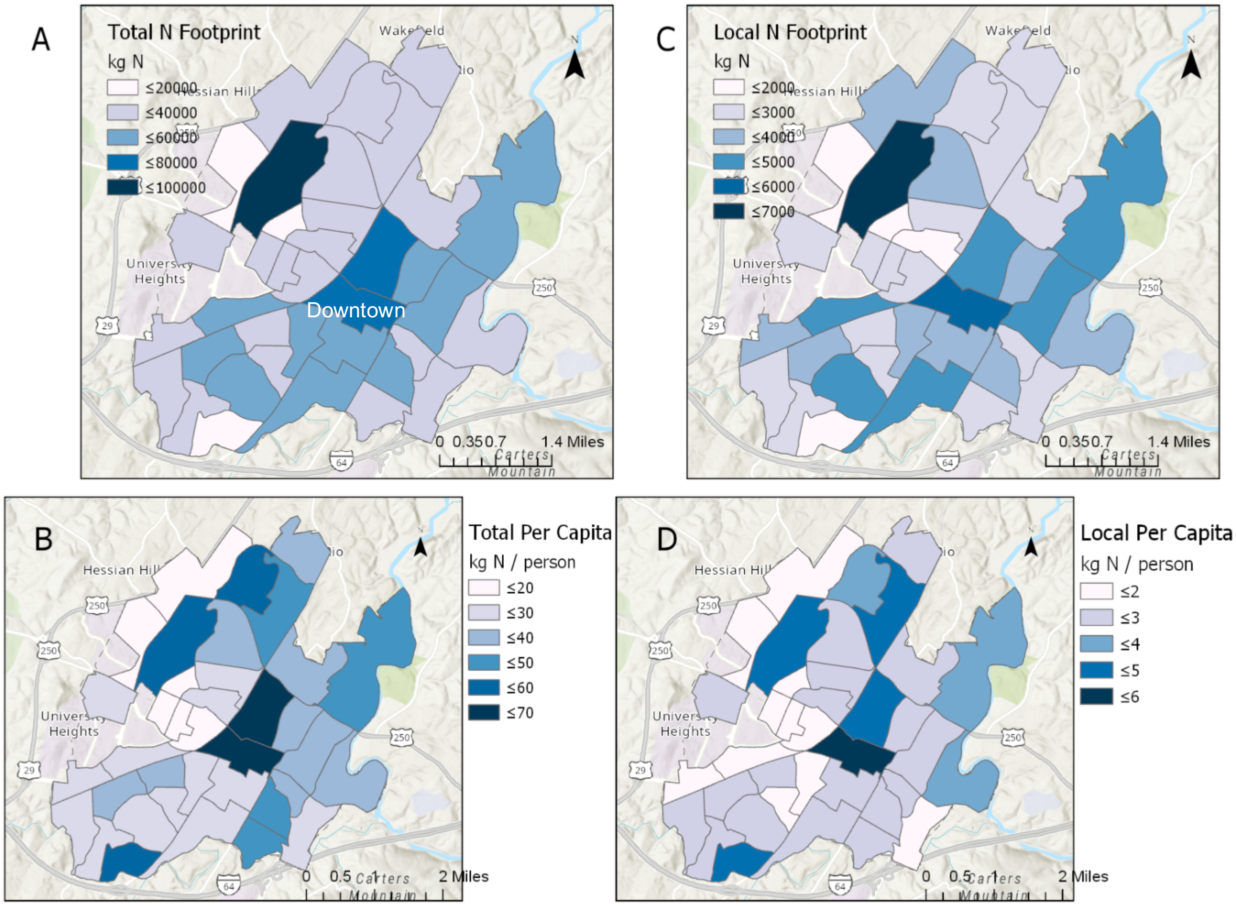


Figure 5: The (A) total N footprint, (B) total per capita N footprint, (C) local N footprint, and (D) local per capita N footprint of Charlottesville City. The total per capita N footprint ranges from 14.3 - 65.5 kg N per person. The local per capita N footprint ranges from 1.38 - 5.36 kg N per person.

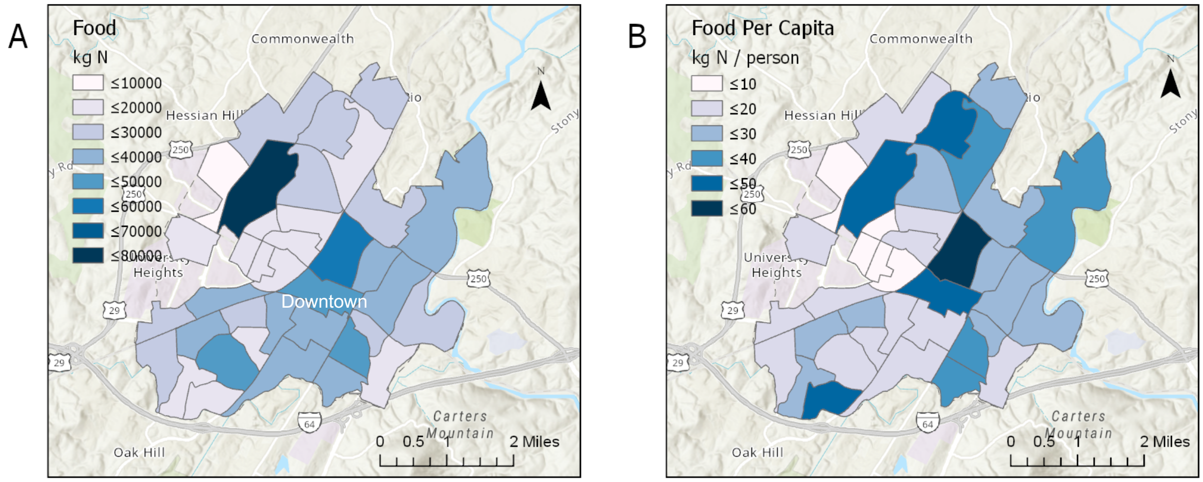


Figure 6: The (A) N footprint from food purchased by Charlottesville City residents, and (B) food N footprint per capita.

