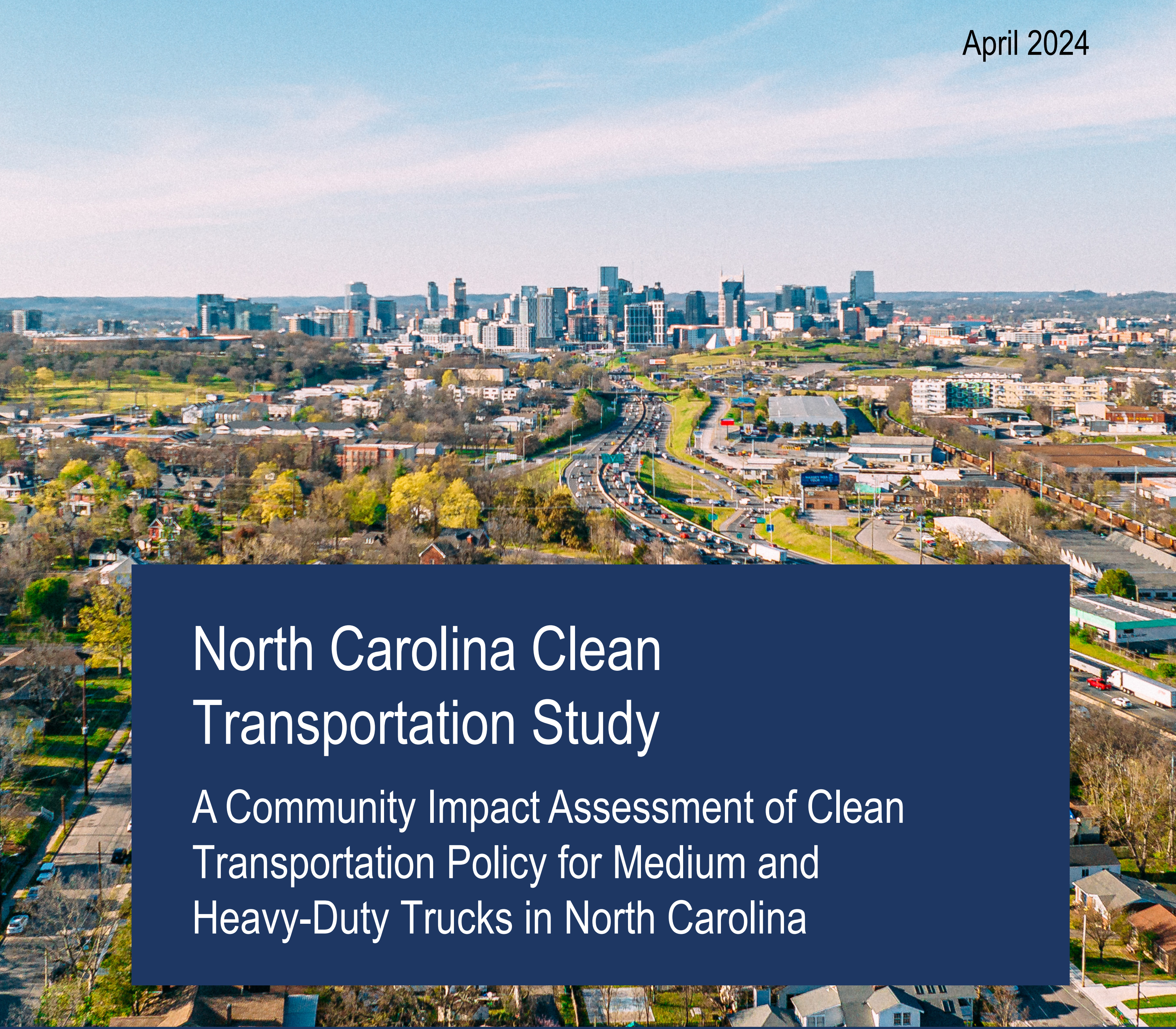

April 2024

North Carolina Clean Transportation Study

A Community Impact Assessment of Clean Transportation Policy for Medium and Heavy-Duty Trucks in North Carolina

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Table of Abbreviations

ACS	American Community Survey
ACT	Advanced Clean Trucks
ALPSS	Accessible Lightweight Power Sector Simulation
ATB	Annual Technology Baseline
CC	combined cycle
CRTPO	Charlotte Regional Transportation Planning Organization
CT	combustion turbine
EIA	Energy Information Administration
EJ	environmental justice
EPA	U.S. Environmental Protection Agency
EV	electric vehicle
GHG	greenhouse gas
GW	gigawatt
HCUP	Healthcare Cost and Utilization Project
HDV	heavy-duty vehicle
IRA	Inflation Reduction Act
ITRE	Institute for Transportation Research and Education
MDV	medium-duty vehicle
MHD	medium- and heavy-duty
MHEV	medium- and heavy-duty electric vehicle
MOVES	MOtor Vehicle Emission Simulator
MRM	Metrolina Regional Travel Demand Model
MW	megawatt
NCDOT	North Carolina Department of Transportation
NCSEA	North Carolina Sustainable Energy Association
NEPA	National Environmental Policy Act
NO_X	oxides of nitrogen
PM	particulate matter
SEDD	State Emergency Department Database
TRM	Triangle Regional Model

TRMSB	Triangle Regional Model Service Bureau
VMT	vehicle miles traveled
ZCTA	Zip Code Tabulation Area
ZEV	zero-emission vehicle

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1. Executive Summary

North Carolina has taken significant steps to reduce greenhouse gas (GHG) emissions from its power sector. In 2021, the General Assembly of North Carolina passed legislation (House Bill 951 [H951]) by wide bipartisan margins that sets ambitious carbon emission targets for the power sector. The state is also focusing on reducing GHG emissions from the transportation sector, which accounts for 36% of total GHG emissions. Within the transportation sector, medium- and heavy-duty (MHD) vehicles account for only 6.5% of on-road vehicles but are responsible for 34.5% of GHG emissions from on-road vehicles. In October 2022, Governor Cooper signed Executive Order 271, which directed the North Carolina Department of Environmental Quality to adopt the Advanced Clean Trucks (ACT) rule to accelerate the market transition to zero-emission MHD trucks and buses. ACT sets increasing sales targets for the zero-emission MHD vehicles.

Our earlier study showed that adoption of the ACT rule is expected to reduce nitrogen oxides (NO_X) emissions by 50% and particulate matter ($PM_{2.5}$) emissions by 73%; however, how the associated improvements in air quality will be distributed is unclear. Adoption of ACT is likely to have a disproportionately positive impact on communities co-located near major transportation routes that experience high volumes of MHD vehicle traffic. These communities are likely to experience a disproportionately larger reduction in primary NO_X and $PM_{2.5}$ emissions.

This study estimated the distributional impacts of the ACT rule by modeling the expected change in roadway emissions using spatially explicit data on current and projected MHD traffic volumes and overlaying this model with community-based sociodemographic data. This modeling exercise allowed us to estimate the distributional impacts of ACT on local North Carolina communities.

Our findings show that the greatest ACT primary pollution reductions accrue to near-road communities that are subjected to higher concentrations of air pollutants from vehicle traffic. Furthermore, we found that low-income households tend to be overrepresented in these near-road communities. As a result, we conclude that these communities receive a disproportionate level of pollution reduction. The reduction in pollution concentrations in these communities is expected to provide significant health benefits and significant health cost savings over the next 25 to 30 years.

In this report, we present the spatially explicit model of mobile and stationary source emissions for NO_X and $PM_{2.5}$ forecasted in years 2030, 2040, and 2050 with and without ACT adoption. For this study, we leveraged the Triangle Regional Model (TRM), which includes a detailed road network and forecasted traffic volume by vehicle and road type out to 2050. Figure ES-1 presents the TRM road network map of the 11-county region selected for this study.

We found that the ACT rule is expected to result in significant reductions in NO_x and $PM_{2.5}$ over the next 25 years, and communities in the 11-county study area will experience a steady decline in emissions, culminating in a 61% reduction in NO_x and a 73% reduction in $PM_{2.5}$ from baseline emissions in 2050. Perhaps more importantly, approximately 42% of emission reductions are concentrated in some of the most vulnerable communities, defined in terms of race, income, and education. Based on the strong body of evidence in the public health and air quality literature, we know that these emission reductions will yield health benefits such as reduced mortality and hospitalization related to respiratory illness for the people living in these communities.

Figure ES-1. Summary of Study Area and Road Network

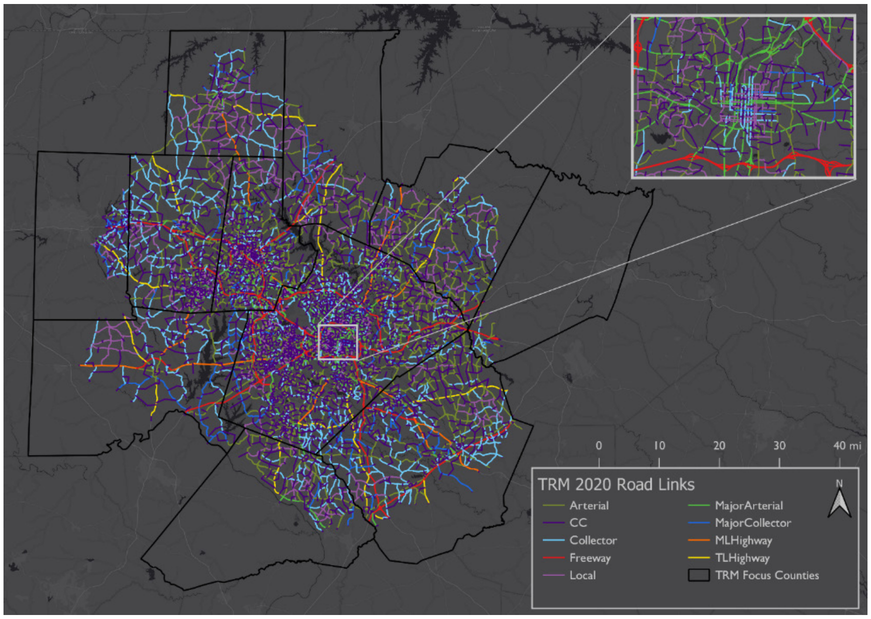
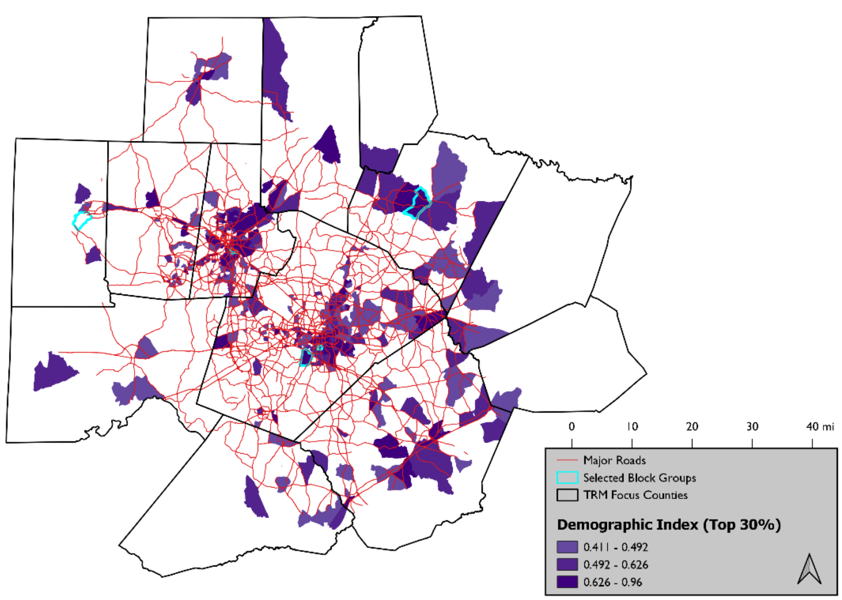


Figure ES-2 depicts the major roadways in the TRM network and the block groups with the highest demographic index values; in other words, the most vulnerable communities in our study area relative to the state average demographic index value. This figure highlights the relationship between traffic emissions and social vulnerability in the study area. As Figure ES-2 shows, areas with high road density generally coincide with areas of high social vulnerability.

Figure ES-2. Major Roads and Top 30% of Block Groups by Demographic Index



In addition to tailpipe emissions, our study modeled ACT's impact on stationary source emissions because we anticipate increased demand for electricity resulting from increased MHD vehicle charging. We modeled two power sector scenarios by adopting the most recently available capacity expansion planning provided by Duke Power in response to North Carolina's net-zero emissions target for the power sector by 2050. We modeled Duke's P1 scenario from the Duke Carbon Plan report and an alternative scenario that we refer to as the Synapse scenario, which represents an alternative capacity expansion scenario that is more reliant on renewables and less reliant on natural gas and nuclear sources used to achieve the net-zero carbon target by 2050.

As the third component of this study, we analyzed demographic disparities to identify those communities in the study area with disproportionately high non-White and low-income populations near sources of NO_x and $PM_{2.5}$ emissions. We identified the vulnerability of communities using the environmental justice (EJ) screening approach defined by the U.S. Environmental Protection Agency. We then conducted a Cochran-Armitage trend test to understand how emission reductions vary in relation to a variety of demographic indicators used to characterize the communities in the study area. The Cochran-Armitage test provides a more robust statistical test that characterizes the significance of disproportionately larger reductions accruing to more vulnerable communities.

The top 25% of communities ranked by demographic index have a much higher emission intensity for both NO_x and $PM_{2.5}$ compared with communities in the bottom half of the demographic index. The Cochran-Armitage test supports this finding by showing a strong correlation between communities with high social vulnerability and high tailpipe emissions from MHD vehicles. Analyzing the demographic index and emissions, we observe a clear positive relationship: greater emissions are found in communities with higher social vulnerability. As a result, assuming uniform electrification of MHDV's, ACT adoption is expected to provide significant reductions in pollution and we would expect improvements in air quality and reduced health burdens in the most socially vulnerable communities throughout much of North Carolina.

1. Introduction

Sweeping decarbonization of the global economy is necessary if society hopes to avoid the most severe impacts of climate change. North Carolina has taken significant steps to reduce the greenhouse gas (GHG) emissions from its power sector. In 2021, the General Assembly passed legislation (House Bill 951 [H951]) by wide bipartisan margins that sets ambitious carbon emission targets for the power sector. The state is also focusing on reducing GHG emissions from the transportation sector, which accounts for 36% of total GHG emissions. Within North Carolina's transportation sector, medium- and heavy-duty (MHD) vehicles account for only 6.5% of on-road vehicles but are responsible for 34.5% of GHG emissions from on-road vehicles. In October 2022, Governor Cooper signed Executive Order 271, which directed the North Carolina Department of Environmental Quality to adopt the Advanced Clean Trucks (ACT) rule to accelerate the market transition to zero-emission MHD trucks and buses. ACT sets increasing sales targets for the zero-emission MHD vehicles.

In April 2022, RTI International completed a study that analyzed statewide impacts of ACT in North Carolina. The study included an analysis of the economic, climate, and health benefits derived from ACT adoption out to mid-century. Unlike carbon dioxide (CO_2), which has a global impact, nitrogen oxides (NO_X) and particulate matter ($PM_{2.5}$) emissions have significant localized health impacts. It is well established in the scientific literature that pollutant emissions are disproportionately distributed in areas with low-income and non-White populations (Finkelstein et al., 2003; Jerrett et al., 2004). Frequently, major roads are located in economically disadvantaged black and brown communities, resulting in higher near-road air pollution concentrations in these neighborhoods (Rowangould 2013; Tian et al., 2013).

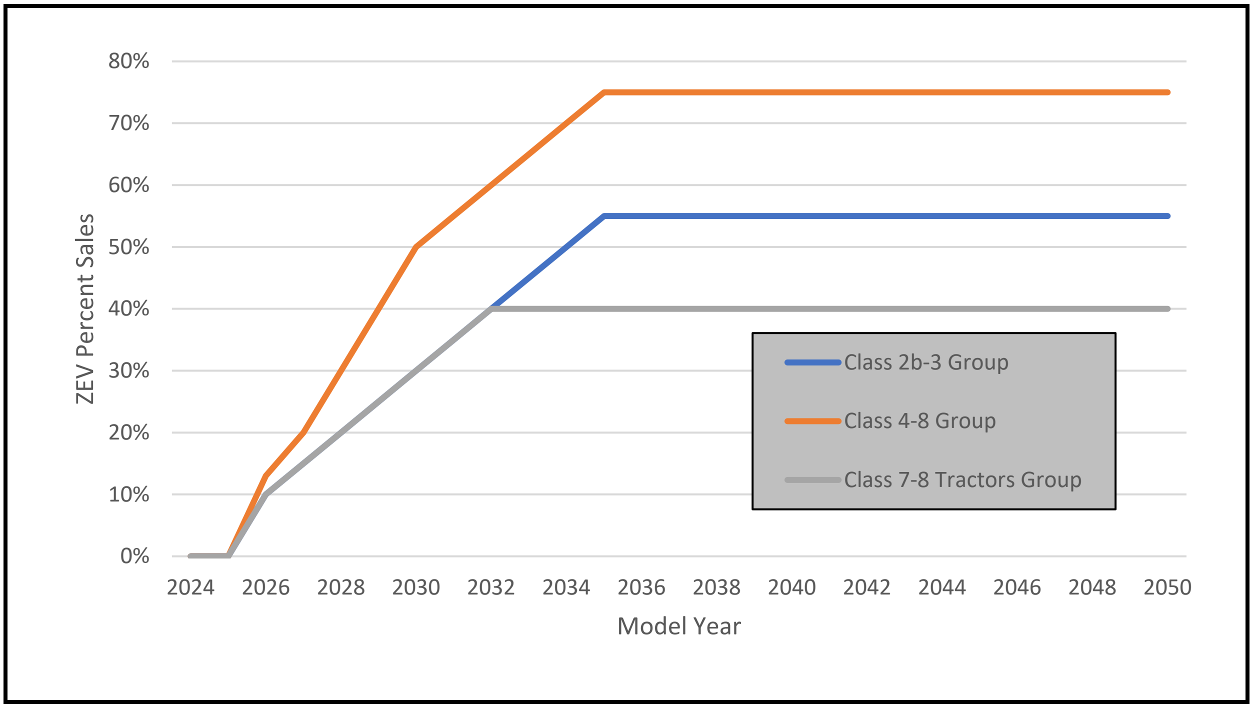
As North Carolina undertakes the adoption of ACT, it is important to understand which communities will see the greatest reductions in primary NO_X and $PM_{2.5}$ emissions. This follow-on study quantified the primary NO_X and $PM_{2.5}$ tailpipe emissions from MHD vehicles and the expected reductions resulting from ACT at the census block group level in an 11-county region. The study then looked at the demographic characteristics of the block groups that will see the largest reductions in primary NO_X and $PM_{2.5}$ emissions.

The transportation sector represents a key opportunity to achieve significant carbon reductions in the near term. Because MHD vehicles produce more emissions than passenger vehicles, electrification of this class of vehicles offers significant GHG emission reductions while also creating significant improvements in local air quality around the state.

MHD vehicle emissions have a greater impact on economically vulnerable communities and high-poverty communities. Electrification of MHD vehicles achieves GHG reductions while also addressing historical inequities in pollution and its associated health impacts around the state.

Consistent with our previous study, we assumed that North Carolina will adopt the requirements of the California ACT rule, mandating that an increasing percentage of new trucks sold in North Carolina be zero-emission vehicles (ZEVs) beginning with the 2026 model year. Sales targets vary by vehicle type, but for all types, the required ZEV percentage increases in each model year between 2026 and 2035. Figure 1 shows the increase in sales targets by model year out to 2050.

Figure 1. ACT ZEV Sales Targets to 2050 by Model Year



Source: Petrusa et al. (2020). North Carolina Clean Transportation Study: Analysis of Environmental, Health, and Economic Impacts to Mid-Century. Available at: https://www.rti.org/publication/north-carolina-clean-transportation-study/fulltext.pdf

Although the previous study quantified the total changes in emissions at the state level and estimated the economic impacts from adopting MHD electric vehicles, in this study, we focused on community vulnerability, with the objective to better understand which individuals may realize the most significant changes in NO_X and $PM_{2.5}$ primary emissions as a result of ACT implementation (see sections 2.3.and 2.4 for measures of community vulnerability). Ultimately, we sought to understand the distribution of primary pollutant reductions and the communities expected to see the greatest reductions in emissions due to ACT implementation.

We developed a geospatial tool that layers high-resolution transportation demand projections and corresponding emissions from MHD vehicles and the power sector with sociodemographic information and health data associated with the 11 counties that make up the Triangle transportation region. This spatial tool allows us to evaluate reductions in primary emissions from ACT at the community level through the lens of environmental justice (EJ).

In this study, a screening methodology, adopted from the U.S. Environmental Protection Agency's (EPA's) EJScreen tool, was applied to identify communities with disproportionately high non-White and high-poverty populations located within a buffer distance of roadways and energy sector point sources[1] for NO_X and $PM_{2.5}$. This screening tool was not used to identify an "environmental justice community" but rather to serve as a starting point for characterizing how changing emission profiles will affect the air quality in vulnerable or disadvantaged communities.

[1] Point sources in this context are defined as a stationary energy generation facility that emits air pollution from an emission stack resulting from the combustion of fossil fuel, such as coal or natural gas.

The subsequent sections of this report describe our analysis of ACT policy impacts on North Carolina's transportation and power sectors while also identifying the types of communities likely to benefit from the expected improvements in air quality. Section 2 briefly defines these policies and discusses our modeling approach, data used to develop our baseline forecast of MHD truck transportation activity over the next three decades, and supporting inputs and assumptions used to model the emissions from the electricity sector. Section 3 presents the expected local air quality impacts associated with ACT and characterizes the communities likely to be affected by the increased adoption of electric MHD vehicles. Finally, in Section 4, we summarize the overall findings, identifying the disproportionate impacts of ACT air quality improvements at a localized level within selected counties in our study region.

2. Data and Methodology

The focus of this study was to use spatially explicit modeling of projected MHD traffic across the network of North Carolina roadways. Ideally, we would include the entire state in our analysis; however, comprehensive statewide projections were not available. As a result, the geographical scope of our study was limited to an 11-county region generally associated with the Durham Chapel Hill Carrboro and Capital Area Metropolitan Planning Organizations.[2] In the study, we looked at how projected changes in MHD transportation demand and concentration of tailpipe emissions change in the communities across the Triangle Regional Model (TRM) region. We then used sociodemographic characteristics for these communities to evaluate the characteristics of the communities that will likely benefit from the improved local air quality via reduced vehicle emissions that would come from the transition to zero-emission MHD vehicles under the ACT rule.

As in our previous study, we assumed that adoption of ACT starts in 2026. We then looked at how primary emissions[3] change over the years 2030, 2040, and 2050 from both the transportation and power sectors.

Electrifying MHD vehicles will result in increased charging demand, which will require an incremental increase in electricity generation by the power sector. Depending on the amount of fossil fuel generation in the grid, this increased charging demand could increase pollution emitted by these sources. Our study captured these emissions and their potential impacts on the communities as well. Under H951, the power sector in North Carolina is expected to move to net-zero carbon emissions by 2050. In its 2022 Carolinas Carbon Plan (Duke, 2022), Duke Energy published a capacity expansion plan to achieve this target. We used these capacity projections and those from a parallel study from Synapse as part of our modeling of the North Carolina power sector to analyze how the systems described by each scenario could respond to increased demand from MHD vehicles per the ACT rule. The difference between these two scenarios is discussed later in this section.

The remainder of this section provides detail on the models, data, and metrics the authors used to analyze ACT's impacts on the communities within 11 counties in the Triangle transportation region.

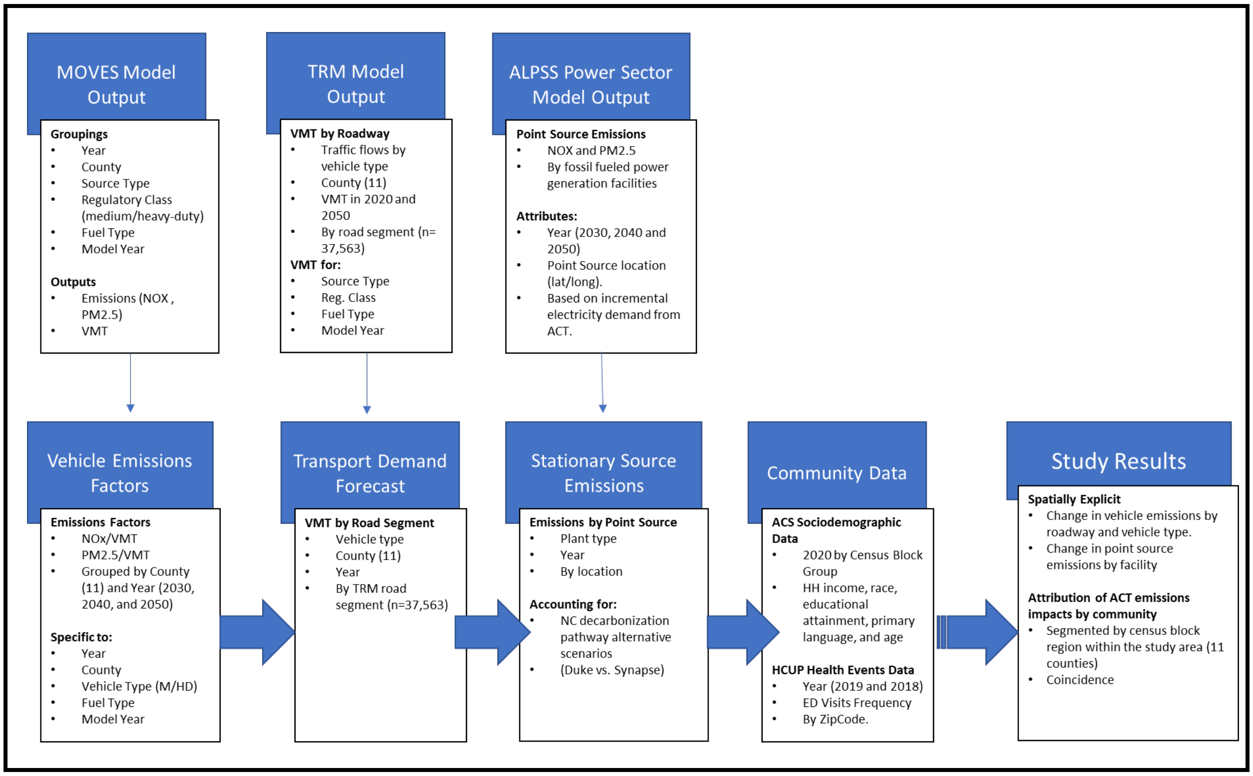
2.1 Data and Modeling Sources

RTI developed daily emission estimates by road link by vehicle type using two data sources: the EPA MOtor Vehicle Emission Simulator (MOVES3) modeling system and a regional traffic demand model called the TRM developed by the Triangle Regional Model Service Bureau (TRMSB) within the Systems Planning and Analysis Group in the Institute for Transportation Research and Education (ITRE) at North Carolina State University. MOVES3 was used to develop emission factors for MHD vehicles in each county, and the TRM was used to allocate vehicle miles traveled (VMT) for MHD vehicles to specific roadway segments included in the model. Power sector emissions were modeled using RTI's Accessible Lightweight Power Sector Simulation (ALPSS) economic dispatch model based on two alternative scenarios that modeled Duke Energy's 2022 Decarbonization Plan (Duke Power and Synapse). Community-based sociodemographic data and health data were also used in this analysis to characterize

[2] Metropolitan Planning Organization planning area mapping is available at http://www.ncampo.org/mpos.
[3] Throughout the report emissions are implied to be primary emissions, estimating changes in secondary air pollutant formation was outside the scope of our study.

the communities likely to be affected by air quality improvements (i.e. emissions reductions) following implementation of ACT in North Carolina. Figure 2 details the data process for the analysis.

Figure 2. Modeling Data Process for Allocating Emissions to Communities



2.1.1 MOVES3 County Data on VMT and Emission Estimates by Vehicle Type

To examine the localized pollution impacts of the implementation of the ACT rule on different communities in North Carolina, RTI developed emission factors for the MHD vehicle populations specific to each county. The emission factors were calculated in units of pollutant (grams of NO_x or $PM_{2.5}$) per VMT.

To calculate the emission factors for each road type by county and year, RTI obtained the emissions and VMT from EPA's MOVES3 modeling system for all 100 counties in North Carolina. RTI exported the data at the county level for the years 2020, 2030, 2040, and 2050. We combined total emissions by pollutant and all vehicle source types with total VMT by county and vehicle type and model year reported in MOVES3 output. Medium-duty vehicles were defined as weight Classes 4–7, while heavy-duty vehicles were weight Class 8.[4] The baseline emission factor for each vehicle group and county is the total emissions divided by the total VMT calculated for each vehicle group by county.

RTI did not create specific emission factors for each road type in MOVES3 because there were only five classifications, and they did not map well to the road types in the TRM. Additionally, RTI used total vehicle emissions, including start emissions, break wear, and other emissions, that may be applicable only to specific roads and conditions. We did not have data to allocate these emissions to specific roads or geographic regions, so in this analysis, we assumed they are evenly distributed across the

[4] The TRM did not include class 2B and 3 vehicles in their MHD modeling. So although ACT covers Class 2B and 3 vehicles, they were not included in this analysis; as a result, the study is likely to underestimate primary emission reductions achieved under ACT.

county. Improved data on distribution of vehicles would provide a more accurate estimate of where emissions and reductions in emissions are likely to occur.

2.1.2 Traffic Datasets and Models

To produce a spatially explicit representation of road-level emissions in road network areas, RTI used outputs from a regional travel demand model to analyze current vehicle travel conditions and future projected traffic conditions.

At the preliminary stages of our study, RTI reviewed several traffic datasets but ultimately decided that ITRE's TRM provided the greatest level of detail and best modeled projections of how traffic volumes grow over the next 25 to 30 years for MHD vehicles. Other traffic models and data sources we reviewed but chose not to include were:

- Metrolina Regional Travel Demand Model (MRM)
  - MRM was developed for the Charlotte-Mecklenburg area by the Charlotte Regional Transportation Planning Organization (CRTPO).
  - The MRM includes MHD vehicle projections.
  - However, projections were based on underlying data that are more than two decades old and based on a different state's traffic behavior.
  - CRTPO is working to incorporate TRM's methods for projecting MHD vehicles; however, the improved MRM was not available for use in the current study.
- North Carolina Department of Transportation (NCDOT) data
  - NCDOT manages the online portal with very specific traffic count data from measurements, including breakdowns by vehicle weight class.
  - MHD data were only available for about 3,000 primary roadway segments statewide.[5]
- University of Vermont Regional Travel Demand Model
  - This national-level model includes North Carolina.
  - The model was still in development and not prepared for inclusion in this study.

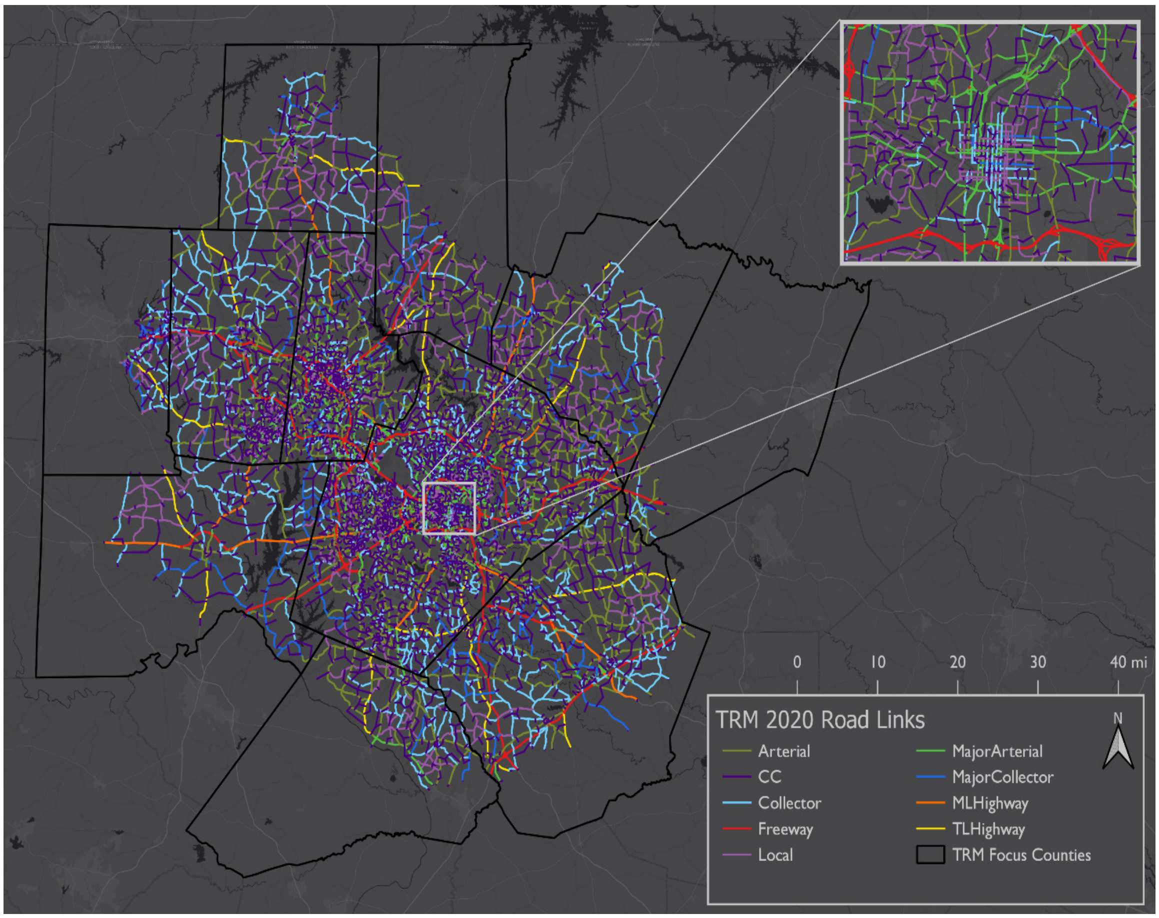
The TRM was recently updated with a new module to forecast MHD vehicle demand specific to the region and tested for validity. Because of the TRM's robust demand forecasting of MHD vehicle traffic, we decided to limit the scope of this analysis to the region covered by the TRM. Although the TRM is the best-of-practice option, it also is currently under development. At the time of our analysis, we were able to obtain only preliminary model outputs for years 2020 and 2050. Intermediate years 2030 and 2040 were interpolated from TRM outputs using the change in VMT by vehicle class from 2020 to 2050 and scaling the change based on VMT growth rates by regulatory class and county in the MOVES3 model.

The TRM includes 37,564 road segments in 11 counties. Four counties have complete coverage in the model, while the remaining seven have partial coverage. The study area accounts for roughly 19% of the 2021 state population. The model includes daily VMT by time of day for an average weekday and the portion of the traffic flow that is medium-duty (defined as weight Classes 4–7) and heavy-duty vehicles

[5] Primary roads include, for example, freeways, on- and off-ramps to other major roadways, multi- and two-lane highways, arterial roads, and connectors.

(defined as weight Class 8) for each road segment. The daily VMT for the MHD vehicles by road segment was calculated using the medium-duty flow, heavy-duty flow, total flow, and total VMT fields. The medium- or heavy-duty flow fields were divided by the total flow and then multiplied by the total VMT to calculate the daily VMT for MHD vehicles. The model includes most major roadways but does not include every minor roadway, such as small residential roads. Figure 3 shows the road links in the TRM coverage area based on the most recent version of modeled output obtained from ITRE.

Figure 3. Overview of Projected TRM Road Network, 2020



2.1.3 Power Sector Emission Modeling: Baseline Demand, Decarbonization Targets, and Assumptions

We simulated the North Carolina electricity sector using RTI's ALPSS electricity dispatch and capacity expansion model. For this analysis, ALPSS outputted the projected hourly level electricity generation by each existing and new power generation unit in Duke Energy's North Carolina service area out to 2050 by solving a cost minimization problem subject to several constraints, including demand satisfaction, generation capacity restrictions such as resource availability, and an emissions cap. Thus, using ALPSS, we can project the localized, generator-level CO_2, NO_x, and $PM_{2.5}$ emissions each hour out to the year 2050. (A detailed formulation of ALPSS can be found in Appendix C.) For this analysis, ALPSS did not solve for the new generation capacity needed to meet projected future electricity demand. Rather, we applied prespecified new generation capacity for each technology as dictated by Duke Energy's Carbon Plan (Duke, 2022) as well as from an independent analysis conducted by Synapse for the North Carolina Sustainable Energy Association (NCSEA) (Duke, 2022).

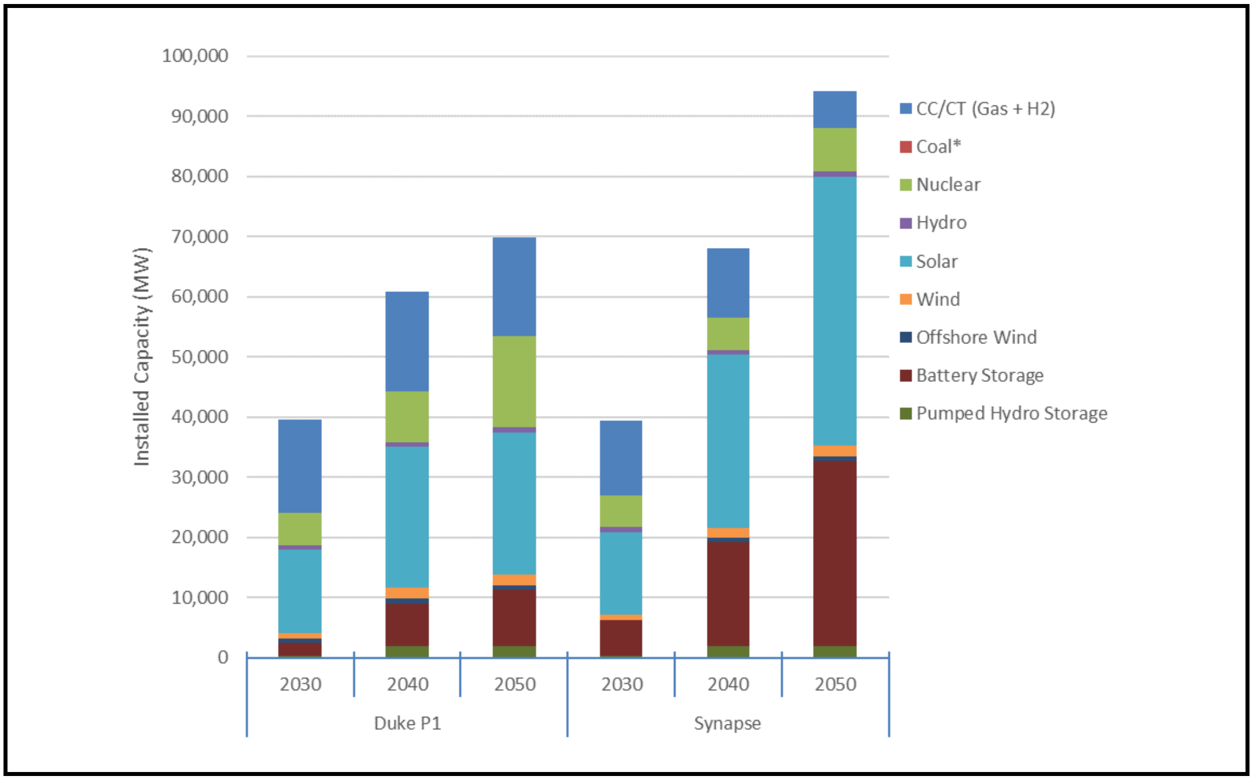
In its Carbon Plan, Duke Energy proposes four possible pathways to adhere to North Carolina's H951 (Fitch et al., 2022), which requires a 70% reduction in CO_2 emissions (relative to 2005 levels) from in-state generation by 2030 and a reduction to net-zero emissions by 2050. Our analysis focused on the first of these four Duke pathways, titled **P1** in the report, which is projected to reduce emissions the most rapidly and relies the least on speculative technology. The Duke P1 scenario specifies the exact gigawatt capacity of each technology (i.e., on-grid solar, offshore wind, battery storage, combined cycle, gas turbine, nuclear, hydropower, and pumped hydro storage) that will be online by specific years between 2022 and 2050. In our analysis, we assumed these capacity goals will be met as we examined the subannual, hourly level dispatch of electricity by each generator. In addition, we analyzed an alternative plan proposed by NCSEA, which modifies Duke Energy's Carbon Plan to achieve the same H951 emission goals while relying more on renewable generation. Here, we refer to this plan as the **Synapse** scenario. For our analyses of both the P1 and Synapse scenarios, coal retirements are dictated by Duke Energy's Carbon Plan schedule. Our model incorporated only generation capacity within Duke's North Carolina service area, so we adjusted the constraints given in the Duke and NCSEA reports by subtracting present-day capacity located in South Carolina. Table 1 provides the adjusted generation capacities used in our analysis. Note that coal generation is treated differently from other technologies. Duke's Carbon Plan defines specific retirement dates for each coal plant, and these retirements were used in this analysis; therefore, we do not represent coal as a total capacity target in Table 1. Although coal capacity is available in the system into the 2030s, it is rarely dispatched by the model, which sees other technologies as more economically viable substitutes. Table 1 shows that the P1 scenario relies more on gas and nuclear generation, while the Synapse scenario invests in more solar and battery storage. Figure 4 presents the same installed capacity assumptions by scenario and year in bar graph form.

Table 1. Total Nameplate Capacity (MW) of Duke's North Carolina Generators Used by the Model as Annual Capacity Constraints.

Technology	Duke P1			Synapse		
	2030	**2040**	**2050**	**2030**	**2040**	**2050**
Combined Cycle (CC) / Combustion Turbine (CT) (Gas + H_2)	15,552	16,552	16,352	12,452	11,652	6,052
Coal	*	*	*	*	*	*
Nuclear	5,355	8,455	15,155	5,355	5,355	7,355
Hydro	777	777	777	777	777	777
Solar	13,805	23,404	23,704	13,805	28,805	44,705
Wind	900	1,800	1,800	900	1,500	1,800
Offshore Wind	800	800	800	800	800	800
Battery Storage	2,100	7,100	9,300	5,900	17,300	30,800
Pumped Hydro Storage	334	1,934	1,934	334	1,934	1,934

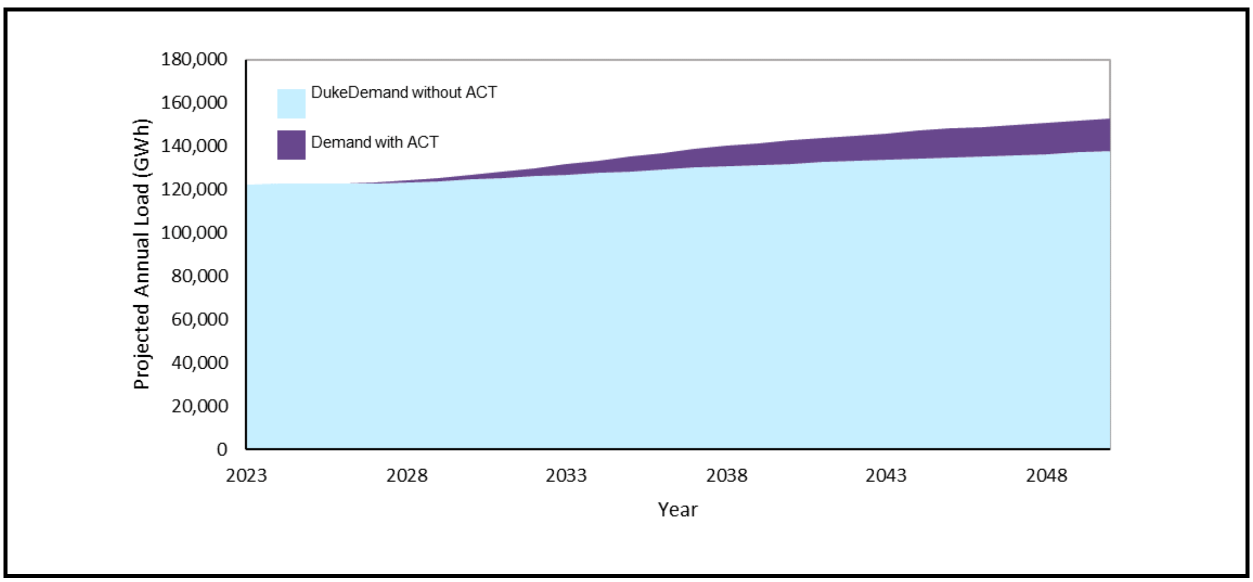
Note: Coal capacity was controlled by retiring individual plants as dictated by the Duke Energy plan rather than by constraining total capacity and, thus, is not shown in this table.