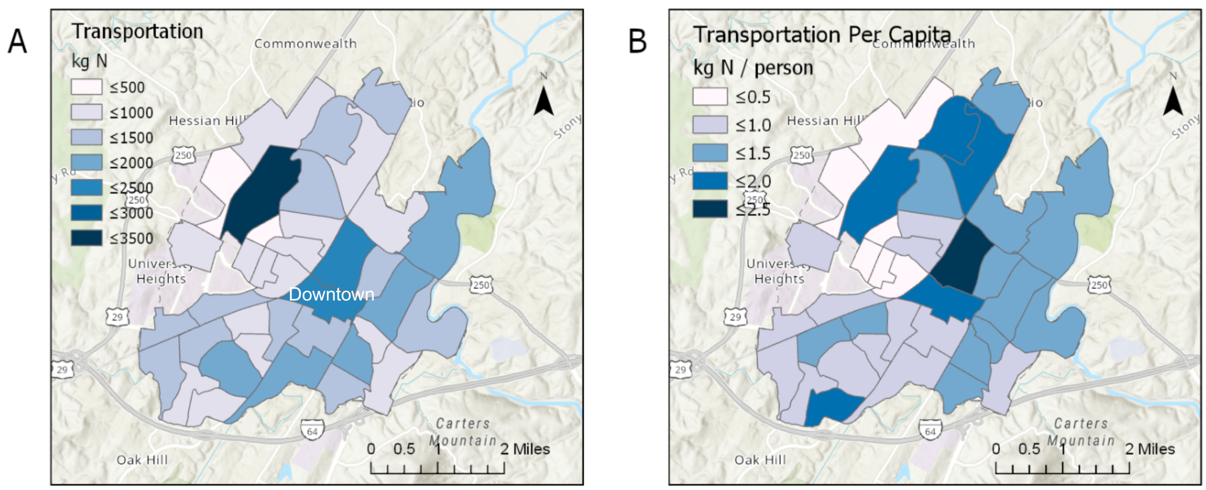


Figure 7: The (A) N footprint due to transportation in Charlottesville City, and (B) transportation N footprint per capita.

A

C

B

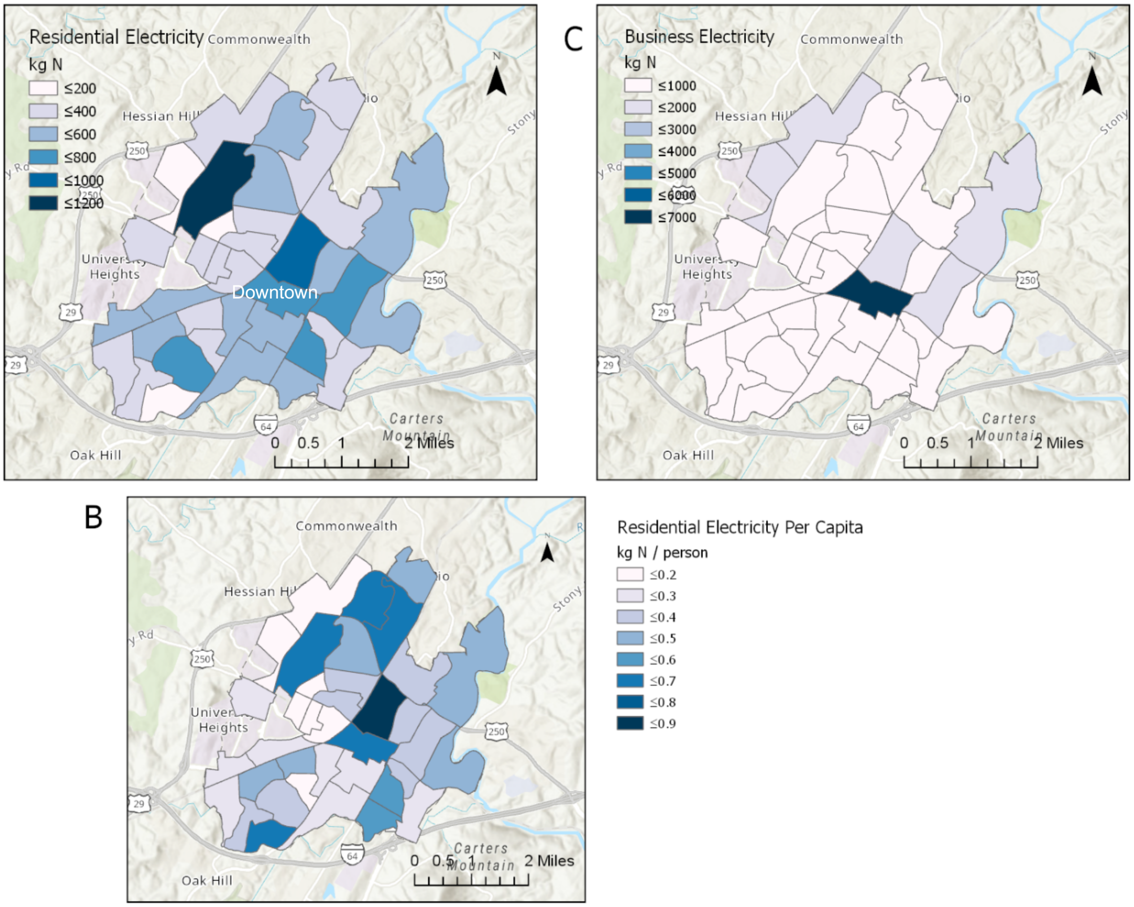


Figure 8: The N footprint due to electricity use in Charlottesville City: (A) residential, (B) residential per capita, and (C) business.

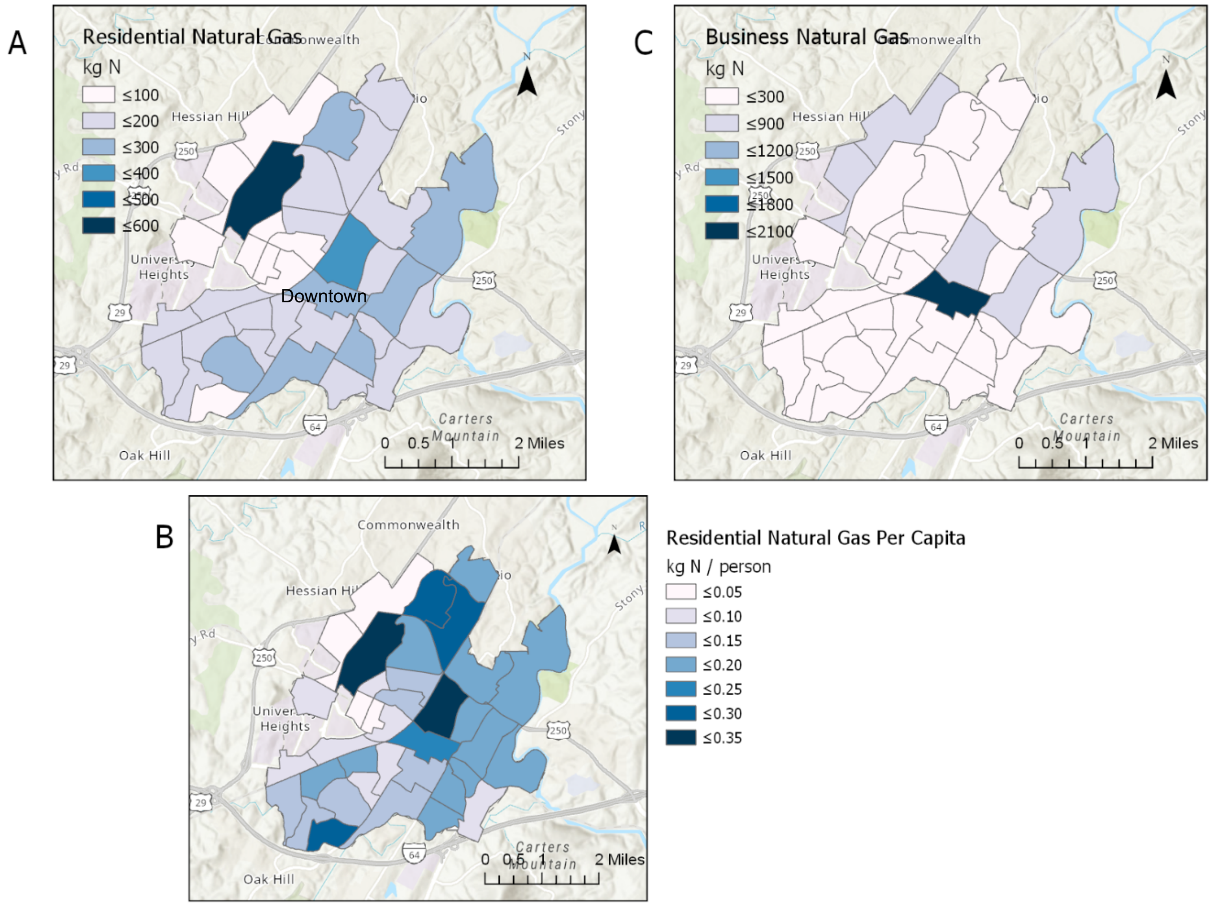


Figure 9: The N footprint due to natural gas use in Charlottesville City: (A) residential, (B) residential per capita, and (C) business.