Figure 4. Total Nameplate Capacity (MW) by Scenario for Years 2030, 2040, and 2050



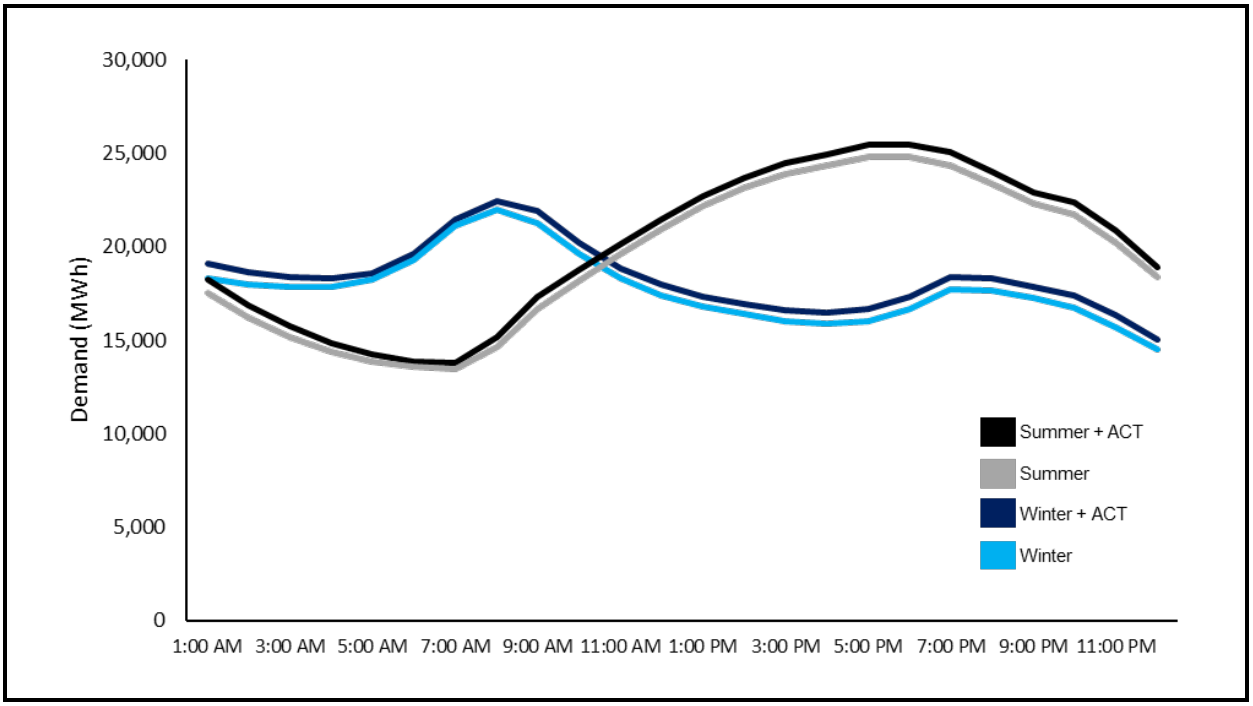
Building on the P1 and Synapse scenarios, our analysis also considered the increased electricity demand from implementing the ACT rule. To do this, we applied Duke Energy's projected electricity demand increase out to 2050, subtracted their estimated demand due to adoption of medium- and heavy-duty electric vehicles (MHEVs), and added in our estimated demand from ACT. Figure 5 shows the projected energy demand from Duke Energy's analysis without MHEVs but with our estimate from ACT.

Figure 5. Estimated Total Energy Demand: North Carolina, 2023–2050



With more MHEVs on the road, not only is annual electricity demand expected to increase, but the state's daily electricity demand profile will shift because of electric vehicle (EV) charging patterns. In particular, we assumed EV charging patterns for the MHD EV fleet based on Jenn et al. (2020), which leads to a more flattened daily load profile across the Duke Energy North Carolina service area (Figure 6). A separate study on MHEVs in California estimated a similar profile (Alexander et al., 2021).

Figure 6. Estimated Hourly Energy Demand (MWh) on Arbitrarily Selected Winter and Summer Days in 2050



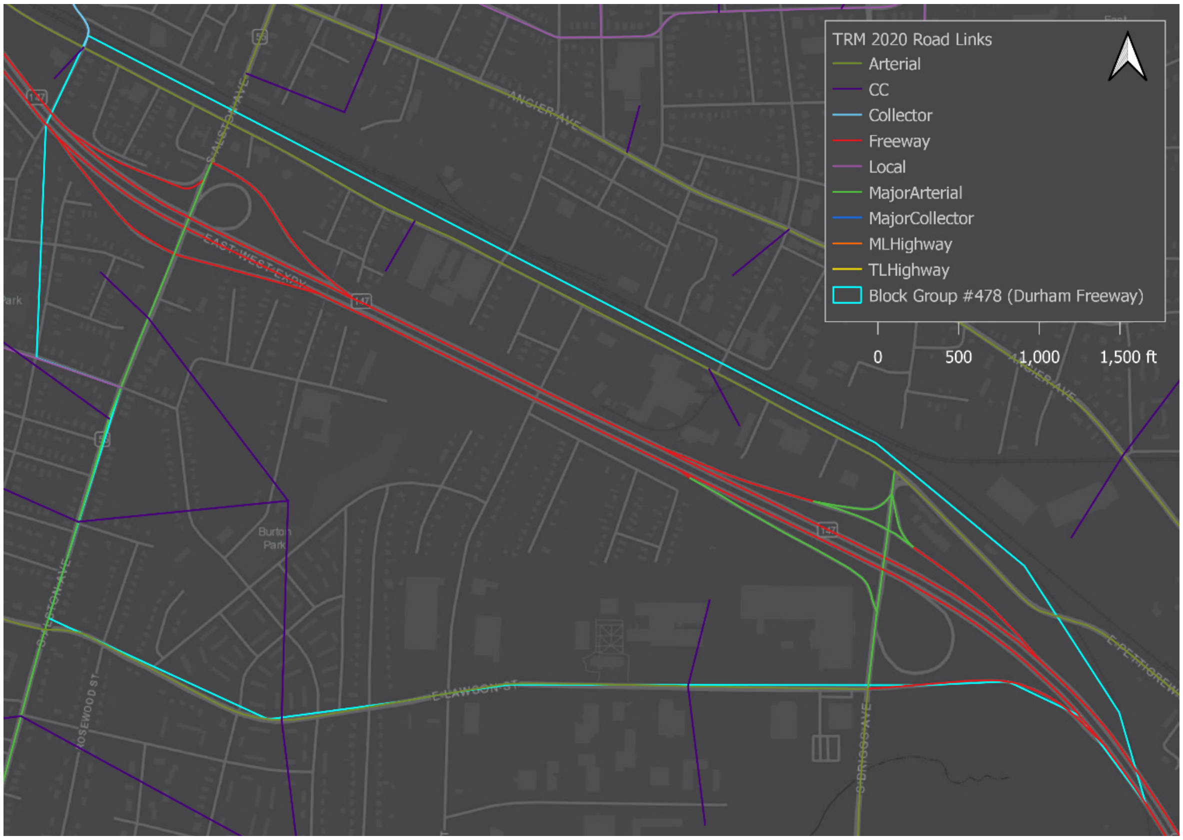
2.2 Combining to Create Geospatial Model and Visualization Tool

To quantify cumulative emissions at the block group level (Figure 7 shows an example), RTI scripted a spatial analysis workflow using Python and ArcGIS Pro. This workflow takes a block group layer and our spatial layers for MHEV and stationary source emissions to estimate the areas of impact from MHD tailpipe and power sector primary emissions and to then perform basic spatial overlap analysis of these areas with the block groups in the region of focus. This workflow allowed RTI to summarize the relationships between each individual block group and all overlapping primary emissions (road link or point source) for a single year. The steps of the workflow are detailed below, using maps of a block group located along the Durham Freeway (i.e., North Carolina Highway 147).

First, buffer layers were created for each input emission layer to create a spatial representation of the presumed area of impact through which primary emissions flow from the emission sources.[6] Based on consultation with internal experts, RTI selected 500 meters for the road link buffer distance and 10 kilometers for the point source buffer distance.

[6] RTI did not perform any spatial modeling of emission dispersion, so the analysis assumed an even distribution of emissions within each buffer.

Figure 7. Durham Freeway (Block Group 478) Local Road Network



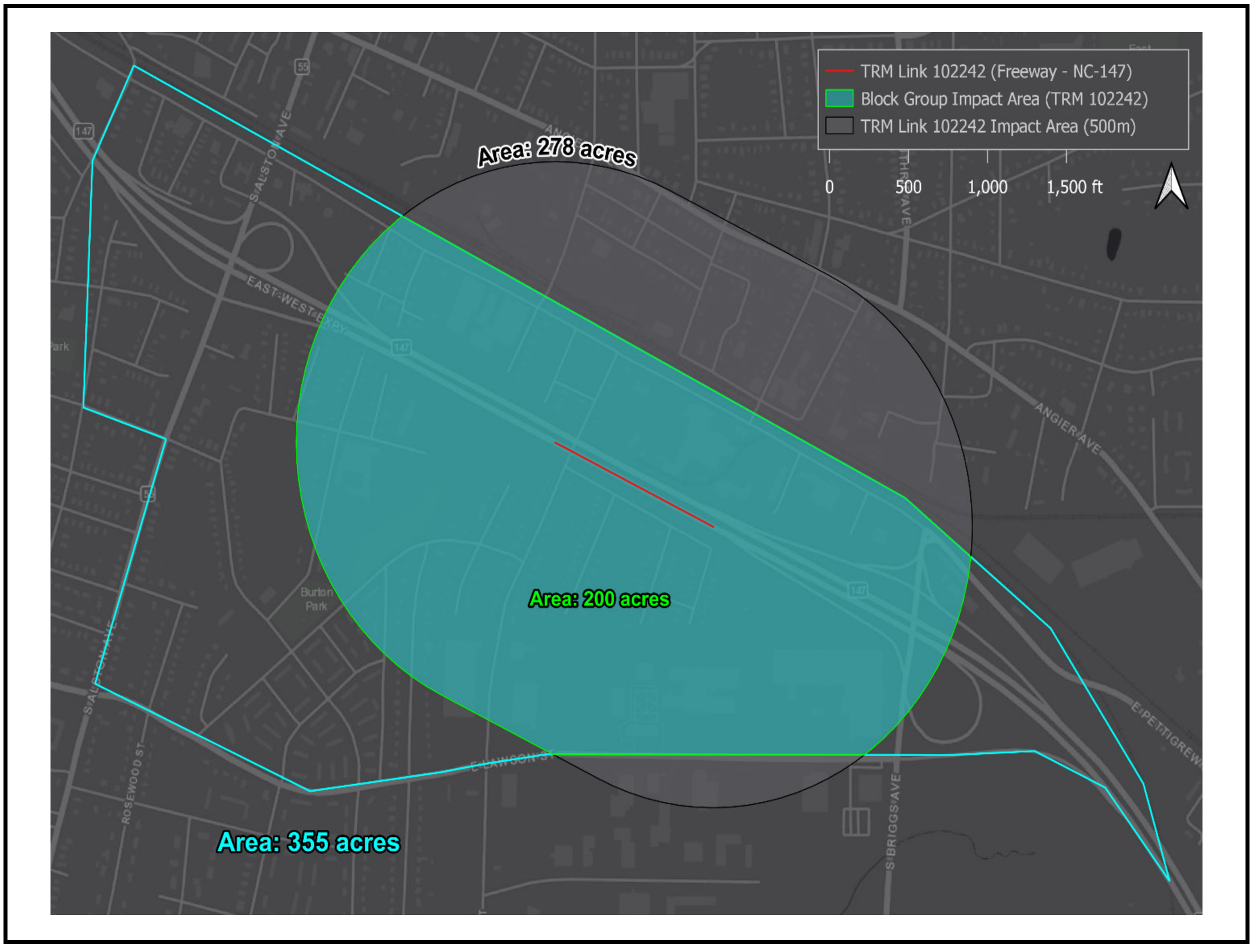
RTI assumed that the percentage of block group area covered by emission buffers equals the percentage of the block group's population that is affected. In cases where a block group's area is completely covered by emission buffers (100% areal coverage), RTI assumed that the entire population living in the block group is affected by emissions.

After the buffer layers were created, each one was passed through the spatial overlap analysis to quantify the total overlap between each emission source's impact area and each individual block group. The overlap analysis was used to estimate the proportional emissions from each road link or point source occurring within each block group by adding a portion of each source's emissions to the block group's total, based on what percentage of the source's impact area overlaps the block group. Using the same Durham Freeway block group shown in Figure 9, the emission proportion calculation is summarized in Figure 8 (basic equation) and Figure 9 (map). The road link in these figures represents a portion of North Carolina Highway 147, which has its own emissions and impact area.

Figure 8. Calculation of Proportional Emissions (one road link, one block group)

$$\frac{Area_{clipped\ buffer}}{Area_{unclipped\ buffer}} = \%_{emissions\ attribution} \quad \Rightarrow \quad \frac{200\ acres}{278\ acres} = 72\%\ of\ emissions$$

Figure 9. Durham Freeway (Block Group 478) Single TRM Link Impact Area



A separate percent-overlap analysis was performed in tandem to calculate the total affected area within each block group. These data were used to represent the share of the affected population in each block group in the absence of spatially explicit data on residential locations.

After all emission layers were passed through the analysis, the result was a block group layer with appended emission data for each decadal step and dataset covered by the inputs. These data were used to compare block groups based on their expected exposures to emissions and their demographic characteristics. Figure 10 shows the annual total $PM_{2.5}$ emissions per block group from the TRM road network in 2020. Figure 11 shows the annual total NO_x emissions for the same scale and year.

2.3 Environmental Justice Screening

EJ indices are used to understand the distribution of environmental risks among populations in a study area. This study applied the EPA's EJScreen tool to identify vulnerable communities by using race/ethnicity and poverty indicators with proximity to NO_X and $PM_{2.5}$ emission sources. These communities were characterized to provide context to the distribution of emissions among communities and ACT's impacts. Calculating the EJ index for any given indicator involves three parts: the environmental indicator, the demographic index, and the affected population (Equation 1). Values from the emission modeling of traffic and power sources were used as the environmental indicator. We calculated the EJ index for both NO_X and $PM_{2.5}$ emissions, and these values were used to inform our community impacts evaluation component, described later in this report.

Figure 10. NO_x Emissions per Block Group (tonnes in 2020)

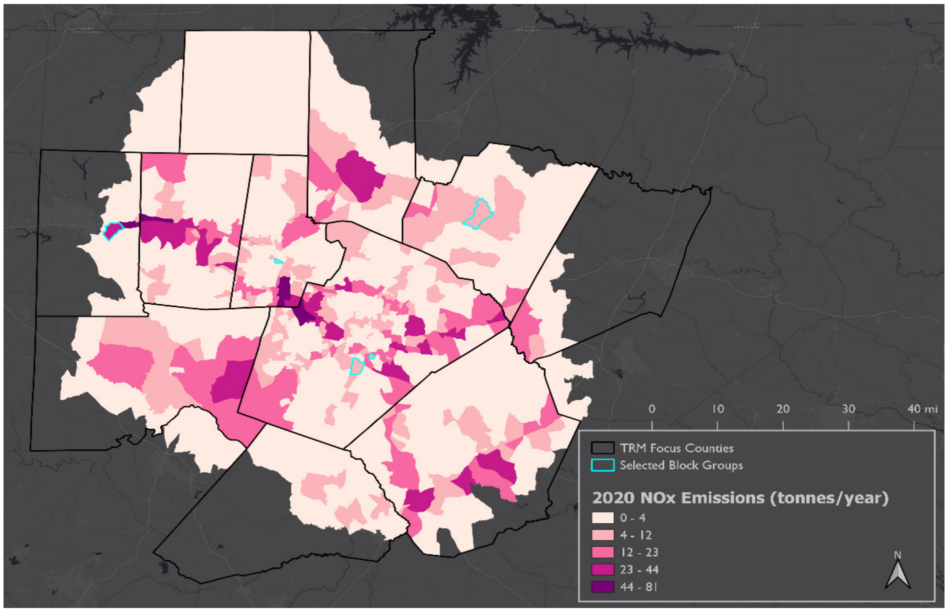
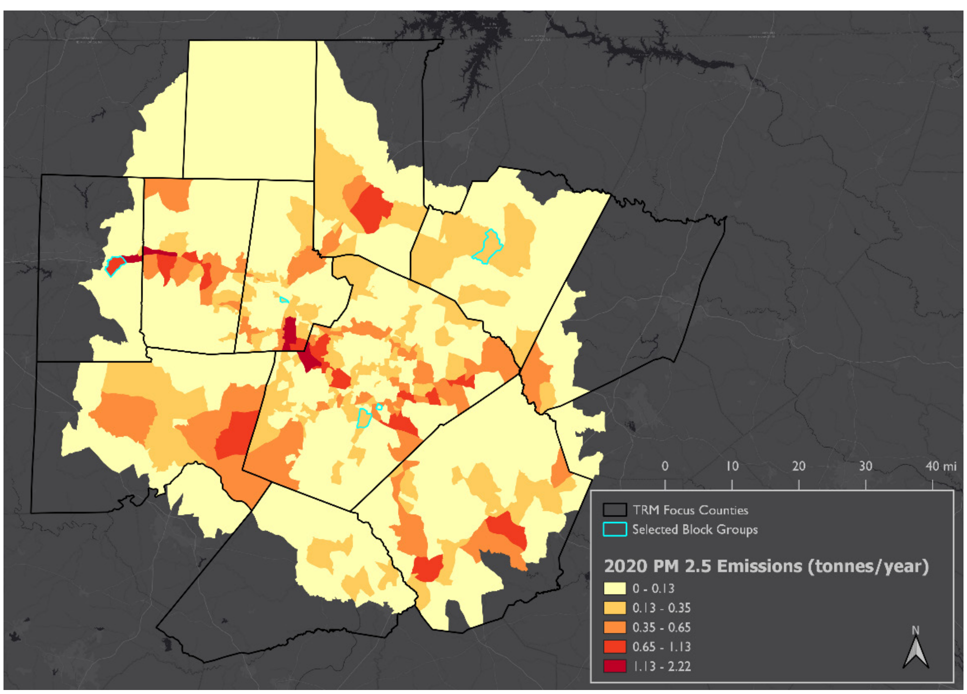


Figure 11. $PM_{2.5}$ Emissions per Block Group (tonnes in 2020)



Equation 1. Environmental Justice Index

$$EJ\ Index = Environmental\ Indicator \cdot (Demographic\ Index\ for\ Block\ Group - Demographic\ Index\ for\ State) \cdot Affected\ Population$$

The core demographic factors considered by EJScreen are low-income and non-White populations[7] (Equation 2). The demographic index is simply an average of low-income and non-White populations within a census block group to determine "potentially susceptible individuals." Data from the 2020 American Community Survey (ACS)—[2020: ACS 5-Year Estimates Detailed Tables]—at the block group level were used for this calculation.

Equation 2. Demographic Index Component of the EJ Index

$$Demographic\ Index = \frac{(\%\ MINORITY + \%\ LOW\_INCOME)}{2}$$

The affected population was determined using areal apportionment by the ratio of the area affected by emission buffers multiplied by the total population of the block group (Equation 3). This method assumed that the population is evenly distributed within each block group (Yu and Stuart, 2013).

Equation 3. Calculation of Affected Population for EJ Index

$$Affected\ Population = \frac{a_j}{A_j} \cdot Total\ Population$$

where:

a_j = area of block group overlapping the buffer zone
A_j = total area of block group

2.4 Demographic Disparities Analysis

Although the EJScreen tool provides a foundation for selecting communities of interest, a true statistical test is needed to characterize the significance of reductions with census block group percentage of race and ethnicity. A Cochran-Armitage trend test was applied to understand how emission reductions vary in relation to a variety of demographic indicators. Block groups were categorized into deciles based on the total modeled baseline emissions for medium-duty, heavy-duty, and total truck NO_X and $PM_{2.5}$ emissions. Similar to the EJ index, we assumed the population to be equally distributed among the block group (Equation 4). Block group-level data from the 2020: ACS 5-Year Estimates Detailed Tables were used for this analysis. In addition to low-income and non-White demographic indicators used in the EJ index, other common demographic indicators included educational attainment, linguistic isolation, and age. Table 2 lists the demographic indicators and their ACS source tables used in this study.

The ACS demographic data used in this study represent a static snapshot of current community demographics. Projecting how these communities are expected to change in the future is outside the scope of this study. For this reason, it is important to note that the community characteristics are assumed to be fixed into the future. Investment, job growth, and other socio-economic developments could lead to very different characterization of these communities in the future in terms of racial composition, education, age, and income.