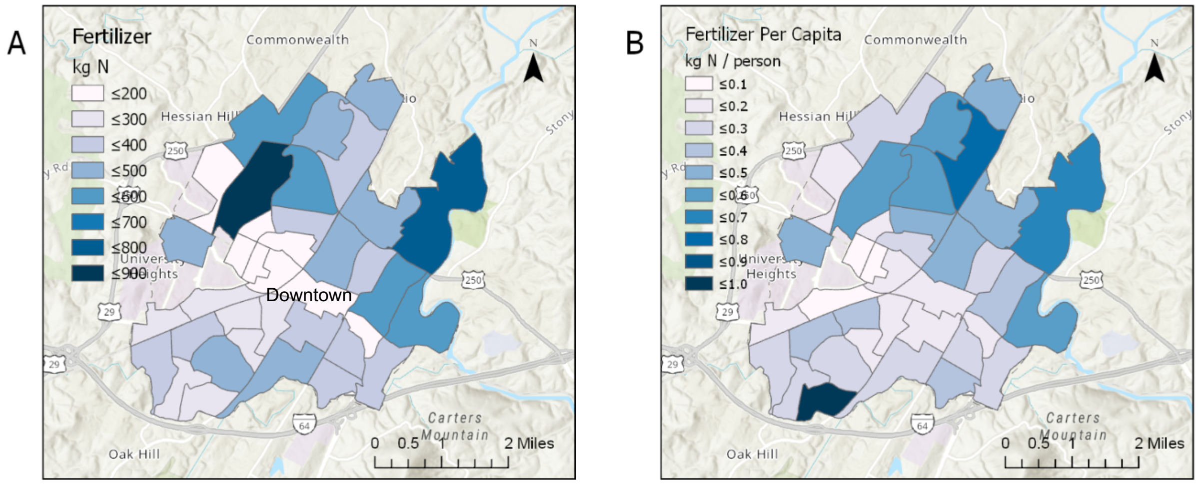


Figure 10: The (A) N footprint from home lawn fertilizer use, and (B) fertilizer N footprint per capita in Charlottesville City.

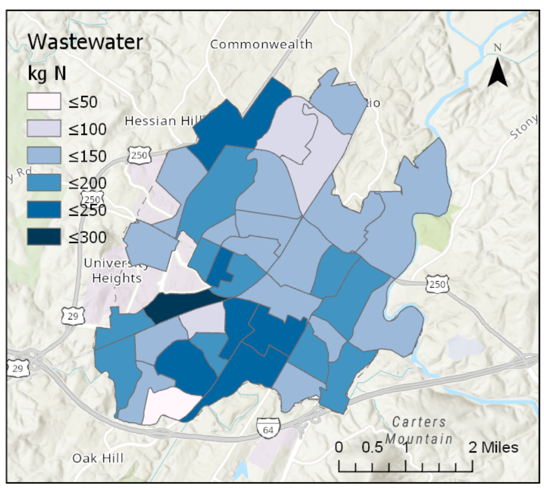


Figure 11: The N footprint from wastewater in Charlottesville City.

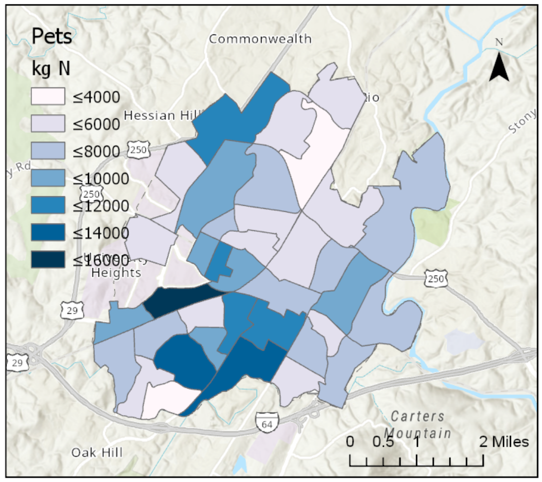


Figure 12: The N footprint from pet (dog and cat) food and waste in Charlottesville City.

Socioeconomic Comparisons with the N Footprint

Median household income (MHHI) by census block group ranges widely in Charlottesville City (Figure 13). Using linear regression, MHHI correlates positively with the total N footprint per capita with p = 0.01, showing that there is a significant positive relationship between the two variables (Figure 14).

The racial demographics of Charlottesville City also range widely by census block group. The proportion of the population in a given census block group that is white ranges from below 30% to above 95% (Figure 15). The percent of the population that is white in a given census block group correlates positively with the total N footprint per capita with p = 0.01 (Figure 16).

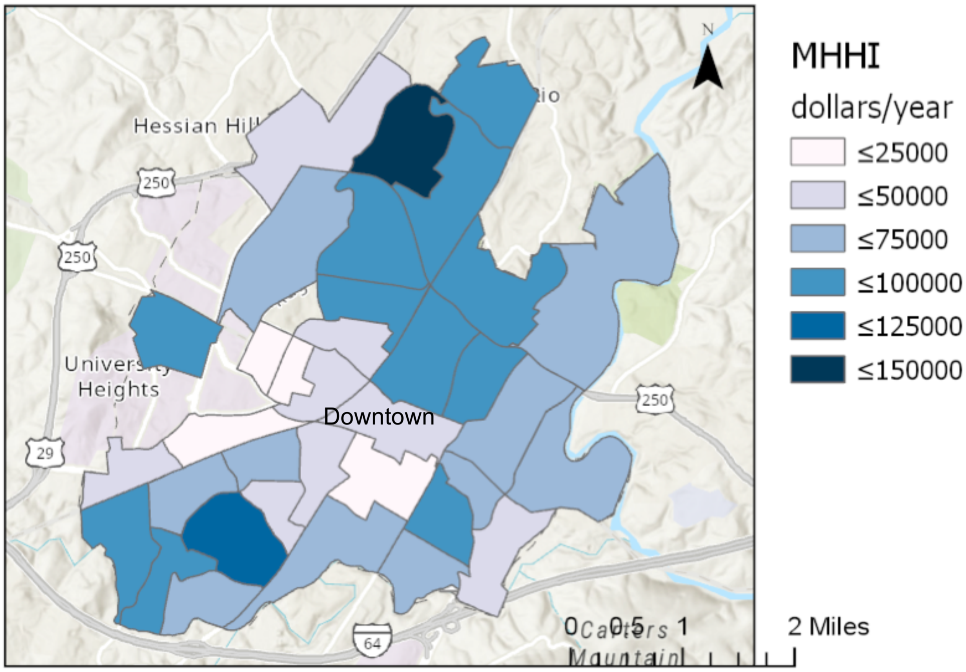


Figure 13: Median household income (MHHI) in Charlottesville City by census block group.