[7] EPA's EJ Screen Demographic Index is baes on the average of two socioeconomic indicators: percent low-income, and percent non-White population. For additional details see: https://www.epa.gov/ejscreen/overview-socioeconomic-indicators-ejscreen

Table 2. Demographic Indicators and Their Corresponding ACS Source Table

Demographic Indicator	Description	ACS Table
Low Income	Households with income less than twice the federal poverty level	C17002
Non-White (Race and Ethnicity)	Individuals who are a race other than White alone and/or Hispanic or Latino	B03002
Educational Attainment	Persons aged 25 years or older whose education is short of a high school diploma	B15002
Linguistic Isolation	Households in which all members aged 14 years or older speak a non-English language and speak English less than "very well"	C16002
Age	Individuals under the age of 5 years and over the age of 64 years	B01001

Equation 4: Calculation for Affected Population and Affected Subgroup Population

$$Total\ Affected\ Population\ =\ \frac{a_j}{A_j}\cdot Total\ Population$$

$$Affected\ Subgroup\ Population\ =\ \frac{a_j}{A_j}\cdot Subgroup\ Population$$

where:

a_j = area of block group overlapping the buffer zone
A_j = total area of block group

The resulting table was run through the Cochran-Armitage trend test in R. Negative values for the z-statistic indicate that the demographic population subgroup will see greater reductions in emissions relative to the total population and vice versa. A p-value of 0.005 was used as the threshold for statistical significance.

2.5 Public Health Data

To gain a better understanding of the distribution of populations with higher respiratory vulnerability, RTI chose to collect 2018 and 2019 data on emergency department visits in North Carolina that were linked to asthma based on ICD-10-CM[8] codes. These data were obtained from the State Emergency Department Database (SEDD) housed under the Agency for Healthcare Research and Quality-sponsored Healthcare Cost and Utilization Project (HCUP). The HCUP site provides multiple script-based methods called "load programs" for parsing and interpreting their datasets, so RTI used the appropriate Stata load program for the data obtained.

Using Stata, we filtered each year of HCUP data for patients from only North Carolina and then filtered the dataset further to only include records referencing at least one asthma diagnosis. Table 3 provides the ICD-10-CM asthma diagnosis codes used for filtering the HCUP data.

Each record in the HCUP datasets includes the zip code of the visiting patient, so these records were joined to 5-digit Zip Code Tabulation Areas (ZCTA5) to enable spatial representation of the data.[9] The zip codes provided in HCUP datasets are not validated against a list of existing ZCTA5 geographies, so some

[8] International Classification of Diseases, 10th Revision, Clinical Modification

[9] The HCUP Data-Use Agreement prohibits the disclosure of information where the number of observations (e.g., number of emergency department visits) in any given cell of tabulated data is "less than or equal to 10." Zip codes with fewer than 11 visits are masked for this reason.

records are not plottable. This is because some 5-digit zip codes only exist in the U.S. Postal Service systems; these areas are not represented by publicly available ZCTA5 datasets. Figure 12 provides the cumulative count of asthma-related emergency department visits in 2018 and 2019 combined, which covers zip codes in our study area and our communities of focus based on social vulnerability. This zip code-level data can be used alongside the emission data to identify hotspots where high social vulnerability and disproportionate exposure to environmental hazards overlap.

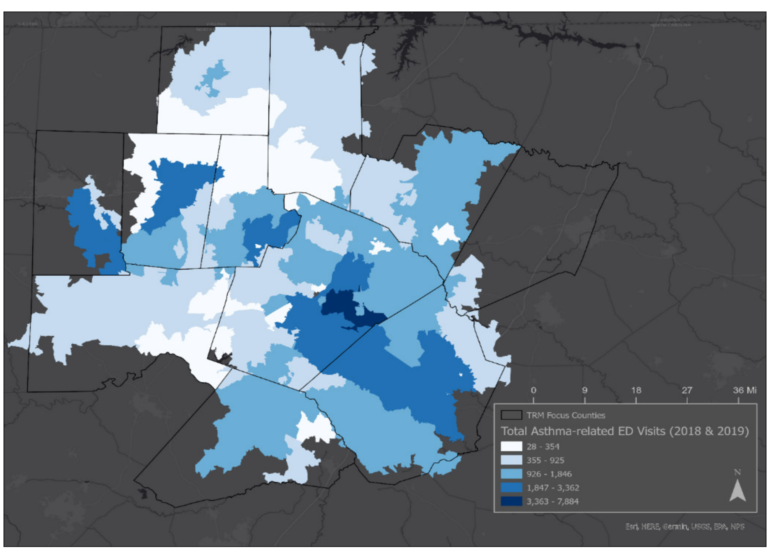
Table 3. ICD-10-CM Asthma Codes Included in HCUP Data

ICD-10-CM Code	Description
J4520	Mild intermittent asthma, uncomplicated
J4521	Mild intermittent asthma with (acute) exacerbation
J4522	Mild intermittent asthma with status asthmaticus
J4530	Mild persistent asthma, uncomplicated
J4531	Mild persistent asthma with (acute) exacerbation
J4532	Mild persistent asthma with status asthmaticus
J4540	Moderate persistent asthma, uncomplicated
J4541	Moderate persistent asthma with (acute) exacerbation
J4542	Moderate persistent asthma with status asthmaticus

ICD-10-CM Code	Description
J4550	Severe persistent asthma, uncomplicated
J4551	Severe persistent asthma with (acute) exacerbation
J4552	Severe persistent asthma with status asthmaticus
J45901	Unspecified asthma with (acute) exacerbation
J45902	Unspecified asthma with status asthmaticus
J45909	Unspecified asthma, uncomplicated
J45990	Exercise induced bronchospasm
J45991	Cough variant asthma
J45998	Other asthma

Source: HCUP SEDD – North Carolina. HCUP. 2018–2019. Agency for Healthcare Research and Quality, Rockville, MD. http://www.hcup-us.ahrq.gov/seddoverview.jsp

Figure 12. Combined Count of Asthma-Related Emergency Department Visits in 2018 and 2019



3. Impacts

AThis section presents the modeled impacts of ACT adoption on the communities included in the study area defined earlier in this report. These impacts include changes in tailpipe emissions from MHD trucks out to 2050. Additionally, we present the modeled impacts of ACT on the power sector. Finally, we characterize the types of communities that are likely to experience a disproportionate impact in terms of health benefits because of the decrease in tailpipe emissions expected under the ACT rule.

3.1 Baseline Assessment

In this section, we discuss the baseline projected emissions from both MHD trucks and the power sector. In Section 3.2, we discuss how these emission pathways are likely to change under the ACT rule.

3.1.1 Tailpipe Emissions

In RTI's first study of the impacts of the ACT rule in North Carolina, we examined the impacts of ACT at the state level. For the baseline population of vehicles, we assumed no implementation of MHD vehicles because the Energy Information Administration's (EIA's) Annual Energy Outlook baseline projections at the time for the Southeast Region were very low (under 1% by 2050). Since the previous study, Congress has passed the Inflation Reduction Act (IRA), which includes additional incentives for purchasing MHD vehicles. We were not able to find suitable estimates for the impacts of the IRA, so its impacts are not included in this study.

Section 2.2 discusses the methods we used to allocate emissions to specific road segments within our study region. This study included full coverage of four counties and partial coverage of seven additional counties. Table 4 lists the average daily emissions from each county for the road segments covered in this study based on the traffic demand modeled vehicle activity.

Table 4. Average MHD Daily Primary Emissions by County for the Study Coverage Area

County	Daily Emissions 2020 (kg)			
	mdv_nox	hdv_nox	mdv_pm	hdv_pm
Alamance	68	302	2	7
Chatham	170	547	6	12
Durham	842	1,391	28	32
Franklin	109	338	4	8
Granville	121	412	4	9
Harnett	71	139	2	3
Johnston	455	1,454	15	33
Nash	15	120	1	3
Orange	362	1,299	12	29
Person	55	112	2	3
Wake	2,675	4,356	91	100

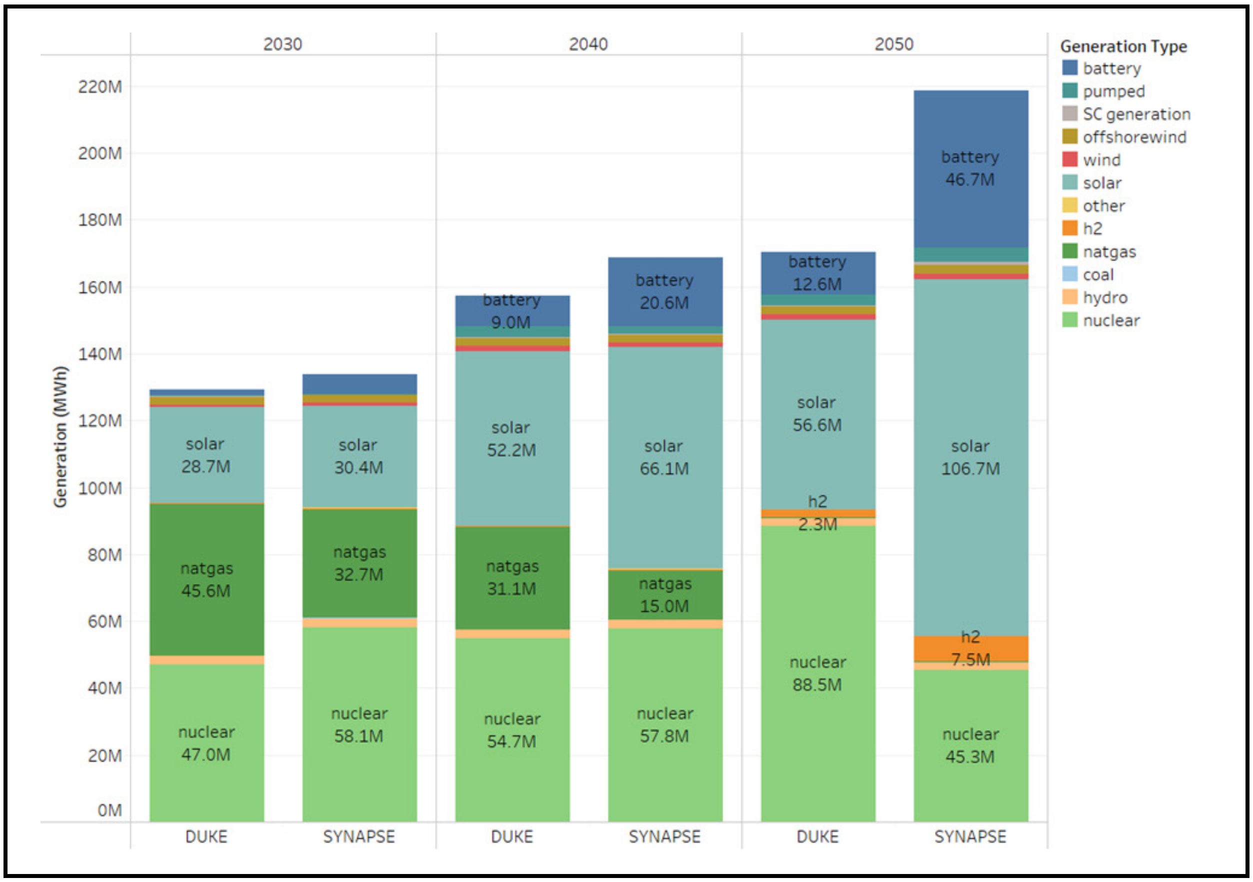
Note: Counties highlighted in yellow have incomplete coverage in TRM.

3.1.2 Power Sector

In this section, we present results from our power sector model comparing the two previously described scenarios: Duke's P1 and Synapse. In this section, we discuss the outputs that arise from using the baseline electricity demand scenario, and in the next section, the outputs that arise from the increased demand resulting from ACT.

Figure 13 shows total energy dispatch categorized by technology for both scenarios in the years 2030, 2040, and 2050. As previously mentioned, the generation capacity for each technology is determined by the constraints given in the Duke P1 and Synapse scenarios, but the ALPSS model dispatches hourly electricity freely in the least-cost manner to satisfy hourly demand. Electricity demand is projected to increase over the course of our time span, and we see that each of the scenarios is capable of producing sufficient electricity to meet this demand. However, the scenarios do so in distinct ways: Duke P1 relies more on combined cycle and combustion turbine plants in 2030 and nuclear in 2050, and the Synapse scenario builds fewer CC/CT and nuclear plants and instead emphasizes constructing and operating substantially more solar and battery storage by 2050.

Figure 13.Total Modeled Annual Generation (MWh) for the Duke P1 and Synapse Baseline Scenarios in Years 2030, 2040, and 2050



We can observe the predicted behavior of the system in greater detail in Figures 14 and 15, which show the hourly generation profile for arbitrarily selected but representative summer (July 1) and winter (February 1) days in each year. We see that in both scenarios, nuclear generators act as the primary baseload. Early in both scenarios, natural gas acts as the primary dispatchable generator, serving demand unmet by variable renewable generators. Later, gas is phased out in both and replaced by a combination of battery and, to a lesser extent, hydrogen, which is able to fill in gaps when battery storage is not sufficient to meet overnight electricity demand. However, by 2050 in the Synapse scenario, solar and battery storage are deployed much more than in Duke P1, which relies much more heavily on nuclear.

Figure 14. Daily Generation Profiles for the Duke P1 (left) and Synapse (right) Baseline Scenarios for Arbitrary Summer Days (July 1) in 2030 (top), 2040 (middle), and 2050 (bottom). Hourly demand is represented by the black line.

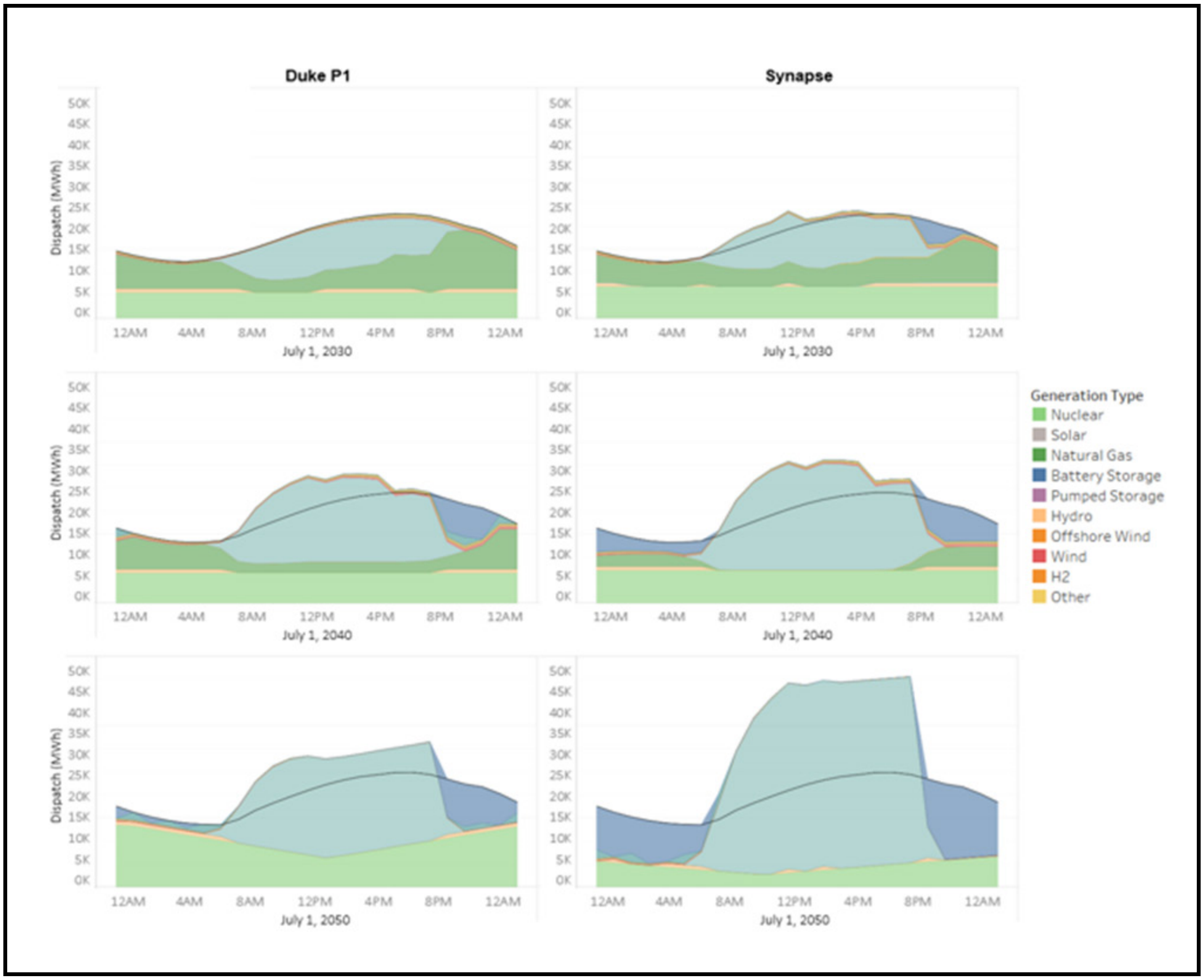
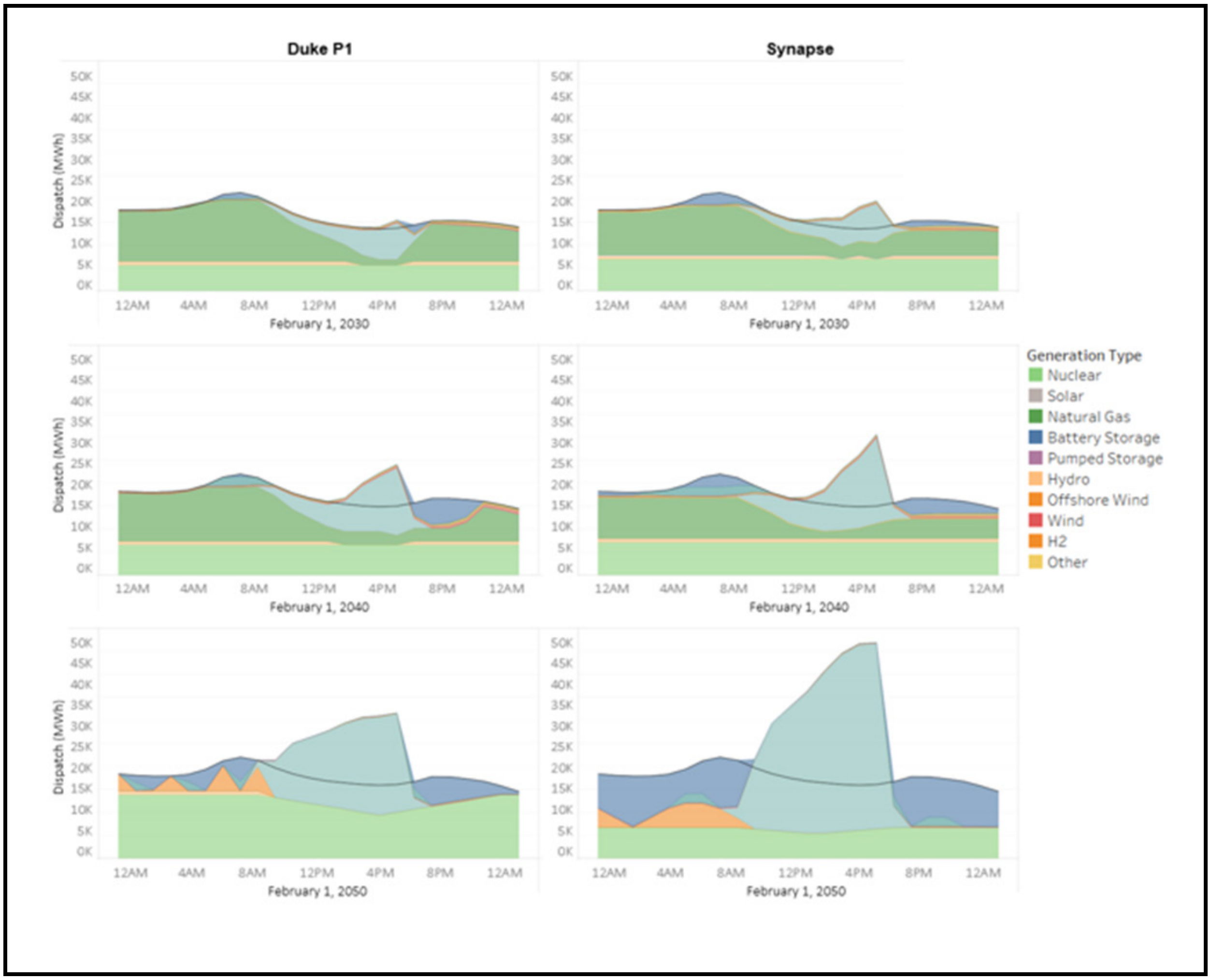
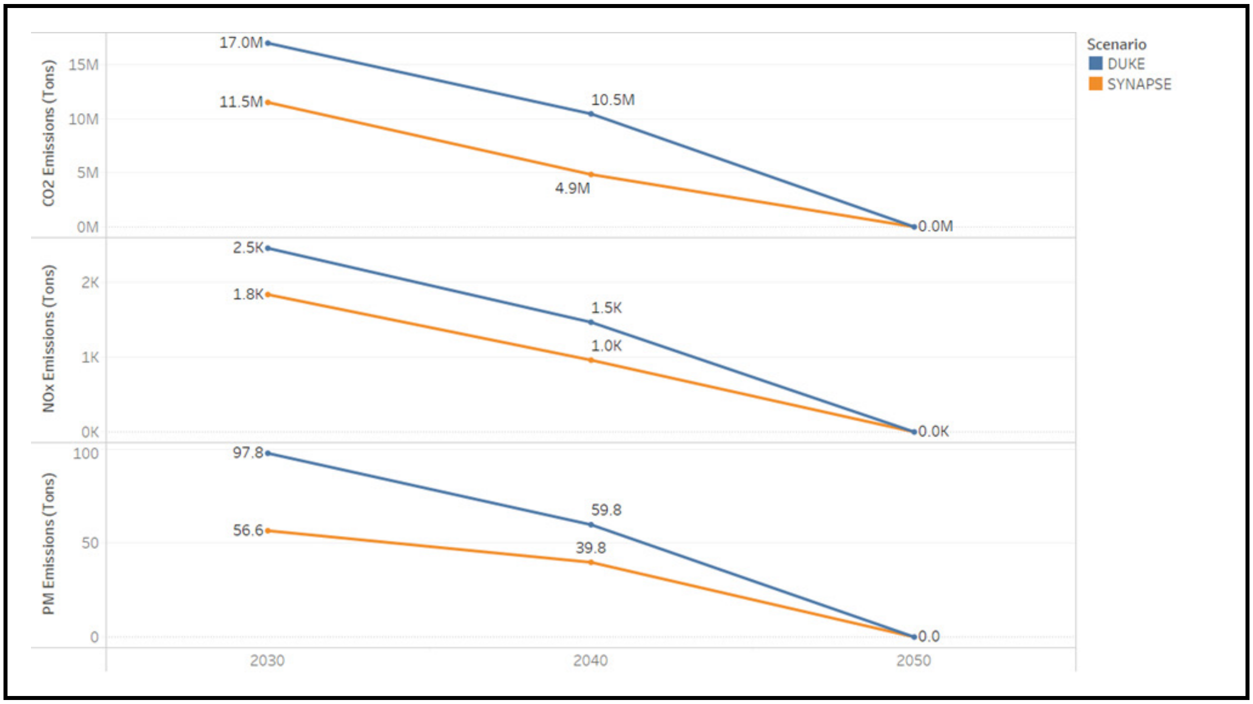


Figure 15. Daily Generation Profiles for the Duke P1 (left) and Synapse (right) Baseline Scenarios for Arbitrary Winter Days (February 1) in 2030 (top), 2040 (middle), and 2050 (bottom). Hourly demand is represented by the black line. The jagged oscillations between multiple scenarios account for the lack of sufficient battery capacity to fulfill demand for an entire night.



Lastly, Figure 16 shows the aggregated annual emissions for the two scenarios. Here, the primary focus is on three pollutants: CO_2, NO_x, and PM. H951 requires that statewide carbon emissions are reduced by 70% relative to 2005 levels by 2030 and reach net-zero by 2050. Both scenarios are able to reach these thresholds, although in different ways. The Synapse scenario—by phasing out coal sooner and not constructing additional gas plants in the coming decade—produces fewer emissions in each year until 2050, whereas the P1 scenario relies more heavily on natural gas plants in the near- and mid-term, until they are converted to hydrogen plants near 2050.

Figure 16. Total Estimated Emissions (tons) of CO_2 (top), NO_x (middle), and PM (bottom) in 2030, 2040, and 2050 from the Duke P1 and Synapse ACT Scenarios



3.2 ACT Policy Impacts

The previous section characterized the baseline projected emissions from both MHD trucks and the power sector. In this section, we discuss how these emission pathways are likely to change under the ACT rule.

3.2.1 Tailpipe Emissions

In the previous study, RTI quantified the emission impacts of implementing the ACT rule at the state level. In this study, RTI focused on showing the specific areas with the highest prevalence of MHD vehicle emissions but did not allocate the nonprimary emission benefits of policy implementation to these specific areas. Air quality modeling was beyond the scope of this study, so this study did not quantify those health benefits.

Three additional data constraints were included. First, we had only vehicle traffic by weight type in two buckets, medium and heavy duty, but not by specific regulatory class or vehicle age distribution by road type to create a more specific differentiator about which road segments would see a greater reduction in emissions because of the ACT rule.

Second, we did not have data on which regions have more traffic from vehicles sold out of state versus in state. Although some road segments, such as the I-95 corridor, will have a higher portion of out-of-state MHD vehicle traffic, we did not have a good data source to quantify that portion of the fleet. Any quantification of emission reductions would need to use a state-level emission reduction factor applied equally across all roadways.

Third, we did not have Class 2b and Class 3 data.

3.2.2 Power Sector Primary Emissions

To meet the additional ACT electricity demand, ALPSS dispatches more electricity in both the Duke P1 and Synapse scenarios relative to the corresponding baseline demand. We found that the built gigawatt capacities from the Duke P1 and Synapse scenarios are sufficient to meet this additional demand without requiring imported electricity from the neighboring South Carolina power plants. Figure 17 shows the total annual generation by technology for the P1 and Synapse scenarios using demand estimates that include ACT additional electricity demand. As expected, generation generally increases over time with increased demand; with incremental ACT demand incorporated, our results show more annual electricity generated than without ACT because of the added electricity demand from EVs. As before, Duke P1 meets this additional demand mainly with substantial new nuclear generation by 2050. While the P1 scenario also relies on new solar, Synapse generates almost two times more electricity from solar in 2050. In addition, Synapse relies on battery storage to dispatch electricity overnight as a supplement to the existing baseload.

Figure 17. Total Modeled Annual Generation (MWh) for the Duke P1 and Synapse ACT Scenarios in Years 2030, 2040, and 2050

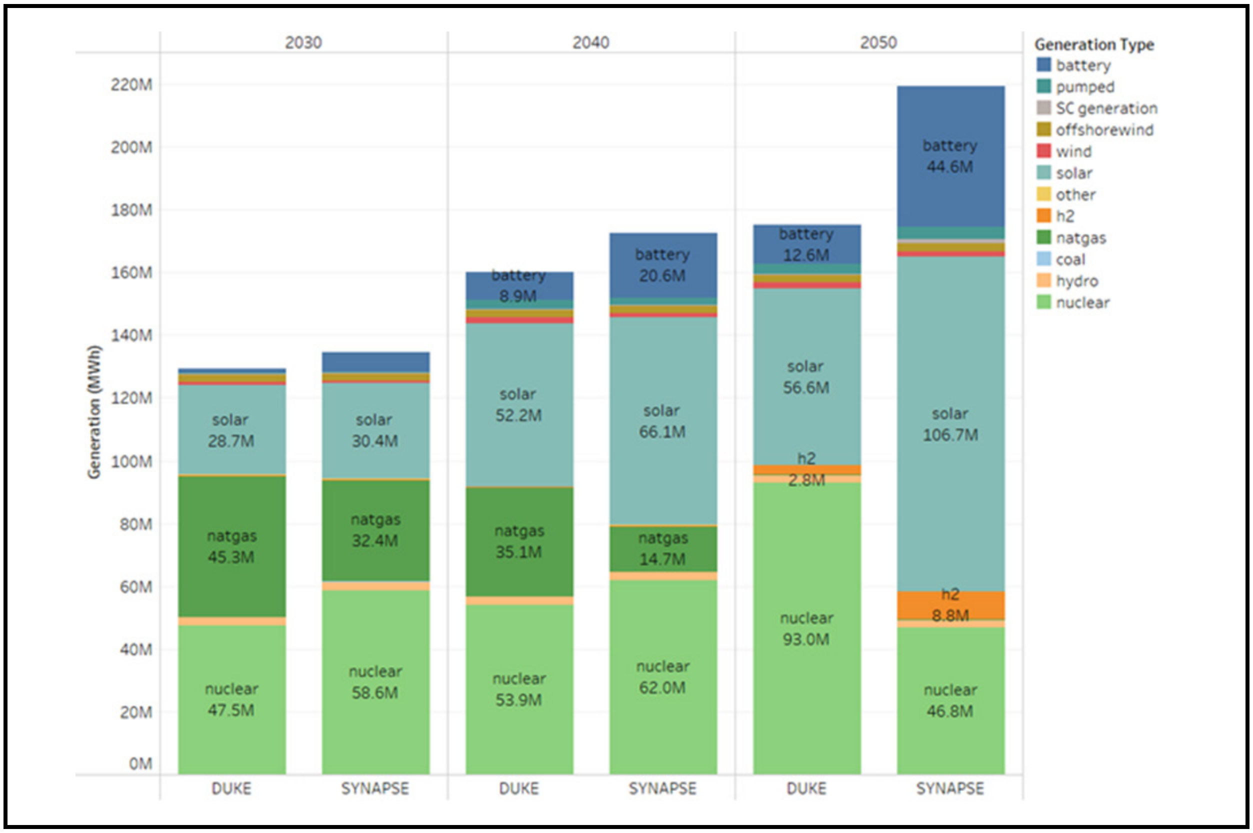


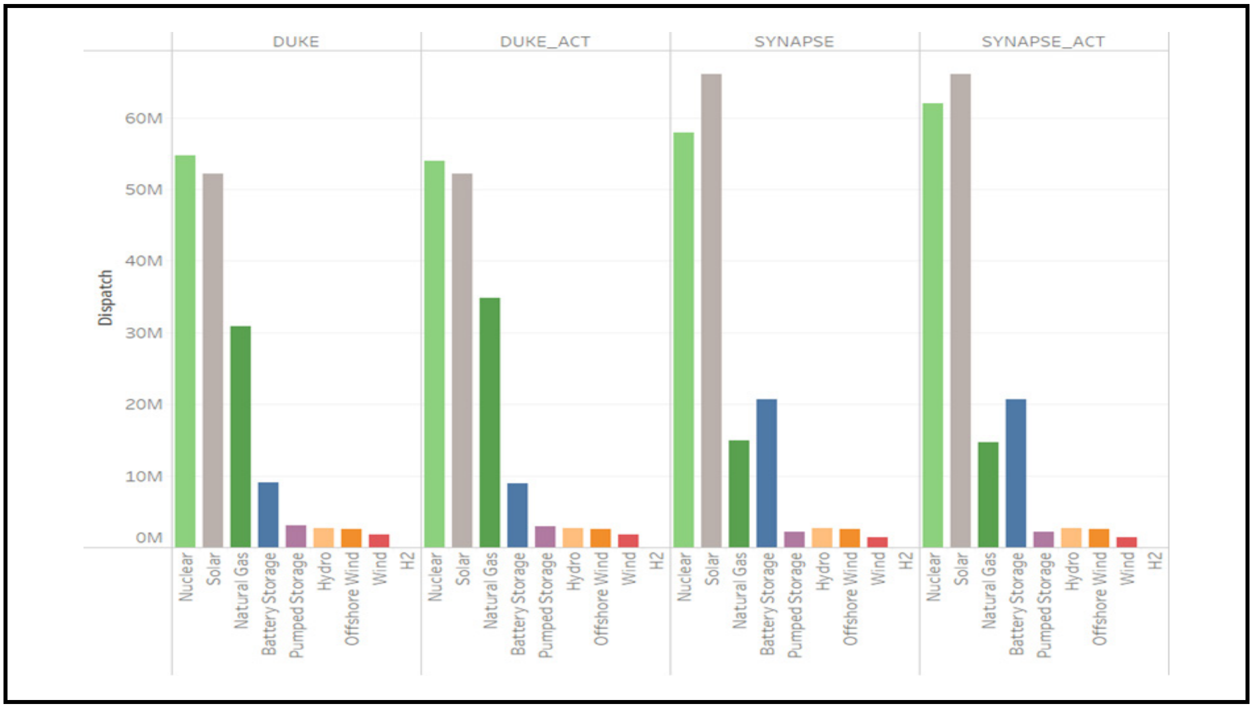
Figure 18 presents another view of the total annual dispatch by technology for each of the four scenarios in 2040 and 2050. We see that the Synapse scenario is generally able to meet demand by dispatching renewable energy or nuclear energy. In contrast, the Duke P1 scenario meets demand by dispatching mainly natural gas or hydrogen in addition to nuclear.[10] Ultimately, this results in an

[10] The ACT rule results in significant net emissions reductions under both carbon plan scenarios evaluated in this study.

increase in power sector emissions from the Duke P1 ACT scenario relative to the Duke P1 baseline scenario, especially in 2040, when the marginal demand difference is greater but most of the natural gas plants have not yet switched fuels to hydrogen (Figure 19).

Figure 18. Total Estimated Annual Generation (MWh) in 2040 and 2050 Categorized by Technology for Each of the Four Scenarios

2040



2050

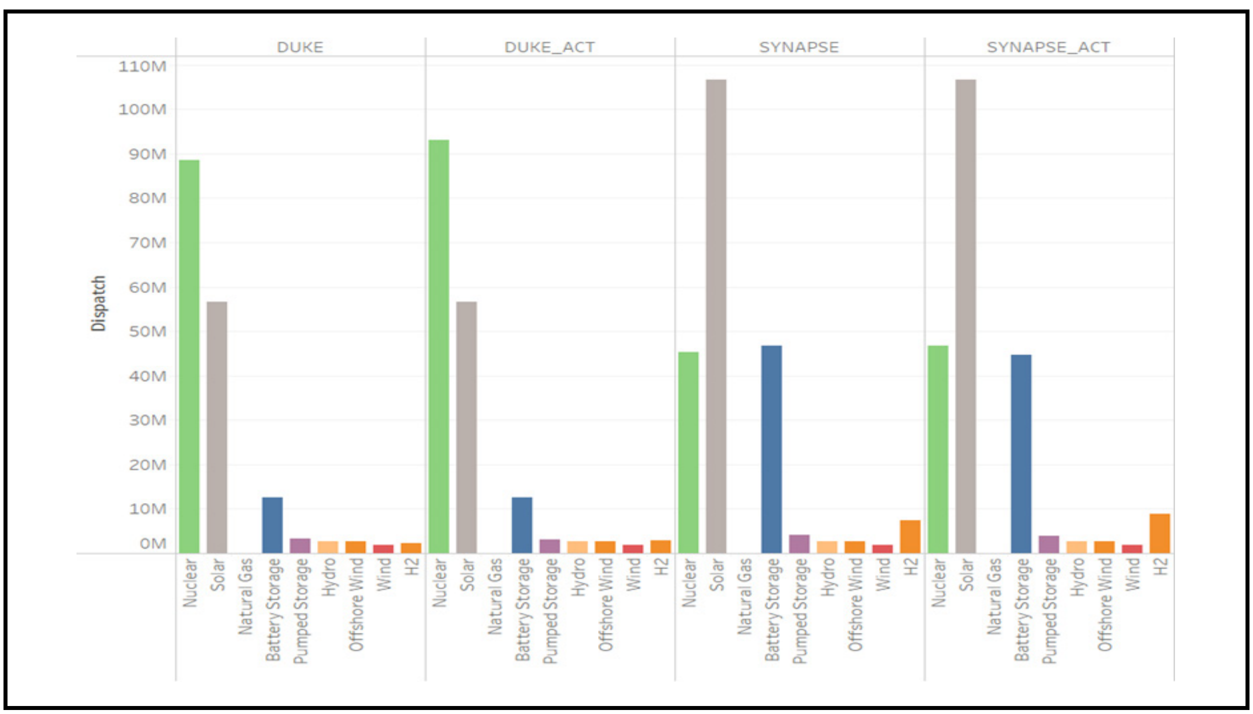
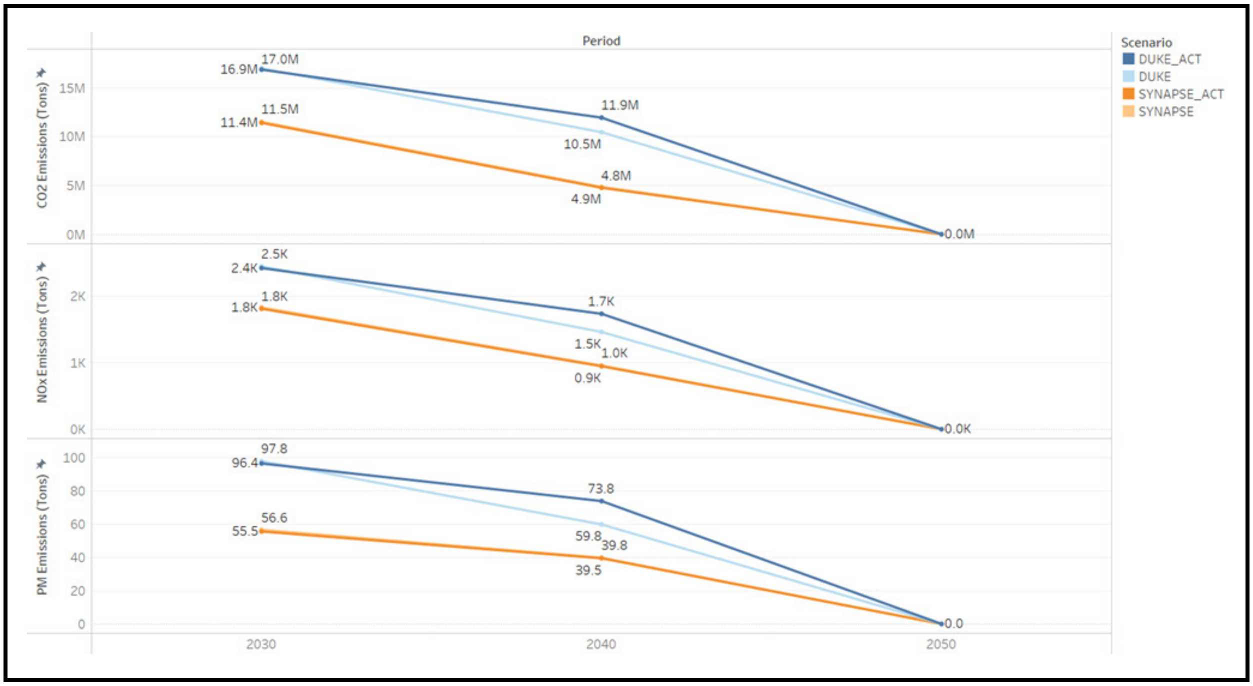


Figure 19 shows the aggregated annual emissions of CO_2, NO_x, and PM for the Duke P1 and Synapse scenarios, as well as with and without ACT additional demand. The carbon emissions still fall below the statewide targets set by H951 and reach net-zero by 2050. The Synapse scenario again produces fewer emissions across all three pollutants. In short, the Synapse scenario results in fewer emissions because of its earlier investment in emissions-free renewable technologies, i.e., solar and batteries. More importantly, this is true even with increased overall electricity demand from ACT EV adoption. Note that Synapse without ACT and Synapse with ACT emission estimates are nearly identical, so are shown as overlapping lines.

These emission estimates, disaggregated to the plant level, are used in the geospatial analyses described in the next section to project where across the state emissions may actually occur.

Figure 19. Total Estimated Emissions (tons) of CO_2 (top), NO_x (middle), and PM (bottom) in 2030, 2040, and 2050 from the Duke P1 and Synapse ACT Scenarios. The P1 and Synapse Scenarios Without ACT Incremental Demand are Also Shown for Comparison.



3.3 Communities of Focus

Earlier parts of Section 3 outline the broad impacts associated with ACT rule adoption across the defined 11-county study area. Findings from our modeling suggest that we expect to see significant reductions in NO_X and $PM_{2.5}$ over the next 25 years, and most communities in the study area in 2050 will experience a steady decline in emissions, culminating in a 61% statewide reduction in NO_x and a 73% statewide reduction in $PM_{2.5}$ from baseline emissions. Based on the strong body of evidence in the public health and air quality literature, we know that these emission reductions will yield health benefits such as reduced mortality and hospitalization related to respiratory illness for the people living in these communities.

Importantly, approximately 42% of emission reductions are concentrated in some of the most vulnerable communities, defined in terms of race, income, and education. Figure 20 depicts the major roadways in the TRM network and the block groups with the highest demographic index values, suggesting these groups are the most vulnerable communities in our study area relative to the state average. This figure highlights the relationship between traffic emissions and social vulnerability in the study area. As Figure 20 shows, areas with high road density generally coincide with areas of high social vulnerability.

In the following sections, we describe five communities of interest to better illustrate the impact ACT will have on the more vulnerable communities in our study area. The selected communities are highlighted in blue boundaries in Figure 20. Table 5 lists percentage of population across the three key demographics for the five block groups we selected to highlight the impact of ACT at a local level.

Figure 20. Major Roads and Top 30% of Block Groups by Demographic Index

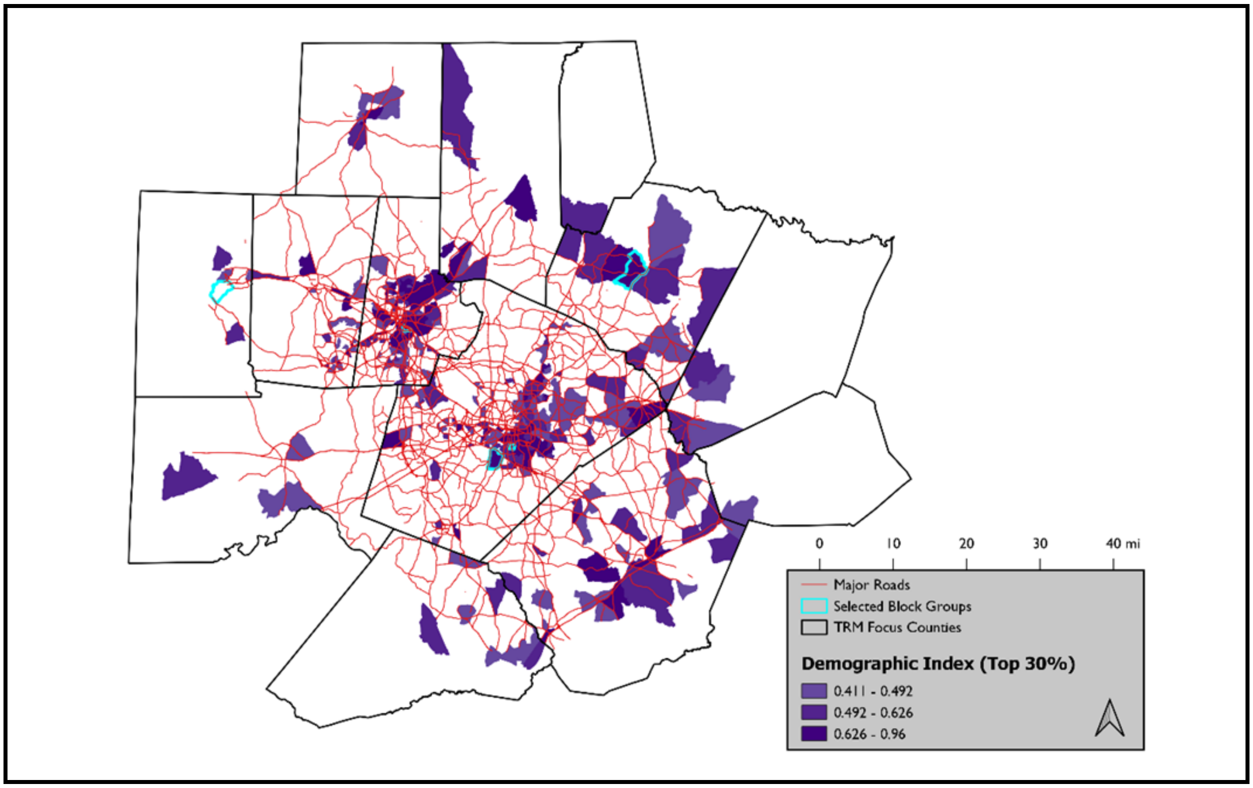


Table 5. Summary Demographic Data for Five Selected Communities

Block Group	Percent, %			
	Non-White	Low Income	Low Educational Attainment	Demographic Index
The Durham Freeway (478)	97.4	82.1	16.2	90.0
Garner Road (299)	100	54.2	19.1	77.1
Cherry Lane (655)	50.3	29.4	8.0	40.0
Louisburg (1062)	81.0	68.2	7.1	74.6
Inwood Road (1102)	63.3	71.8	9.9	67.5
Study Area Average	**37.4**	**33.0**	**11.5**	**35.2**

Table 6 presents the changes in emissions expressed in grams per day for these selected communities in 2020 and 2050 following adoption of ACT in the state. We observe over a 90% drop in $PM_{2.5}$ across all selected communities and between 70% and 85% reduction in NO_X emissions.