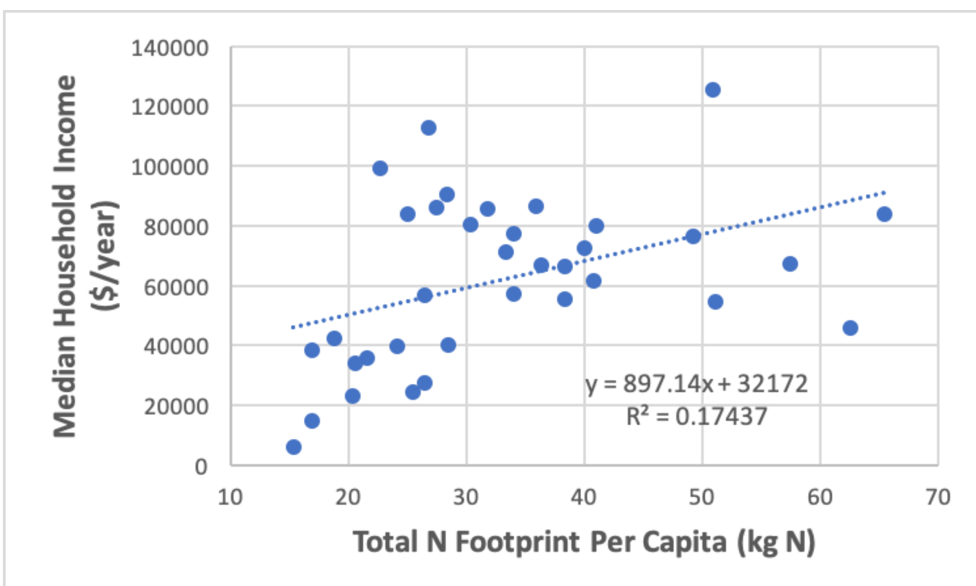


Figure 14: Median Household Income (MHHI) ($/year) vs. total N footprint per capita (kg N) in Charlottesville City. MHHI correlates positively with the total N footprint per capita with p = 0.01.

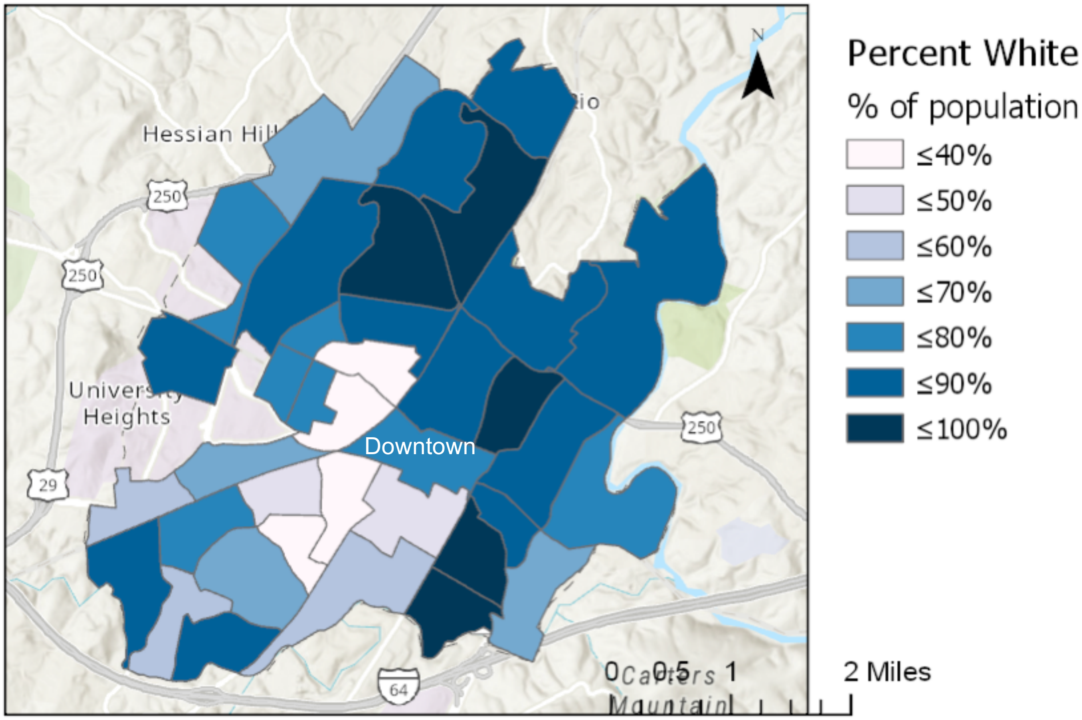


Figure 15: Proportion of the population that is white in Charlottesville City by census block group.