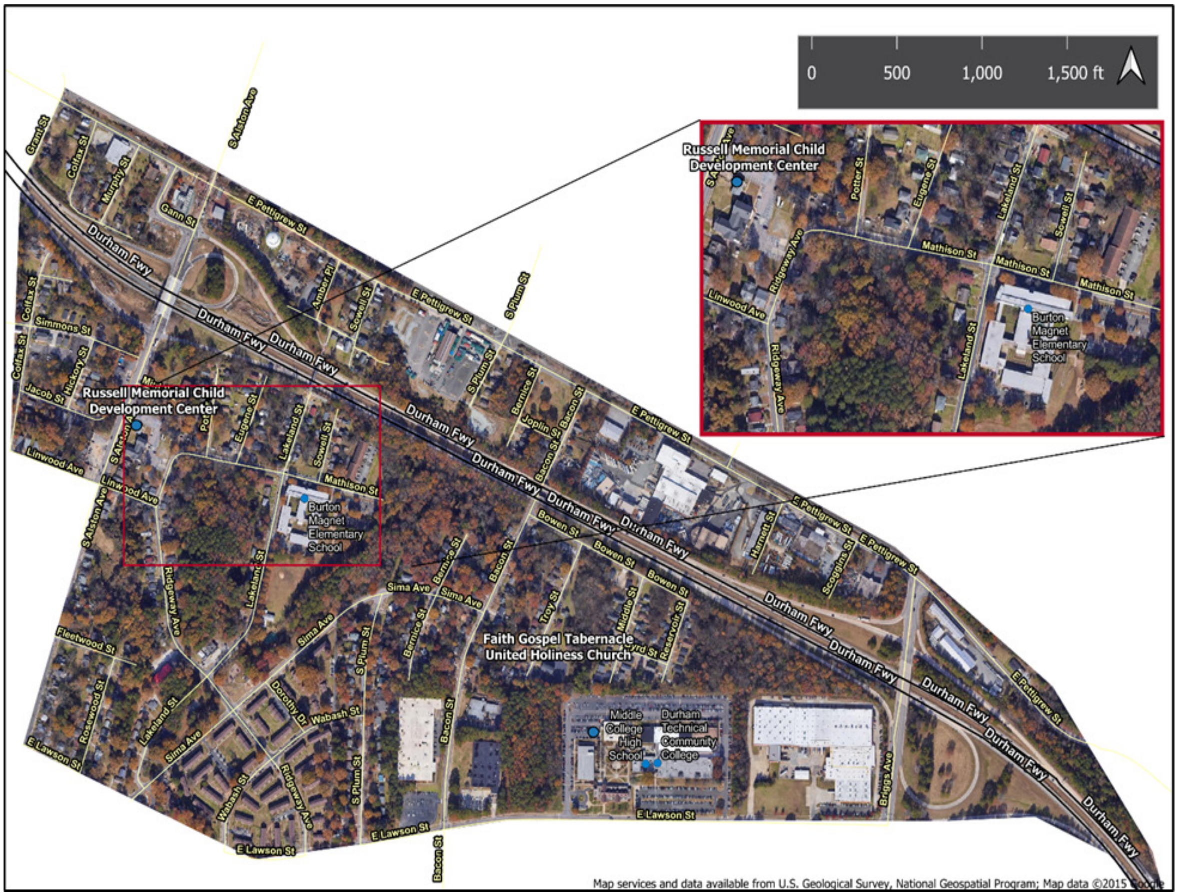
Table 6. Summary of Modeled Emissions in 2020 and 2050 for Five Selected Communities

Block Group	2020		2050		%Reduction 2020 to 2050	
	PM2.5 (g/day)	NOx (g/day)	PM2.5 (g/day)	NOx (g/day)	PM2.5 (%)	NOx (%)
The Durham Freeway (478)	471.2	16,279.5	19.9	2,473.0	-95.8%	-84.8%
Garner Road (299)	342.5	12,627.4	26.5	3,828.9	-92.3%	-69.7%
Cherry Lane (655)	1,819.2	75,241.1	150.8	22,554.1	-91.7%	-70.0%
Louisburg (1062)	556.2	21,421.9	44.8	6,055.0	-91.9%	-71.7%
Inwood Road (1102)	594.5	20,320.5	46.4	5,948.9	-92.2%	-70.7%
Study Area Average	**308.7**	**11,725.3**	**24.3**	**3,300.1**	**-92.1%**	**-71.9%**

3.3.1 The Durham Freeway: (Block Group_478)

The first community is located adjacent to North Carolina Highway 147, also referred to as the Durham Freeway. As shown in Figure 21, North Carolina Highway 147 bisects the community area. To the north of the freeway is a collection of commercial and distribution buildings. Residential communities are located south of the freeway. This area also includes two K–12 schools (Burton Elementary School and Middle College High School) and Durham Technical Community College at the southeastern edge. The community population is 97% non-White and 82% low income. Using the 2020 demographic data, this community is in the 9th decile for both NO_X and $PM_{2.5}$ emissions. In the 2050 model year, the Durham Freeway block group will have reduced NO_x emissions by 13,805.5 g/day and $PM_{2.5}$ emissions by 446.6 g/day relative to 2020 baseline emissions. These 2050 emission reductions are 86.7% higher for NO_X and 77.2% higher for $PM_{2.5}$ than estimated reductions for block groups with demographic indexes lower than the study area average.

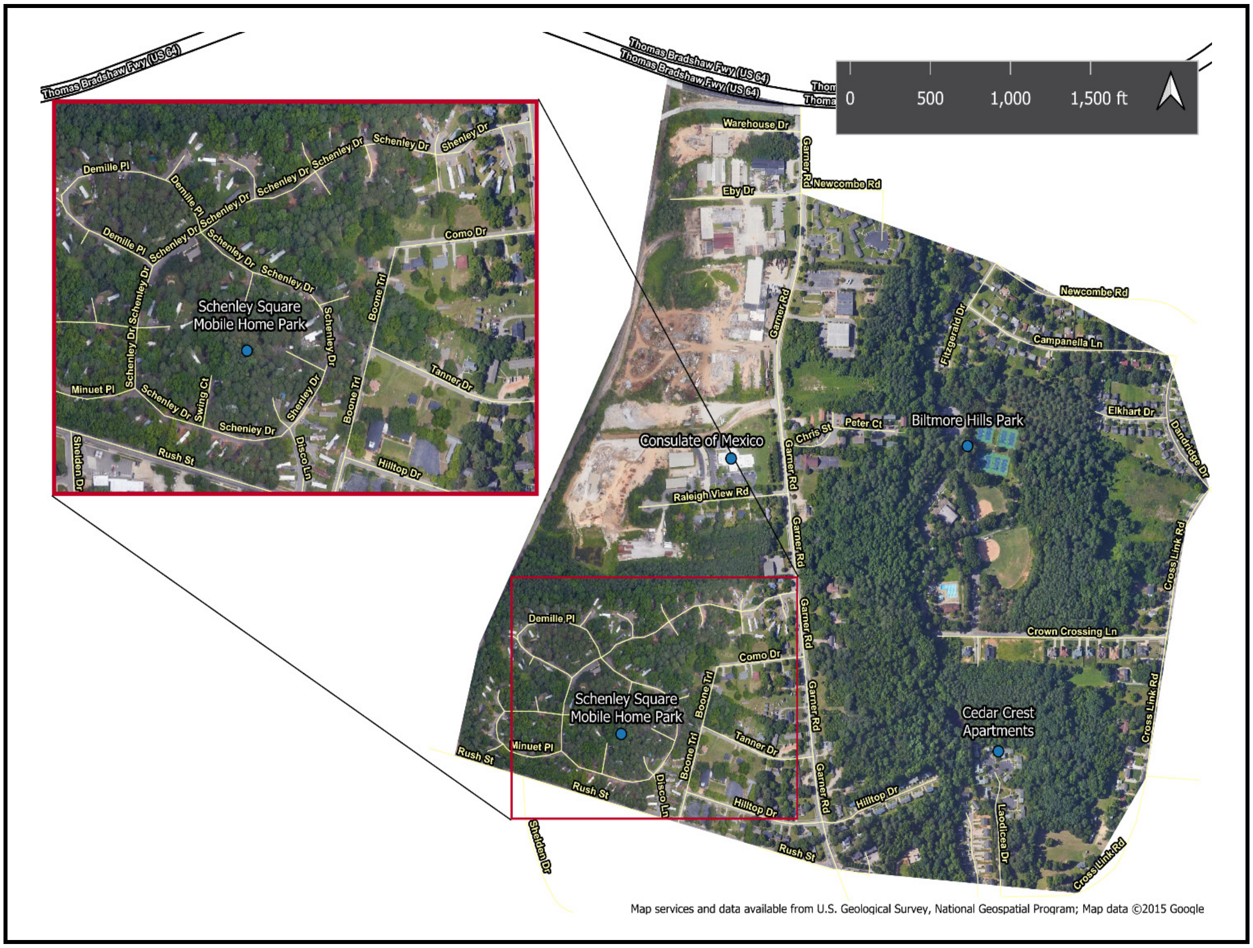
Figure 21. Durham Freeway Community (Block Group_ 478)



3.3.2 Garner Road: (Block Group_299)

Our next community of focus is the Garner Road block group located just south of downtown Raleigh and bordered to the north by the Raleigh Beltline, shown in Figure 22. The community is split into two areas by Garner Road; to the northwest are several waste management centers, while the eastern and southern areas are largely residential. Notably, a number of community centers and recreation areas are directly across from the waste management areas. The population of this block group is 100% non-White and 54% low income. In 2020, this community was within the 8th decile for total daily emissions. By the 2050 model year, the Garner Road block group will experience reduced NO_x emissions by 8,797.3 g/day and $PM_{2.5}$ emissions by 310.7 g/day relative to the 2020 baseline. These 2050 emission reductions are 18.9% higher for NO_x and 23.3% higher for $PM_{2.5}$ than estimated reductions for block groups with demographic indexes lower than the study area average.

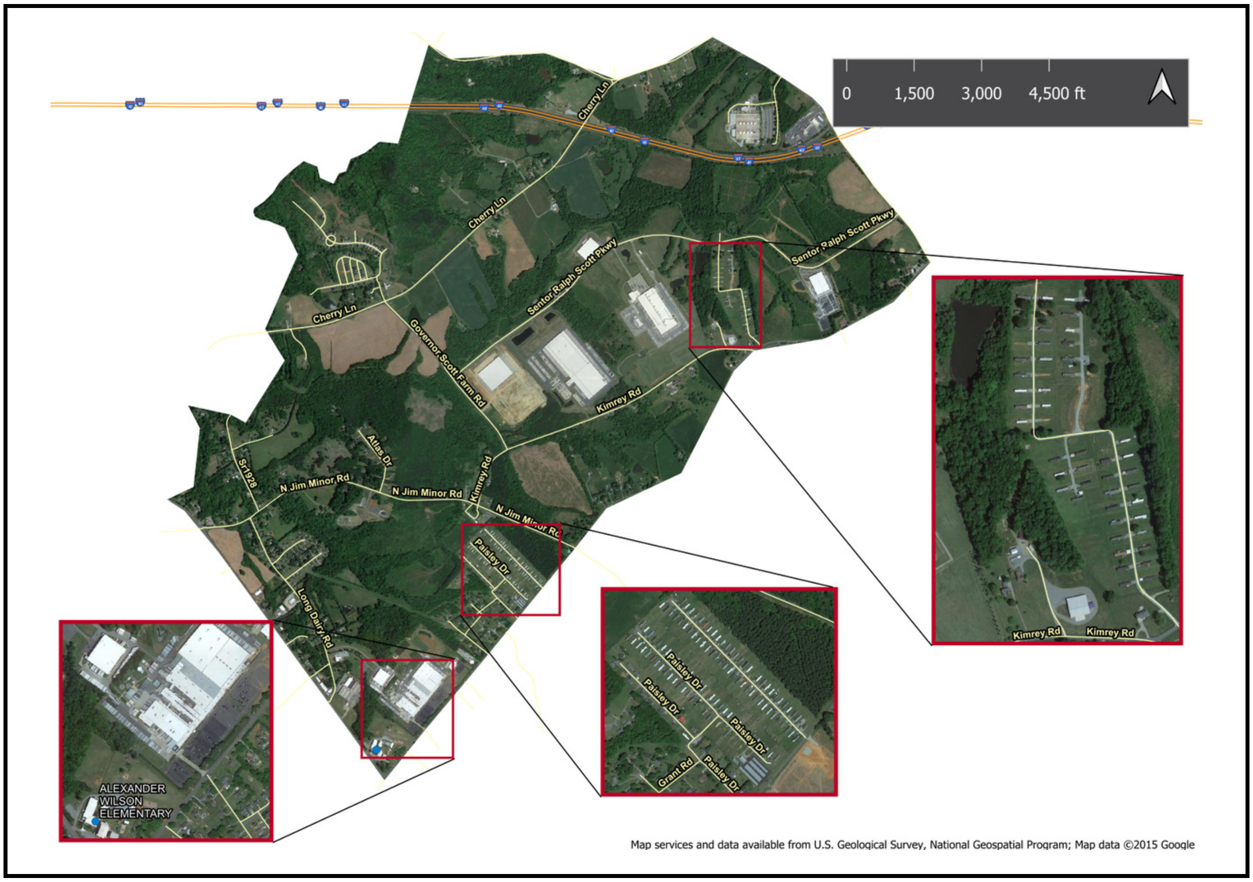
Figure 22. Garner Road Area (Block Group_ 299)



3.3.3 Cherry Lane (Block Group_655)

Cherry Lane is a community on the east side of the city of Graham. This community is bordered on all sides by major roadways, including Interstate 40, Highway 54, and Highway 119 (see Figure 23). This rural area is largely covered with agricultural or undeveloped land with few exceptions. In the center and south of the block group are several large distribution warehouses. The neighborhoods near the warehouses largely comprise mobile homes. Lastly, an elementary school is located in the southernmost corner across from a large warehouse and at the intersection of Highways 54 and 119. This community is 50% non-White and 29% low income. Cherry Lane's 2020 baseline emissions are some of the highest in the study area, falling into the 10th decile. In 2050, this community will see emission reductions of 52,693.2 g/day of NO_x and 1,638.4 g/day of $PM_{2.5}$ relative to the 2020 baseline. These 2050 emission reductions are 612.6% higher for NO_x and 650.0% higher for $PM_{2.5}$ than estimated reductions for block groups with demographic indexes lower than the study area average.

Figure 23. Cherry Lane (Block Group_655)



3.3.4 Louisburg (Block Group_1062)

This block group falls to the southwest of Louisburg, North Carolina, and is bordered to the east by U.S. 401. As shown in Figure 24, the Louisburg block group is dominated by rural and forested areas, save for a lumber yard in the center, and some commercial and residential areas to the east. Notably, the Vance-Granville Community College is located directly across from the lumber yard. This community is 81% non-White and 68% low income. Louisburg's high emissions place it in the 9th decile for 2020 daily emissions. In the 2050 model year, this community will see NO_x emissions reduced by 15,367.1 g/day and $PM_{2.5}$ emissions reduced by 501.4 g/day relative to the 2020 baseline. These 2050 emission reductions are 107.8% higher for NO_x and 98.9% higher for $PM_{2.5}$ than estimated reductions for block groups with demographic indexes lower than the study area average.

Figure 24. Louisburg (Block Group 1062)

3.3.5 Inwood Road (Block Group_1102)

The Inwood Road block group is located in Wake County to the south of Raleigh and borders U.S. 401 to the east (shown in Figure 25). This block group hosts several zones of interest, including academic, residential, agricultural, and commercial areas. Wake Christian Academy's main campus is located along the southern edge, and North Carolina State University hosts several agricultural education plots in the northwest portion of the block group. Central to the block group is the neighborhood of Inwood, comprising single-family homes. To the south of Inwood is Monk Drive, a neighborhood of mobile homes. To the east, along U.S. 401, is a large commercial zone. The Inwood Road block group is 63% non-White, is 72% low income, and falls within the 9th decile for 2020 emissions. By the 2050 model year, NO_x emissions will be reduced by 13,635.6 g/day and $PM_{2.5}$ emissions will be reduced by 539.7 g/day relative to the 2020 emission baseline. These 2050 emission reductions are 84.4% higher for NO_x and 114.1% higher for $PM_{2.5}$ than estimated reductions for block groups with demographic indexes lower than the study area average.

Figure 25. Inwood Road (Block Group 1102)

These selected communities highlight examples of how the ACT rule will lead to reductions in air pollutant concentrations in vulnerable communities. Furthermore, given these communities' proximity to existing high levels of MHD traffic, they are likely to receive a disproportionately higher level of improvements relative to the statewide average.

3.4 Distributional Analysis Results

Although the EJ index provides a descriptive assessment of selected communities, it does not enable us to describe widespread trends with any statistical backing. To that end, we performed a series of Cochran-Armitage trend tests to assess the statistical significance of disproportionate exposures to traffic emissions. The Cochran-Armitage test assessed trends between affected population subgroups and emission deciles for block groups in the entire study area. The resulting z-scores indicate whether the population subgroup is disproportionately exposed to increasing emission categories. Negative values indicate that the population subgroup is disproportionately affected. A positive value indicates that a "non-vulnerable" population is disproportionately affected.

The results of the Cochran-Armitage test (Table 7) indicate that MHD truck emissions in 2020 are disproportionately concentrated in vulnerable communities in the Triangle area. For 2020, all selected population subgroups are exposed to significantly higher emissions from MHD trucks.[11] These trends are consistent with few significant changes through 2030, 2040, and 2050 (Appendix F, Tables F-1 through F-3).

Table 7. Cochran-Armitage Test Results for Traffic Emissions in 2020

	Emissions					
	Medium-Duty Trucks		Heavy-Duty Trucks		Combined Trucks	
Population Subgroup	$PM_{2.5}$	NO_x	$PM_{2.5}$	NO_x	$PM_{2.5}$	NO_x
Poverty	−42.4	−44.2	−9.6	−12.1	−27.2	−26.2
Non-White	−77.9	−78.8	−17.6	−19.1	−45.6	−40.1
Age: Under 5 Years	−39.4	−38.6	−21.6	−21.3	−30.5	−27.5
Age: Over 64 Years	−28.8	−29.2	−15.3	−15.4	−21.8	−18.3
Limited English Proficiency	−12.6	−12.6	−2.46*	−2.70	−8.25	−7.85
No High School Diploma or Equivalent (Ages >24)	−42.3	−43.8	−42.8	−43.7	−43.6	−43.2

*Indicates a p-value greater than 0.005.

3.5 Health Impacts

Pairing demographic vulnerability values with our health data allows the identification of communities where social vulnerability, traffic emissions, and asthma prevalence coincide. The coexistence of high social vulnerability and exposure to traffic emissions presents an elevated level of risk for poor health outcomes in a large number of communities in the study area. Although this study cannot enumerate the change in health impacts, it does work to identify communities in need of further investigation.

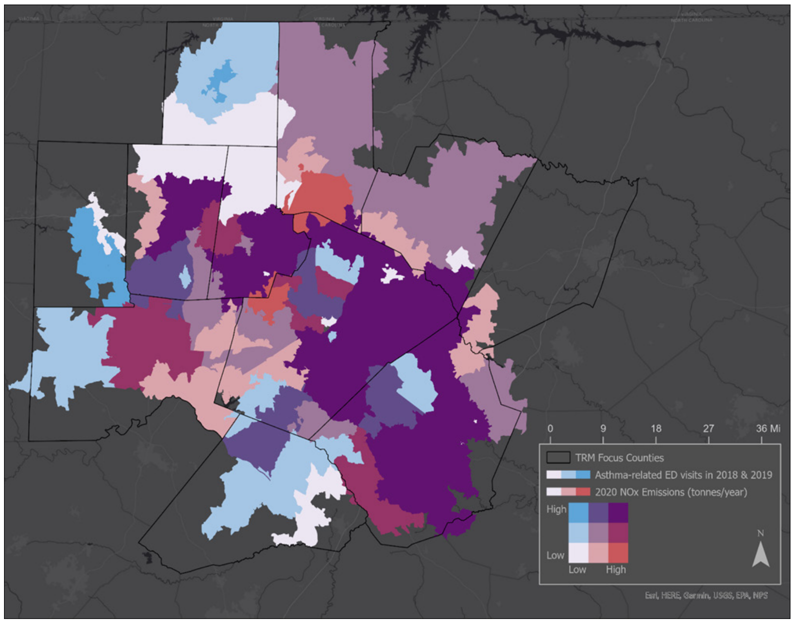
Communities experiencing both high social vulnerability and elevated environmental health risks are proposed as areas for EJ initiatives. Examples of expansions of this work might include high-resolution modeling on the distribution of traffic pollutants in socially vulnerable communities. Also, conducting a full air quality modeling study and benefits assessment would allow for the quantification of expected health benefits in each community as a result of the expected air quality improvements by way of reductions in MHDV emissions.

Overlaying our asthma-related emergency department visits on top of our study area spatial model of emissions, we can better illustrate the trends in co-location of health burden and emission concentrations in communities that rank highest in terms of social vulnerability. Figures 26 and 27 display bivariate maps showing the distribution of 2018 and 2019 asthma-related emergency department visits and 2020 emission concentrations at the ZCTA5 level for NO_x and PM, respectively. This allows us to identify areas characterized by the coincidence of tailpipe emissions and asthma-related emergency department visits and high social vulnerability. Dark purple areas represent high levels of both asthma incidence and $PM_{2.5}$ traffic emissions.

[11] This is true for combined, medium- and heavy-duty trucks for all selected population subgroups with the exception of households with limited English proficiency near heavy-duty truck emissions, where the results were not statistically significant.

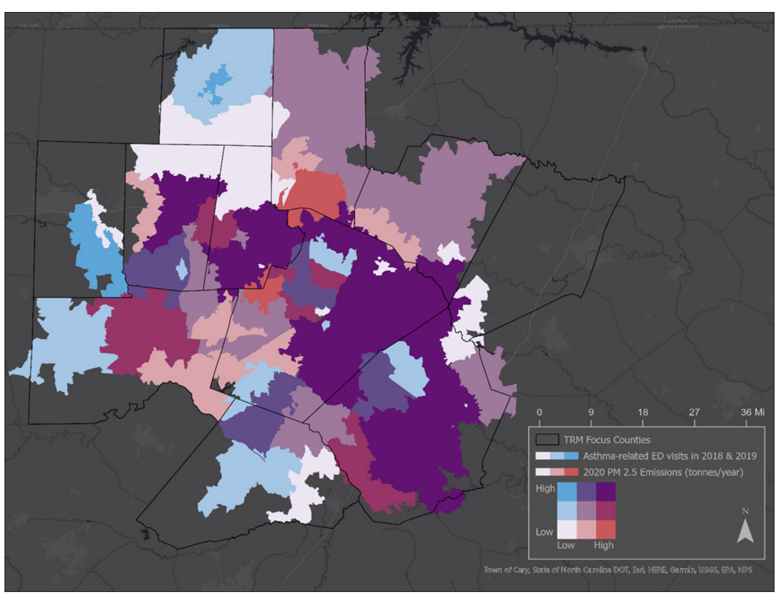
Previous studies have established a strong relationship between NOx and respiratory health issues (Boogaard et al. 2022). These areas of coincidence suggest that tailpipe emissions in Raleigh, Durham, and Smithfield are contributing to asthma-related emergency department visits.

Figure 26. Bivariate Map of 2018–2019 Asthma-Related Emergency Department Visits and 2020 NO_x MHD Tailpipe Emissions



Note: To avoid misrepresentation of the health data, we chose to drop all zip code areas with minimal emission buffer overlap (<10% of the zip code area) in the outer counties of our study area.

Figure 27. Bivariate Map of 2018–2019 Asthma-Related Emergency Department Visits and 2020 $PM_{2.5}$ MHD Tailpipe Emissions



Note: To avoid misrepresentation of the health data, we chose to drop all zip code areas with minimal emission buffer overlap (<10% of the zip code area) in the outer counties of our study area.

4. Conclusion and Discussion

Reducing emissions from the MHD vehicle fleet is important not only for reducing GHG emissions to mitigate the impacts of climate change, but also for reducing criteria pollutants to improve human health. Environmental injustice and exclusionary zoning practices have resulted in a disproportionate health burden on marginalized communities resulting from inequities in the distribution of pollution associated with MHD vehicle transport in North Carolina. The objective of this study was to analyze which communities have the highest prevalence of criteria pollutants from the MHD vehicle sector and, therefore, would likely realize significantly greater health benefits from implementing the ACT rule.

The results of this analysis show that emissions from MHD vehicles are generally more concentrated in more marginalized communities. Table 8 details the emission concentrations for the block groups in the study region grouped by demographic index quartile.

Table 8. Emission Intensity by Block Group by Demographic Index Quartile

	Demographic Index		2020 Emission Intensity ($g/mi^2/day$)				2050 Emission Intensity ($g/mi^2/day$)			
			NO_x		PM2.5		NO_x		PM2.5	
Quartile	**Min**	**Max**	**MDV**	**HDV**	**MDV**	**HDV**	**MDV**	**HDV**	**MDV**	**HDV**
1	0.00	0.171	0.78	0.42	0.0177	0.0142	0.38	0.19	0.0024	0.0018
2	0.171	0.285	0.56	0.27	0.0126	0.0093	0.27	0.12	0.0017	0.0012
3	0.285	0.451	0.82	0.34	0.0186	0.0116	0.39	0.15	0.0025	0.0014
4	0.451	0.960	1.36	0.63	0.0308	0.0215	0.65	0.26	0.0041	0.0026

MDV = medium-duty vehicle; HDV = heavy-duty vehicle.

The top 25% of block groups ranked by demographic index have a much higher emission intensity for both criteria pollutants than the block groups in the bottom half of the demographic index. The Cochran-Armitage test, detailed in Section 3.4, supports this finding, showing a strong correlation between communities of high social vulnerability and tailpipe emissions from MHD vehicles. Analyzing the demographic index and emission concentrations, we observe a clear positive relationship: high concentrations of emissions are found in communities with high social vulnerability. Figures 28 and 29 show the relationship between emission intensity and demographic index values. Both NO_x and PM concentrations are higher in communities that rank high on social vulnerability.

This study also included an updated analysis of the impacts of the ACT rule on emissions from the power sector under two scenarios: the Duke P1 and Synapse scenarios. Both scenarios showed much smaller emission increases in the power sector as a result of MHD vehicle electrification than decreases in tailpipe emissions that would result from ACT implementation statewide. The results also show that ACT under the Synapse portfolio resulted in negligible changes in power sector emissions. Duke's P1 scenario would result in slightly higher power sector emissions in 2030 and 2040 because of the increased reliance on natural gas and lower levels of solar and battery storage. Decreases in tailpipe emissions outweigh any potential increases by the power sector in years 2030 and 2040. No power sector emissions are related to ACT in 2050 under either portfolio because both plans assume that Duke Energy meets its net-zero carbon emissions 2050 goal. The localized impacts from the power sector were not included in our study region because the Synapse portfolio has negligible changes in emissions and the Duke P1 portfolio does not have any Duke-owned generation units operating in the study region after 2030. In figures 28 and 29 the colored dots represent decile bins (1 to 10) of block groups within the study area by increasing sociodemographic vulnerability.

Figure 28. Summary Plot of Block Groups by Demographic Index and NO_x Concentrations

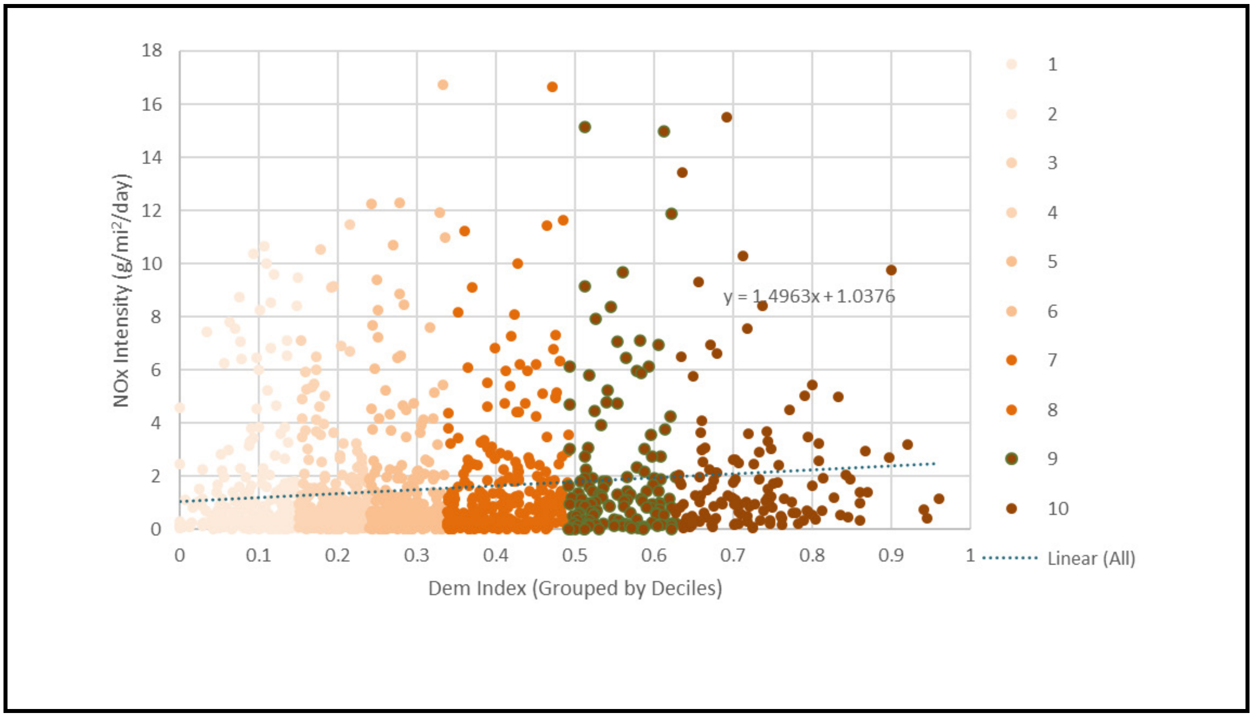
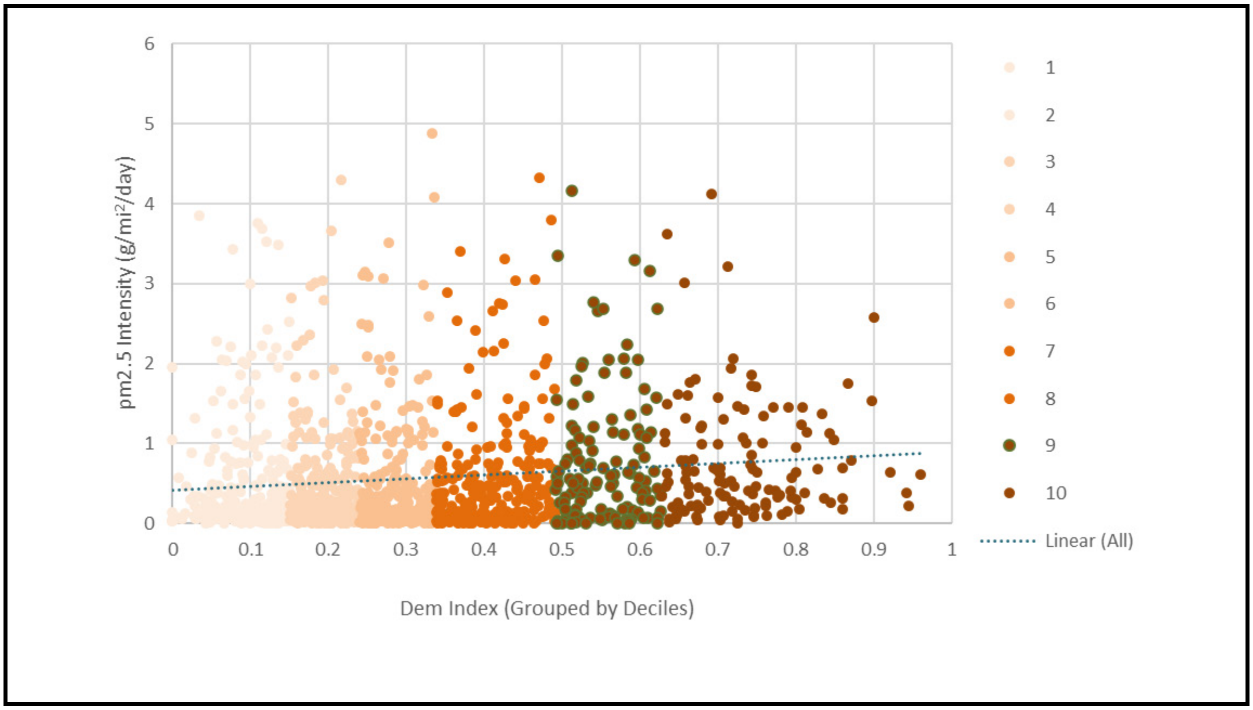


Figure 29. Summary Plot of Block Groups by Demographic Index and $PM_{2.5}$ Concentrations



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A. Environmental Justice Background and Definitions

The environmental justice (EJ) movement first gained national attention in the early 1980s as civil rights and community activists protested the dumping of hazardous waste in Warren County, North Carolina's most predominantly African American county (Mohai et al., 2009). News of the protest inspired investigations of environmental disparities and injustice around the country. The findings of these studies generally concluded that people of color, low-income people, indigenous peoples, and other historically disadvantaged communities face a disproportionately higher burden of exposure to environmental hazards. The scientific work and attention the EJ movement gained after the Warren County protests spurned political action in the 1990s. Title VI of the Civil Rights Act of 1964 (Civil Rights Act, 1964), Executive Order 12898 of 1994 (Exec. Order No. 12898, 1994), and the National Environmental Policy Act of 1970 (NEPA, 1970) now form the legal foundation for EJ requirements at federal, state, and local agencies.

The definition of EJ has changed several times since the movement first started, evolving to include a broader scope of actions and populations. The U.S. Environmental Protection Agency (EPA) currently defines EJ as "the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies" (EPA, 2022). It further defines fair treatment as meaning "no group of people shall bear a disproportionate share of the negative environmental consequences resulting from industrial, governmental and commercial operation or policies". This framework directs agencies to solicit perspectives and provide opportunities for participation during the decision-making process for communities that may be impacted by potential projects. .

It is well established in the scientific literature that emissions from pollutants are disproportionately distributed in areas with low-income and non-White populations (Finkelstein et al., 2003; Jerrett et al., 2004). In addition, these communities often suffer from a history of segregation and discriminatory policies, such as redlining, government siting decisions, and divestment of economic opportunities. These incidents stem from lack of equal protection under the law, absence of representation in decision-making agencies, and systematic, institutionalized discrimination that often disqualifies low-wealth individuals and people of color from federal funding and participation in programs to address legacy pollution.

In this investigation, a screening methodology, adopted from the EPA's EJScreen tool, was applied to identify communities with disproportionately high non-White and low-income populations located within 500 meters of roadways and 10 kilometers from energy sector point sources of NO_X and $PM_{2.5}$. This screening tool was not used to identify an "environmental justice community" but rather to serve as a starting point for characterizing how changing emission profiles will affect the air quality in communities with disproportionately large non-White and low-income populations.

B. Traffic Model Description

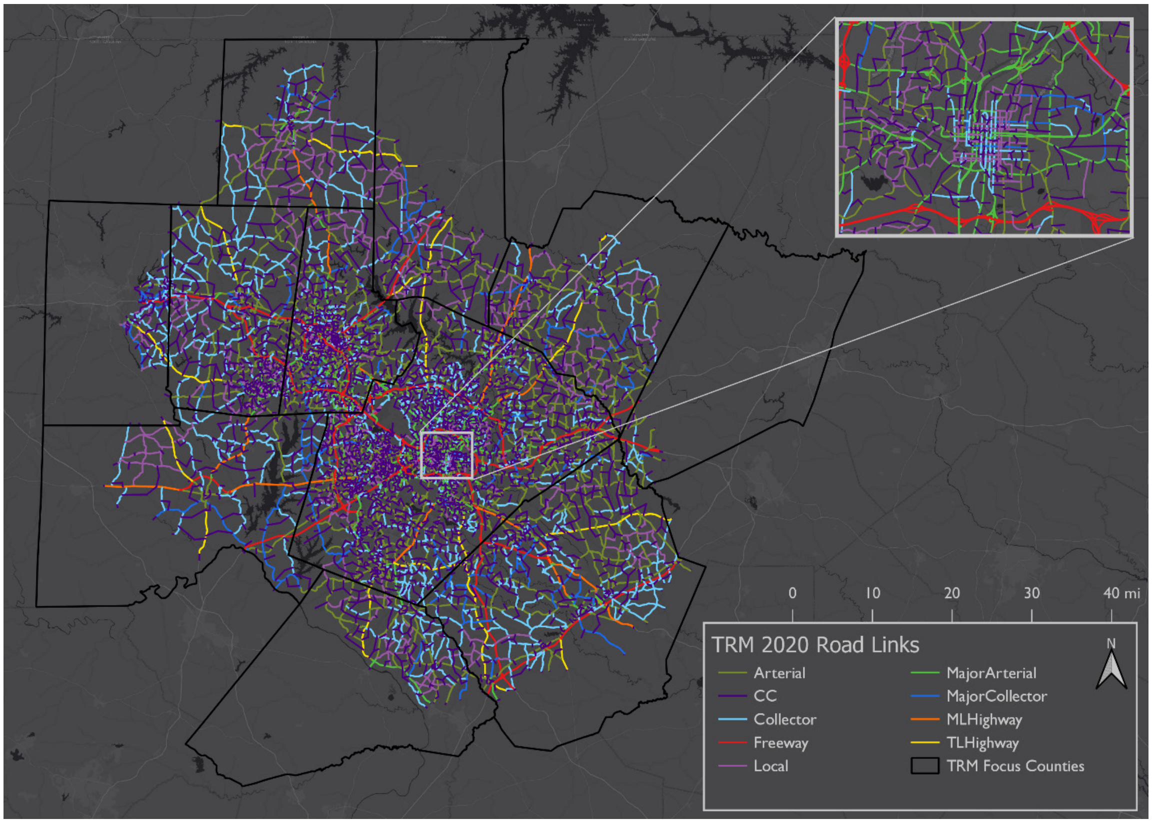
The Triangle Regional Model (TRM) is a joint project of the Capital Area Metropolitan Planning Organization, Durham Chapel Hill Carrboro Metropolitan Planning Organization, North Carolina Department of Transportation, and GoTriangle. The model was developed and maintained by the Triangle Regional Model Service Bureau (TRMSB), a team of modelers and developers within the Institute for Transportation Research and Education (ITRE) at North Carolina State University.

TRM is the travel demand forecast model for the Triangle region of North Carolina. The model covers an area that spans Chatham, Orange, Durham, Wake, and Johnston Counties, with partial coverage of Alamance, Granville, Harnett, Nash, and Person Counties. The model region covers 4,707 square miles (approximately 9% of North Carolina's total land area) and 8,066 miles of North Carolina roadways across the 11 counties.

The TRM is a state-of-practice aggregate trip-based, four-step model. Described in the most recently available model documentation (TRMSB, 2016) for TRM version 6, the model's four steps are: (1) trip generation (number of trips made and for what purpose), (2) trip distribution (where the trips go), (3) mode choice (what transportation mode is used to make the trip), and (4) trip assignment (what route and facilities are used to make the trip).

One of the advanced features of TRM is that it includes a commercial vehicle model that distinguishes MHD vehicles from light-duty passenger vehicle transportation activity. The commercial vehicle model was developed based on a 2010 commercial vehicle survey that surveyed 500 establishments that owned commercial vehicles used in the transport of goods or provided some type of service. Data collected tracked the activities and travel conducted by establishments operating single-unit and multi-unit trucks, in addition to light-duty passenger cars and trucks. Figure B-1 shows an overview of the projected TRM road network in 2020.

Figure B-1. Overview of Projected TRM Road Network in 2020



C. MOVES Data Summaries by County and Vehicle Type

Table C-1 summarizes the transportation data available in the MOtor Vehicle Emission Simulator (MOVES) and compares the vehicle miles traveled (VMT) with those included in the Triangle Regional Model (TRM) modeled outputs. We found good correlation between the two data sources except for those counties in TRM that have only partial coverage. Furthermore, Table C-1 shows that the relative split in VMT by vehicle type is consistent across the two data sources.

Table C-1. Summary of Transportation Data by County and Vehicle Type from MOVES

	MOVES			TRM		
County	MDV Percent	HDV Percent	Annual VMT	MDV Percent	HDV Percent	Annual VMT
Alamance	3%	6%	1,685,784,822	4%	5%	376,380,455
Chatham	4%	6%	1,061,696,132	5%	8%	740,302,099
Durham	4%	3%	3,245,563,288	4%	5%	3,500,100,402
Franklin	3%	5%	731,734,781	5%	6%	555,603,741
Granville	5%	7%	811,705,924	5%	8%	440,584,783
Harnett	3%	3%	1,245,583,506	5%	7%	375,494,318
Johnston	3%	5%	2,583,012,243	5%	8%	2,205,526,176
Nash	3%	10%	1,749,535,583	5%	10%	89,684,781
Orange	3%	5%	1,757,771,637	4%	7%	1,837,804,104
Person	4%	4%	322,941,160	5%	5%	215,925,754
Wake	4%	3%	10,318,338,556	4%	4%	11,405,420,141

Note: Counties highlighted in yellow have incomplete coverage in TRM.
MDV = medium-duty vehicle; HDV = heavy-duty vehicle.

D. Power Sector Model Detail

In this appendix, we first present the Accessible Lightweight Power Sector Simulation (ALPSS) mathematical formulation and then our modeling assumptions for this specific analysis.