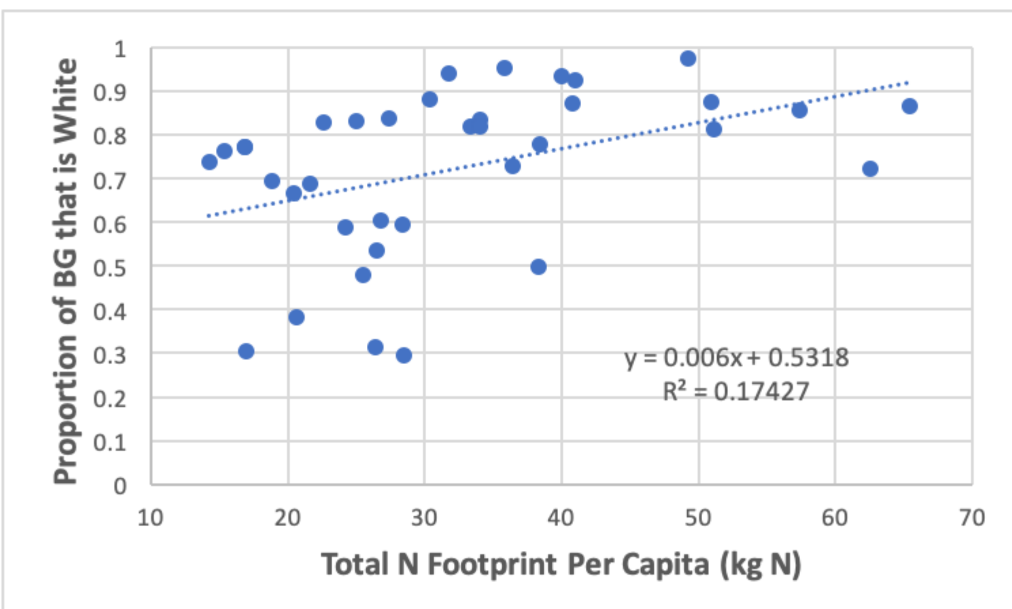


Figure 16: The proportion of the population of the census block group that is white vs. total N footprint per capita (kg N) in Charlottesville City. Percent white correlates positively with the total N footprint per capita with $p = 0.01$.

Potential Reductions in the Charlottesville City N Footprint

Sectors that contribute the most to the total and local N footprints were targeted for reductions. Census block groups that have the greatest opportunities for reduction are located downtown, and in the north/northeast area of the city. In order to reduce the N footprint of the food sector, if residents of Charlottesville City were to switch 10% of their beef consumption to chicken and 10% to beans by weight, there would be 1.4% and 2.1% reductions in the total N footprint of the city respectively. If city residents were to consume closer to the Recommended Daily Allowance (RDA) for protein (Pendick 2015), reducing the protein consumption to 75g per person per day for those census blocks that are consuming on average over this level, the total N footprint would decrease by an additional 22.1%. The local N footprint would also decrease by 3%. Most (70%) of census block groups in Charlottesville City, according to data from the CEX report, eat more than 75g per person per day of protein currently.

In terms of transportation, if 10% of car use was replaced with bus use, 10% of fossil fuel-powered cars were replaced with electric cars, 10% of car use was replaced with biking, and 10% was reduced via carpooling, there would be a 12.6% reduction in the local N footprint, and a 1.1% reduction in the total N footprint. If 10% each of electricity and natural gas use was replaced with renewable energy, there would be a 1.1% reduction in the local N footprint, and a 0.4% reduction in the total N footprint. If the rate of fertilization on home lawns was decreased by 25%, the local N footprint would decrease by 2.8% and the total N footprint would decrease by 0.2%

All together, these scenarios would reduce the local N footprint by 19.5%, and the total N footprint by 27.3%.

Table 6: Percent reductions in the sector N footprint, local N footprint, and total N footprint for given scenarios for food, transportation, energy use, and fertilizer.

Reduction Scenario	**% Sector Reduction**	**% Local Reduction**	**% Total Reduction**
Food: Replace 10% of Beef with Chicken	1.9%	<0.1%	1.4%
Food: Replace 10% of Beef with Beans	3.0%	<0.1%	2.1%
Food: Residents consume closer to Recommended Daily Allowance (RDA) for protein	30.7%	3.0%	22.1%
All Food Scenarios	**35.6%**	**3.0%**	**25.6%**
Transportation: Replace 10% of Car Use with Bus Use	7.7%	3.0%	0.3%
Transportation: Replace 10% of Fossil Fuel-Powered Cars with Electric Cars	6.8%	3.2%	0.2%
Transportation: Replace 10% of Car Use with Biking	8.3%	3.2%	0.3%
Transportation: Decrease Car Use by 10% with Carpooling	8.3%	3.2%	0.3%
All Transportation Scenarios	**31.1%**	**12.6%**	**1.1%**
Energy: Replace 10% of Electricity Use with Renewables	10.0%	n/a	0.3%
Energy: Replace 10% of Natural Gas Use with Renewables	10.0%	1.1%	0.1%
All Energy Scenarios	**n/a**	**1.1%**	**0.4%**
Fertilizer: Decrease lawn fertilizer application rate by 25%	**25%**	**2.8%**	**0.2%**
ALL SCENARIOS	**n/a**	**19.5%**	**27.3%**

Discussion

Comparison of Charlottesville City N Footprint with US and Baltimore

Overall, the average per capita N footprint for Charlottesville City is lower than that of the US and of Baltimore (Figure 4). This may be due to a variety of reasons. First, all residents within the city limits of Charlottesville City are connected to a municipal wastewater treatment plant, where 79% of the N from human waste is removed before it enters the environment (Rivanna Water & Sewer Authority 2017), while the average US N footprint takes into account localities with wastewater treatment systems varying from septic systems to tertiary systems. The N footprint in Charlottesville City from wastewater is thus relatively low. This is in part due to the efforts of Chesapeake Bay Foundation, which protects the Chesapeake Bay watershed in which Charlottesville City lies. The foundation has made great strides in raising awareness of and funding for updating wastewater treatment (Chesapeake Bay Foundation 2020). The Virginia Department of Environmental Quality (DEQ) also determines and implements Total Maximum Daily Loads (TMDLs) for various bodies of water across the state, limiting the amount of pollution that is allowed (DEQ 2020).