ALPSS is a linear optimization model that is solved using the Gurobi solver. It is a reduced-form model that does not take into consideration unit commitment, power flow dynamics (e.g., AC/DC conversion), or distribution-level constraints. Through rigorous testing, we have found that the absence of these details does not have a substantial impact on outputs when examining long timescales (i.e., decades). First, we define the following dimensions of the optimization problem. Let:

- T be the set of time periods in the model. A time period t can be an hour, day, month, or year. For nonhourly runs, we defined τ as the number of hours per time period (e.g., for a daily run in the year 2023, we have $T = \{Jan\ 1, \ldots, Dec\ 31\}$ and $\tau = 24$). Similarly, let t_0 be the first time period and t_f be the final time period in the run. We also allowed the users to define subsets of time periods as follows:
  - Each technology was assigned a lag period simulating the duration of a construction project. Let T^l be the set of time periods during the lag period where new capacity is under construction and not active.
  - The user can assign a year after which investment in a certain type of generation capacity (e.g., coal) must be ceased. Let T^i be the set of corresponding time periods.
  - The user can assign a year after which all capacity of a certain type of generator (e.g., coal) must be retired. Let T^r be the set of corresponding time periods.
- N be the set of nodes or regions in the model. A node n can be a balancing authority, a North American Electric Reliability Corporation region, an interconnect, or the entire country.
- U be the set of technologies or generating units in the node. A unit u can be a generator (u in subset U^g), a fixed generator ($u \in U^f$), a storage technology ($u \in U^s$), transmission ($u \in U^t$), curtailment ($u \in U^r$), lost load ($u \in U^l$), or an import ($u \in U^i$).
- P be the set of pollutants in the model. A pollutant p can be one of CO_2, CH_4, NO_x, N_2O, SO_x, Hg, or PM.

Next, we describe the following exogenous model parameters. Let:

- $NP_{n,u}$ be the initial aggregate nameplate capacity (MW) for technology $u \in U$ in node $n \in N$. In this analysis, fossil and nuclear generators are disaggregated at the unit level, but all other technologies (e.g., solar, wind, hydropower) are aggregated at the technology level. This helps minimize the model solve time and does not substantially affect results because we are only interested in generator-specific details for fossil power plants.
- $CF^h_{n,u}$ be the historical capacity factor for technology $u \in U$ in node $n \in N$. The historical capacity factor is calculated as the annual generation by a technology as a fraction of the potential generation as defined by the nameplate capacity. This needs to be distinguished from the maximum capacity factor, $CF^m_{n,u}$, defined next.
- $CF^m_{n,u}$ be the maximum per-period capacity factor for technology $u \in U$ in node $n \in N$. Maximum capacity factor is the highest hourly historical generation achieved by a technology as a fraction of the nameplate capacity.

- $C_{n,u,t}^{f}$ be the fixed cost ($/MW) for technology $u \in U$ in node $n \in N$ at time $t \in T$.
- $C_{n,u,t}^{v}$ be the variable cost ($/MWh) for technology $u \in U$ in node $n \in N$ at time $t \in T$.
- $C_{n,u,t}^{k}$ be the capital cost ($/MW) for technology $u \in U$ in node $n \in N$ at time $t \in T$.
- $C_{u,t}^{r}$ be the retirement cost ($/MW) for technology $u \in U$ in node at time $t \in T$.
- $D_{n,t}$ be the demand or load (MWh) in node $n \in N$ at time $t \in T$. For runs at the subnational level, this demand includes an external "export demand" based on historical transmission to neighboring regions outside the scope of the model run. This is distinct from energy exports from one model region to another, which is endogenous to the model. For the North Carolina runs, we have set this export demand to be zero.
- $CT_{n,u}$ be the charging time (hours) for storage technology $u \in U^{s}$ in node $n \in N$. Note that this, along with the remaining storage-specific parameters, is currently only applicable in daily and hourly model runs.
- $E_{n,u}$ be the round-trip efficiency (%) for storage technology $u \in U^{s}$ in node $n \in N$.
- $Y_{n,u}$ be the decay rate (%) for storage technology $u \in U^{s}$ in node $n \in N$.
- RR_{u} be the ramp rate (hours) for generating unit $u \in U^{g}$. This parameter is only relevant for hourly runs at the individual generator level.
- $F_{n,u,p}$ be the emission factor (tons/MWh) for pollutant $p \in P$ from generating unit $u \in U^{g}$ in node $n \in N$.
- $PC_{t,p}$ be the system-wide pollution cap for pollutant $p \in P$ in period $t \in T$.

Finally, we define the following decision variables in the model. Let:

- $X_{n,u,t}$ be the dispatch (MWh) by a technology $u \in U$ in node $n \in N$ at time $t \in T$. For generation technologies, this dispatch represents the amount of energy generated by that technology; however, the variable also applies to battery charging, curtailment, and transmission, so we will refer to this variable as dispatch rather than generation. Note that for storage technologies $u \in U^{s}$, this variable contains multiple series of values: one for charging and one for discharging. We will represent the discharging variables as with other energy generating technologies. For charging, we add a superscript i: $X_{n,u^{i},t}$.
- $I_{n,u,t}$ be the investment or added capacity (MW) for technology $u \in U$ in node $n \in N$ at time $t \in T$. Investment can be manually set to be zero to disable capacity expansion in model runs.
- $R_{n,u,t}$ be the retirement of existing capacity (MW) for technology $u \in U$ in node $n \in N$ at time $t \in T$. Retirement can be manually set to be zero to disable capacity expansion in model runs.
- $S_{n,u,t}$ be the energy stored (MWh) by storage technology $u \in U^{s}$ in node $n \in N$ at time $t \in T$.

Given these sets, parameters, and decision variables, we can now define the model.

$$\sum_{n,u,t} C^f_{n,u,t}\left(NP_{n,u} + I_{n,u,t} - R_{n,u,t}\right) + \sum_{n,u.t} C^v_{n,u,t}X_{n,u,t} + \sum_{n,u,t} C^k_{n,u,t}I_{n,u,t} + \sum_{n,u,t} C^r_{u,t}R_{n,u,t} \qquad (1)$$

s.t.

$D_{n,t} - \sum_{u} X_{n,u,t} = 0$	$\forall n \in N, t \in T$	**(2)**
$X_{n,u,t} \leq \tau\left(NP_{n,u} + I_{n,u,t} - R_{n,u,t}\right)CF^m_{n,u}$	$\forall n \in N, u \in U^g \cup U^f, t \in T$	**(3)**
$X_{n,u,t} \leq \tau\left(NP_{n,u} + I_{n,u,t} - R_{n,u,t}\right)$	$\forall n \in N, u \in U^s \cup U^t \cup U^i, t \in T$	**(4)**
$\sum_{t} X_{n,u,t} \leq \tau\left(\sum_{t} \left(NP_{n,u} + I_{n,u,t} - R_{n,u,t}\right)\right)CF^h_{n,u}$	$\forall n \in N, u \in U^g$	**(5)**
$\left\lvert X_{n,u,t+1} - X_{n,u,t}\right\rvert \leq \frac{\left(NP_{n,u} + I_{n,u,t} - R_{n,u,t}\right)}{RR_u}$	$\forall n \in N, u \in U^g, t \in T$	**(6)**
$I_{n,u,t} = 0$	$\forall n \in N, u \in U, t \in T^l \cup T^i$	**(7)**
$\left(NP_{n,u} + I_{n,u,t} - R_{n,u,t}\right) = 0$	$\forall n \in N, u \in U, t \in T^r$	**(8)**
$S_{n,u,t} \leq \left(NP_{n,u} + I_{n,u,t} - R_{n,u,t}\right)CT_{n,u}$	$\forall n \in N, u \in U^s, t \in T$	**(9)**
$S_{n,u,t+1} = S_{n,u,t}\left(1 - \tau Y_{n,u}\right) + E_{n,u}X_{n,u^i,t} - X_{n,u,t}$	$\forall n \in N, u \in U^s, t \in T$	**(10)**
$S_{n,u,t} = 0$	$\forall n \in N, u \in U^s, t = \{t_0, t_f\}$	**(11)**
$\sum_{n,u} X_{n,u,t}F_{n,u,p} \leq PC_{t,p}$	$\forall t \in T, p \in P$	**(12)**
$X_{n,u,t} \geq 0$	$\forall n \in N, u \in U^g \cup U^f \cup U^s \cup U^t \cup U^i \cup U^l, t \in T$	**(13)**
$X_{n,u,t} \leq 0$	$\forall n \in N, u \in U^r \cup U^{s_i} \cup U^{t_i}, t \in T$	**(14)**
$I_{n,u,t} \geq 0, R_{n,u,t} \geq 0$	$\forall n \in N, u \in U, t \in T$	**(15)**
$S_{n,u,t} \geq 0$	$\forall n \in N, u \in U^s, t \in T$	**(16)**

Equation 1 describes the objective function. Our optimization is a cost minimization problem. The total system cost is the sum of fixed costs of operating a plant of a certain capacity, variable costs of generation and operation, capital costs from investments in new capacity, and retirement costs from decommissioning existing capacity.

Equation 2 is our network flow constraint. The demand in each node in each time period must be satisfied by some combination of electricity generation, discharging of energy storage technologies, transmission from adjacent regions, and imports from outside of the system or declared to be lost load.

Equations 3–6 constrain the generating units. For generators and fixed generators, dispatch must be less than the product of nameplate capacity and the maximum per-period capacity factor. Storage technologies, transmission, and imports are not constrained by these capacity factors. Equation 5 introduces a separate capacity factor, which is used to constrain the average of dispatch for generators. This historical capacity factor is generally much lower than the per-period maximum capacity factor, which allows generating units to dispatch aggressively in certain periods as long as they do not stray too far from historical behavior over the course of a year. Equation 6 only is added to the model in hourly runs at the generator level (rather than aggregating generators by technology type). This is the ramp rate constraint that prohibits large swings in dispatch in consecutive periods. Note that Equation 6 is not a linear constraint as written and can be reformulated to be two linear constraints.

Equations 7 and 8 control capacity addition and retirement in the model. Investment is not allowed in the initial periods of a model run because it would be infeasible to construct new capacity in such a short period. After this initial lag period, capacity addition and retirement are controlled only by the cost function unless the user decides to constrain these further. The user can set a year after which investment in a certain technology (e.g., coal) is prohibited. Similarly, the user can set a year after which capacity of a certain technology must be completely retired. Otherwise, the model will automatically retire plants based on their age or vintage. In the detailed, generator-level runs, the user can also manually set a retirement year for individual plants.

Equations 9–11 deal specifically with storage technologies. Dispatch into and out of storage technologies is constrained by Equation 4 as with other technology types but is further constrained by the amount of energy stored. Equation 9 defines storage capacity to be the product of nameplate capacity and charging time. For example, a 4-hour, 100 MW battery can store up to 400 MWh of energy but can only dispatch 100 MWh or less per period. Equation 10 then links stored energy across periods and to charging and discharging. Note that storage technologies are assigned a round-trip efficiency that is applied once by the model as the battery is charging, and a decay rate that affects energy that is stored across multiple periods. Equation 11 deals with edge cases and ensures that there is zero energy stored at the beginning and end of the simulation.

Equation 12 is our emission constraint. The user can set a system-wide pollution cap for one or more pollutants. Emissions are calculated by multiplying dispatch by a constant emission factor, and the total pollution across all generators and regions must satisfy the pollution cap. Note that the pollution cap is set hourly regardless of the model time step.

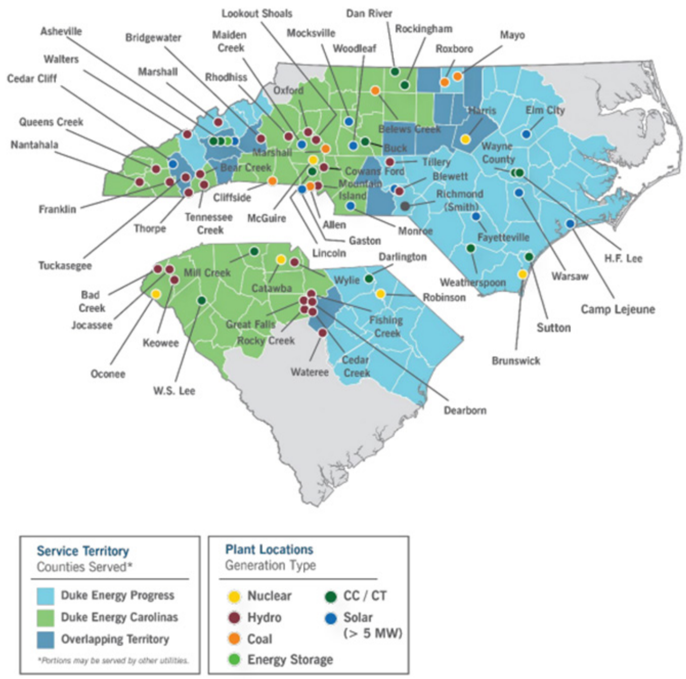
Finally, Equations 13–16 are the standard positivity constraints with a few important exceptions. Battery discharging is defined to be positive, so battery charging must be negative. Similarly, transmission into a region is defined as positive, so transmission out of a region must be negative. Curtailment is also defined to be negative.

The remainder of this section describes the specific modeling assumptions applied to this analysis. Duke Energy operates generators in North and South Carolina, with territory divided into three large balancing authorities: Duke Energy Carolinas, Duke Energy Progress East, and Duke Energy Progress

West. See Figure D-1 for Duke's representation of its territory. To best represent the system of interest, we made the following modeling decisions:

- Our dataset includes all generating units active as of 2021 that are located in North Carolina and in one of the three Duke Energy balancing authorities; we excluded the non-Duke territories in northeast and northwest North Carolina, which are operated as part of other balancing authorities, from our analysis.
- Any new generation technology constructed by the model to comply with Duke's or the North Carolina Sustainable Energy Association's (NCSEA's) capacity plans is assumed to be constructed in North Carolina. New solar capacity in North Carolina is substantial. This results in the 2050 annual generation of solar to be relatively high compared with nuclear and other existing generators in North Carolina.
- The Duke Carbon Plan provides estimates of electricity demand in its territory for the years 2023–2037. Using historical data from the Energy Information Administration (EIA) and Federal Energy Regulatory Commission, we estimated that approximately 78.5% of demand in Duke's territory occurs in North Carolina. (The remainder of demand comes from South Carolina.) We applied this ratio to Duke's load forecast for all years in our simulation.
- To align ourselves with Duke's own modeling assumptions, we assumed that no energy flows into and out of the system. However, because Duke's territory extends into South Carolina, we allowed excess demand in North Carolina to be met by importing energy from South Carolina after accounting for South Carolina's own energy demand. We assumed that this transmission is free and lossless.
- We made several assumptions with regard to individual generation technologies. Beginning in 2035, combustion turbine (CT) and combined cycle (CC) plants are planned to commence switching fuels from natural gas to hydrogen to continue operating through 2050 while abiding by the strict emission requirements. In the model, we gradually transition these plants as well. Per the Duke Energy plan, we transitioned 3% of gas capacity to hydrogen in 2035, 15% in 2040, and 100% by 2050 with linear interpolations between these dates. Hydrogen plants were assumed to operate similarly to gas plants but with a higher variable cost (mainly because of higher fuel costs) and no emissions. We also matched Duke's energy storage assumptions when possible: all battery storage added to the system was placed in North Carolina and operates with a 4-hour charge time and 86% round-trip efficiency. This storage technology operates independently and is not explicitly paired with solar generation capacity.

Figure D-1. Duke Energy Service Territory



Source: Duke Energy Carbon Plan (Duke, 2022).

Then, the optimization model was constructed on these data. The model is a modified network flow model where flow into nodes (energy generation) must equal flow out of nodes (energy demand) in each time period. In this case, we consolidated all three balancing authorities into a single node with a corresponding time series of exogenous demand values that must be satisfied.[12] To satisfy regional demand, the model operates each of the currently active generators in the region.

Generation data used by the model came mainly from RTI's MEEDE dataset (Fitch et al., 2022), a compilation of publicly available power sector data that include generation capacity, historical generation, generation costs, and emissions at the boiler level. In the model, generators are divided into three segments:

- **Fixed generators** include wind and solar that rely on exogenous environmental factors to determine their energy output. We used geophysical inputs such as historical solar radiation and wind speeds from the Copernicus Climate Change Service ER5 dataset to estimate solar and wind capacity factors at an hourly resolution. These historical capacity factors were also applied to future years and multiplied by the corresponding generator nameplate capacity to determine energy dispatch in each period.
- **Variable generators** include nuclear, hydropower, and assorted fossil generators that can be manually dispatched. These generators are restricted by their nameplate capacity and historical capacity factors.

[12] Because of this regional consolidation, the North Carolina model does not need to represent transmission within the region; therefore, we assumed all transmission within the Duke territory is free and lossless.

- **Energy storage technologies** include battery and pumped hydro storage. These technologies cannot dispatch energy to the system without first charging using excess energy available in the corresponding node. Energy dispatch from storage technologies is restricted by a nameplate capacity along with a round-trip efficiency value and a charge/discharge rate.

The model is also capable of handling capacity additions and retirements, but for this analysis, we accepted the capacities specified in the Duke Energy P1 and Synapse plans and forced our model to meet those constraints.

The model was set up to minimize total system cost subject to the constraints described in this section. Costs were divided into variable costs per watt-hour of generation, fixed costs per watt of nameplate capacity per year, and capital costs per watt of additional capacity. Present-day values for each of these cost data points were included at the generator level as part of the MEEDE dataset. For model runs into the future, we incorporated cost projections from the National Renewable Energy Laboratory's Annual Technology Baseline (ATB) dataset. The ATB projects variable, fixed, and capital costs for each generator technology out to 2050. We took these projected costs relative to present-day costs and applied this time series to the present-day costs from MEEDE to use in the model.

E. Health Data Detail

Table E-1 summarizes health data in combination with baseline tailpipe emissions by community type. The table compares the distribution of all asthma cases that resulted in ED treatments and compared those percentages with the distribution of NO_X and $PM_{2.5}$ emissions in 2020.

Table E-1. Summary of Health Data in Combination with Baseline Tailpipe Emissions by Community Type

	Vulnerable			Non Vulnerable		
County	**% Asthma ED Visits**	**% Baseline 2020 NO_x**	**% Baseline 2020 $PM_{2.5}$**	**% Asthma ED Visits**	**% Baseline 2020 NO_x**	**% Baseline 2020 $PM_{2.5}$**
Alamance	29.8%	83.3%	82.0%	16.7%	18.0%	0.4%
Chatham	33.2%	23.1%	22.4%	76.9%	77.6%	3.4%
Durham*	95.3%	53.0%	53.0%	47.0%	47.0%	7.0%
Franklin	74.8%	46.1%	46.0%	53.9%	54.0%	1.5%
Granville	63.3%	38.4%	38.2%	61.6%	61.8%	2.0%
Harnett	37.0%	27.2%	27.5%	72.8%	72.5%	1.0%
Johnston*	41.9%	49.7%	49.4%	50.3%	50.6%	6.0%
Nash	100.0%	100.0%	100.0%	0.0%	0.0%	0.0%
Orange*	0.0%	32.8%	32.7%	67.2%	67.3%	6.8%
Person	47.4%	30.4%	30.5%	69.6%	69.5%	0.7%
Wake*	43.2%	44.6%	43.9%	55.4%	56.1%	26.4%
Total	46.2%	45.0%	44.6%	%	55.4%	55.4%

*Only Durham, Johnston, Orange, and Wake Counties have full coverage for emissions. Nash county coverage withing our study is limited to the southwest corner that borders Franklin, Wake and Johnston counties (see Figure B-1).

F. Additional Demographic Disparities Tables

Tables F-1 through F-3 provide the Cochran-Armitage trend test results for the years 2030, 2040, and 2050.

Table F-1. Cochran-Armitage Test Results for Traffic Emissions in 2030

Population Subgroup	Emissions					
	Medium-Duty Trucks		Heavy-Duty Trucks		Combined Trucks	
	NO_x	$PM_{2.5}$	NO_x	$PM_{2.5}$	NO_x	$PM_{2.5}$
Poverty	−42.4	−40.8	−12.0	−13.6	−25.0	−27.3
Non-White	−85.3	−79.4	−23.1	−23.0	−44.0	−45.1
Age: Under 5 Years	−41.0	−40.5	−23.6	−20.9	−30.0	−31.1
Age: Over 64 Years	−27.8	−28.4	−14.4	−12.3	−17.6	−18.5
Limited English Proficiency	−13.6	−12.5	−3.1	−5.3	−8.6	−9.5
No High School Diploma or Equivalent (Ages >24)	−41.7	−40.6	−42.3	−44.6	−41.7	−44.4

*Indicates a p-value greater than 0.005.

Table F-2. Cochran-Armitage Test Results for Traffic Emissions in 2040

Population Subgroup	Emissions					
	Medium-Duty Trucks		Heavy-Duty Trucks		Combined Trucks	
	NO_x	$PM_{2.5}$	NO_x	$PM_{2.5}$	NO_x	$PM_{2.5}$
Poverty	−39.2	−31.9	−8.3	−10.9	−21.8	−22.2
Non_White	−80.5	−74.1	−21.6	−19.9	−46.1	−38.1
Age: Under 5 Years	−41.0	−36.8	−25.2	−20.6	−31.7	−30.8
Age: Over 64 Years	−27.2	−20.0	−12.9	−8.7	−18.2	−20.7
Limited English Proficiency	−14.1	−14.6	−3.6	−7.0	−9.1	−7.9
No High School Diploma or Equivalent (Ages >24)	−39.2	−37.7	−42.3	−43.8	−43.0	−43.4

*Indicates a p-value greater than 0.005.

Table F-3. Cochran-Armitage Test Results for Traffic Emissions in 2050

Population Subgroup	Emissions					
	Medium-Duty Trucks		Heavy-Duty Trucks		Combined Trucks	
	NO_x	$PM_{2.5}$	NO_x	$PM_{2.5}$	NO_x	$PM_{2.5}$
Poverty	−32.2	−26.9	2.4*	−3.9	−13.2	−14.4
Non-White	−69.8	−65.8	−10.7	−19.2	−32.0	−31.0
Age: Under 5 Years	−39.1	−36.7	−25.6	−24.9	−31.9	−30.1
Age: Over 64 Years	−27.2	−16.8	−10.8	−4.2	−16.1	−14.3
Limited English Proficiency	−11.9	−15.5	−2.3*	−4.5	−6.7	−7.3
No High School Diploma or Equivalent (Ages >24)	−35.9	−36.6	−34.9	−41.0	−36.2	−38.6

*Indicates a p-value greater than 0.005.