Additionally, the contributions to the N footprint due to electricity and natural gas use are lower per person in Charlottesville City than the US average. This could indicate that Charlottesville City residents have to use less energy to heat or cool their homes. One study offers evidence that Virginia overall does not have a relatively high heating or cooling burden when compared to the rest of the US (Petri & Caldeira 2015) which would decrease the amount of energy used for heating and cooling. Further research could be done on the energy use patterns in Charlottesville City in particular.

The N footprint from transportation also seems to be lower on average in Charlottesville City. This could mean that people in Charlottesville City rely less heavily on personal transportation than in the US on average. However, the data used in this study on vehicle miles traveled only capture miles traveled within the city, so they may underestimate the N footprint from transportation. Additionally, this analysis does not include air travel, which would increase an individual's N footprint.

The per capita N footprint due to home lawn fertilizer use, while relatively small, is about twice the size in Charlottesville City (Figure 4) than it is in Baltimore City. It is not included in the US average per capita N footprint. It is possible that Charlottesville City residents have larger lawn sizes, on average. Additionally, there is likely to be error in the estimate of the Charlottesville City fertilizer N footprint. The total area of turfgrass used is presumed to include some public areas, such as medians, that are not a part of home lawns, though most parks and a golf course were excluded. Further analyses could opt to include these areas, using unique estimates of fertilizer use for these areas specifically. The estimates used for fertilizer application rate and the percentage of households using fertilizer (Fraser et al. 2013), were also based on Baltimore survey data, and thus are another source of error when used in the Charlottesville City context.

Geographical Variability in the Charlottesville City N Footprint

Great geographical variability was found in the Charlottesville City N footprint, ranging from 14.3 to 65.5 kg N/person between census block groups. The total and local N footprints per capita for Charlottesville City have the highest values in the downtown area and in the north/northeast areas of the city (Figure 5). Many of the sectors contributing to the N footprint have higher values of kg N per capita in these areas (Figures 6-12).

Food overwhelmingly has the largest impact on the total N footprint of Charlottesville City (Figure 3a). This closely parallels what was seen in Baltimore City (Dukes et al. 2020), as well as what can be seen when comparing the average per capita N footprint of Charlottesville City to the US overall (Leach et al. 2020). In Charlottesville City, it appears that people living close to downtown and in the north/northeast areas of the city contribute relatively more to the community's N footprint through their food purchases (Figure 6). This has implications for consumer choices when it comes to food purchasing, as well as for a city when looking at reducing their total N footprint.

Locally, transportation has the largest impact on the N footprint, specifically in the form of NOx and N_2O emissions from vehicles (Figure 3b). When looking at the transportation N footprint per capita, the data shows that people living in the downtown and north/northeast areas of Charlottesville City contribute the most, similar to the food N footprint (Figure 7). Emissions from transportation can directly impact local air quality and human health, as well contribute to the formation of tropospheric O_3 (Erisman et al. 2013). In addition to transportation, pet waste also plays a large role in the local N footprint, as pet waste is not treated via wastewater treatment plants to remove Nr as human waste is (Figure 3b). This has implications for local water quality.

Comparison of the N Footprint and Socioeconomic Patterns

The positive correlation between median household income and total N footprint per capita provides evidence that census block groups with a higher average income contribute more to the overall N footprint of Charlottesville City (Figure 14). This is a pattern that was seen in Baltimore City (Dukes et al. 2020). This means that wealthier census block groups in Charlottesville City engage more in consumption activities that have a higher N footprint, such as purchasing meat items, driving personal vehicles, and using more energy in homes, relative to poorer census block groups.

In terms of food purchasing, the sector with the highest N footprint, there is likely to be error due to the fact that this study methodology estimates food weight from dollars spent on given food items. One could argue that wealthier census block groups could buy more expensive food items in general, artificially raising their N footprint. However, when looking at the kg of meat purchased (beef, pork, and chicken) by census block group, normalized by total kg of food purchased (excluding liquids, oils, spices, and sugars), there is a negative correlation with median household income ($p = 0.04$). This indicates that wealthier census block groups not only have a significantly higher N footprint, but also specifically consume more food with a higher N footprint relative to poorer census block groups. This supports, on a local scale, the growing evidence that wealthier populations have a relatively greater negative environmental impact than poorer populations, shown on a global scale by Preston et al. (2014).

Not only are wealthier census block groups contributing more to the N footprint of Charlottesville City, but there is evidence that it is also the census block groups where a higher proportion of the population is white (Figure 16). While this study focused on the contributions to the N footprint, rather than the effects of excess Nr such as water and air pollution, it is possible that the negative impacts of the N footprint are unequally distributed across the population as well. In addition to the fact that wealthier populations may have a greater negative environmental impact on a large scale (Preston et al. 2014), it has been shown that in local contexts, certain groups, namely people of color, have been disproportionately impacted by environmental degradation, and associated public health issues (Walker 2009). In Charlottesville City, a preliminary study showed that NO_2 pollution may be greater in majority low-income African American communities relative to higher-income white communities (Knowles 2019). More research should be done on how the negative impacts of Charlottesville City's N consumption, such as associated air pollution, are distributed to the population.

Possibilities for N Footprint Reduction

Census block groups with the highest overall and per capita N footprints, mostly downtown and in the north/northeast of the city, have the highest potential to reduce their N footprint. Much of the potential for reduction comes in consumer choices, but can be encouraged by city planning. For example, the largest possibility for reduction in their contributions to the community N footprint that a person has is in their food choices (Table 6). Reducing beef consumption and overall protein overconsumption has a high potential to reduce the upstream Nr losses to the environment caused by food. Changes in food purchasing habits are most likely to occur on an individual level, but could be impacted by the presence or absence of meat-heavy or vegetarian restaurants within Charlottesville City. Choices could also be influenced by greater consumer education on the environmental and also human health benefits of eating less red meat and more plant-based meals.

In terms of the local Charlottesville City N footprint, the largest possibilities for reduction come in switching modes of transportation (Table 6). City planning could impact this, in terms of making buses more accessible, affordable, and attractive to residents, or expanding the presence and accessibility of bike lanes within the city. Reductions in the N footprint could happen in the energy sector with a more widespread use of renewable energy, for both residents and businesses, as well as improved weatherization of homes and buildings in order to reduce energy use itself. These reductions in the N footprint of Charlottesville City are possible through shifts in consumer choice, and could be encouraged by city planning decisions.

Engaging Local Governments and City Planners

As stated above, reductions in the N footprint can occur by shifting consumer choices, and city planners and local governments can play a large role in this. This study engaged with the Charlottesville City local government to garner feedback on the study design, collect various data needed, present preliminary results, and solicit input on research gaps, opportunities for further analysis, and the usefulness and feasibility of various reduction scenarios. The goal in engaging local stakeholders, namely the local government, throughout the process was to make this study usable and helpful for potential future research, initiatives, and projects.

Susan Elliott, the Climate Protection Program Manager for Charlottesville City, was the primary contact, assisting with data collection and offering feedback in all stages of the project. Other members of the Charlottesville Public Works Department that offered feedback and suggestions were Kristel Riddervold, the Environmental Sustainability Manager, and Dan Frisbee, the Water Resources Specialist. David Tungate and Phillip McKalips from RWSA also assisted in providing wastewater data for the city. Jason Vandever, the City Treasurer, also assisted in communicating about dog license information and data.

The conclusions of this study could be used in the future by local stakeholders including those listed above in order to support sustainable initiatives, planning decisions, or further research on the impacts of Charlottesville City's N footprint. For example, the results found here could be used to support local government carbon footprint reduction strategies through synergies with the N footprint, as suggested by Riddervold. Additionally, non-governmental stakeholders such as non-profits and environmental groups could use the results from this study for educational or other purposes to support their missions.

Conclusion

In summary, this study estimated the total and local N footprints of Charlottesville City for 2017. The total N footprint per capita for Charlottesville City was lower than that of the US and Baltimore City. Great geographical variability in the N footprint and its components was found, which correlated positively with median household income and the percent of the population in a given census block group that was white. There are large opportunities for N footprint reduction, particularly in the downtown and north/northeast areas of Charlottesville City. Decreases in the amount of beef and overall protein consumed could lead to the greatest reductions in the total N footprint, and changes in transportation could lead to the greatest reductions in the local N footprint. The results from this study could be used by local stakeholders to support future research, sustainable initiatives, consumer education, and planning decisions. Additionally, further research should be conducted on how the negative local impacts of Charlottesville City's N footprint, such as air pollution, are being distributed to the population.

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Appendix A: Vehicle classifications based on FWHA Class Groups for motorcycles, passenger cars, light trucks, buses, and medium-heavy duty trucks.

FHWA Class Group	FHWA Class Definition	FHWA Class Includes	Number of Axles	NFT Designation
1	Motorcycles	Motorcycles	2	**Motorcycles**
2	Passenger Cars	All cars Cars with one-axle trailer Cars with two-axle trailers	2, 3, or 4	**Passenger Cars**
3	Other Two-Axle Four-Tire Single Unit Vehicles	Pick-ups and vans Pick-ups and vans with one- and two- axle trailers	2, 3, or 4	**Light Trucks**
4	Buses	Two- and three-axle buses	2 or 3	**Buses**
5	Two-Axle, Six-Tire, Single-Unit Trucks	Two-axle trucks	2	**Medium-Heavy Duty Trucks**
6	Three-Axle Single-Unit Trucks	Three-axle trucks Three-Axle tractors without trailers	3	**Medium-Heavy Duty Trucks**
7	Four or More Axle-Single-Unit Trucks	Four-, five-, six-, or seven-axle single-unit trucks	4 or more	**Medium-Heavy Duty Trucks**
8	Four or Fewer Axle Single-Trailer Trucks	Two-axle trucks pulling one- and two-axle trailers Two-axle tractors pulling one- and tow-axle trailers Three-axle tractors pulling one-axle trailers	3 or 4	**Medium-Heavy Duty Trucks**

9	Five-Axle Single-Trailer Trucks	Two-axle tractors pulling three-axle trailers Three-axle tractors pulling two-axle trailers Three-axle trucks pulling tow-axle trailers	5	**Medium-Heavy Duty Trucks**
10	Six or More Axle Single-Trailer Trucks	Multiple configurations	6 or more	**Medium-Heavy Duty Trucks**
11	Five or Fewer Axle Multi-Trailer Trucks	Multiple configurations	4 or 5	**Medium-Heavy Duty Trucks**
12	Six-Axle Multi-Trailer Trucks	Multiple configurations	6	**Medium-Heavy Duty Trucks**
13	Seven or More Axle Multi-Trailer Trucks	Multiple configurations	7 or more	**Medium-Heavy Duty Trucks**
14	Unused	----	----	Not classified
15	Unclassified Vehicle	Multiple configurations	2 or more	Not classified