Road Network Structure and Air Pollution: Moving Beyond the Fundamental Law of Road Congestion

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Abstract

Pollution emitted from transportation is one of the primary contributors to local pollution stocks and flows. This paper considers how the structure of local road networks might affect pollution stocks and flows through vehicular emissions. A pollution stock and flow model building on the Fundamental Law of Road Congestion which also considers the impact of road network structure is presented and used to generate hypotheses for how the structure of road networks should affect pollution stocks and flows via both congestion and the opportunity cost of driving. These hypotheses are tested using a Hausman-Taylor approach and rely on the use of relevant topological indices to describe the structure of road networks with a measure of urban form serving as an instrument. Evidence is found supporting the hypotheses that better connected road networks, i.e., those with fewer bottlenecks and which generally allow for more efficient traversal, lead to lower levels of pollution stocks and flows. Evidence is also found indicating that drivers adapt to more circuitous road networks with lower levels of driving in equilibrium. Finally, these mechanisms are confirmed by regressing measures of congestion and the opportunity cost of driving against the topological indices.

Keywords: Air Pollution; Bottleneck; Edge Betweenness Centrality; Opportunity Cost of Driving; Particulate Matter; Road Network; Topological Index

1 Introduction

Air pollution is one of the most extensive economically significant externalities facing the world today. Whether one considers global climate change, health outcomes, or productivity, the economic consequences of air pollution are extensive (Oswald and Stern, 2019). This is especially true in urban settings where dense populations live with some of the worst air quality (Liu et al., 2018).

One of the largest emitters of pollutants, especially of acutely harmful pollutants, is the transportation sector (Kahn and Schwartz, 2008). Transportation accounts for approximately 30% of total greenhouse gas emissions in the US (Knittel, 2012). These emissions contribute to as many as 400,000 premature deaths per year in Europe (Amato et al., 2014). Given these excessive numbers, a pressing concern of policy makers across the globe is to reduce vehicular emissions.

One option policy makers have, especially in rapidly growing regions, is strategic development of their local road network. The famous fundamental law of road congestion from Downs (1962) and confirmed by Duranton and Turner (2011) asserts that simply building more roads will not reduce emissions, and in fact should increase emissions. This is because, according to the fundamental law of road congestion, increases in lane miles will lead to an equiproportional increase in vehicle miles travelled, yielding constant levels of congestion. If we view vehicular emissions as a function of driving duration and the instantaneous emissions over the duration of the trip (e.g., congestion), then increased vehicle miles travelled with unchanged congestion should lead to more pollution.

However, Duranton and Turner (2011) did not consider that strategic placement of additional lane miles could potentially mitigate this effect. By prioritizing adding new roads over adding additional lane miles to existing roads, local policy makers can create alternative routes which improve the connectivity of the road network and eliminate bottlenecks. While the existing literature on the fundamental law of road congestion makes it clear that adding additional lane miles to existing roadways will only increase vehicular emissions, building new roads to create these additional lane miles alters the structure of the local road network. This increases the connectivity of the local road network, and, in particular if newly constructed roads intersect with many existing roads, offers a plethora of alternative routes. This in turn leads to dispersing traffic traversing a fixed route across many routes rather than just one, thereby creating the potential for a reduction in congestion. Furthermore, new roads could offer more direct or emissions-efficient routes.

In light of these possibilities, this paper seeks to determine if the structure of a municipal road network affects local ambient air pollution levels. This will be done by developing hypotheses on the impact of the structure of road networks on pollution stocks and flows through a simple theoretical application of the fundamental law of road congestion to a pollution stock and flow model. These hypotheses will be tested empirically using municipal level data on road networks in Virginia and ambient levels of the transportation-relevant air pollutant fine particulate matter (PM2.5). By considering a municipality as a set of road segments and intersections, the structure of the road network tells us about the nature of alternative routes/detours and thus the efficiency of driving with respect to vehicular emissions. Using a series of topological indices which describe specific aspects of the structure of road networks, and density as a measure of urban form as an instrument, an estimate of the effect of road network structure on ambient air pollution levels will be obtained using a Hausman-Taylor instrumental variables approach. A first-differenced model using the same instrument will then be used to estimate the effect of road network structure on vehicular emissions (flows). The results indicate that stocks and flows of PM2.5 can be reduced through more efficient road network structures as characterized by denser, more robustly connected topologies. To verify that the mechanisms claimed to be responsible for this effect, namely congestion and the opportunity cost of driving, are indeed responsible, measures of each of these mechanisms are regressed against the topological indices.

2 Theoretical Framework

In order to motivate the econometric analyses in this paper, consider the following theoretical framework which we will build upon the fundamental law of road congestion. Begin by letting $E_{i,t}$ denote the emissions of a given pollutant in municipality i at time t. Emissions sources are numerous, and the source we are particularly interested in is from driving as measured by vehicle miles traveled ($VMT_{i,t}$). By letting $\rho_{s,i}$ denote the emissions intensity from pollution source s in municipality i, we obtain the following expression for emissions.

$$E_{i,t} = \rho_{v,i,t} \cdot VMT_{i,t} + \sum_{s \neq v} (\rho_{s,i,t} \cdot S_{i,t}) \tag{1}$$

Here, emissions from a single source are the product of the quantity consumed or produced of that emissions producing process, e.g., driving, and $E_{i,t}$ is simply the sum of emissions from all emissions sources.

As emissions are flows of pollutants, pollution levels represent the pollution stocks. Given a pollutant decay rate δ, the pollution stock can be modelled as follows

$$P_{i,t} = E_{i,t} + (1-\delta)P_{i,t-1} \tag{2}$$

Rewriting Equation 2 purely in terms of emissions and differentiating between emissions from vehicles and emissions from other sources yields

$$P_{i,T} = \rho_{v,i,t} \sum_{t=0}^{T} (1-\delta)^{T-t} VMT_{i,t} + \sum_{s \neq v} \rho_{s,i,t} \sum_{t=0}^{T} (1-\delta)^{T-t} S_{i,t} \tag{3}$$

The impact of $VMT_{i,t}$ on $E_{i,t}$ and $P_{i,T}$ are given by Equations 4 and 5, respectively.

$$\frac{\partial E_{i,t}}{\partial VMT_{i,t}} = \rho_{v,i,t} \tag{4}$$

$$\frac{\partial P_{i,T}}{\partial VMT_{i,t}} = \rho_{v,i,t}(1-\delta)^{T-t} \tag{5}$$

So $\rho_{v,i,t}$ is clearly critical to pollution dynamics in the model. The basis of this paper, ultimately, is the functional form of $\rho_{v,i,t}$ and $VMT_{i,t}$ which are given by the following two equations.

$$\rho_{v,i,t} = \rho_{v,i,t}(T_{i,t}, C_i(N_i)) \tag{6}$$

$$VMT_{i,t} = VMT_{i,t}(C_i(N_i), \theta_{i,t}(N_i)) \tag{7}$$

where $T_{i,t}$ denotes the level of vehicular pollution abatement technology (e.g., the age of cars, the distribution of electric v. gasoline v. diesel, etc.), N_i denotes the structure of the road network, $C_i(N_i)$ denotes the level of traffic congestion across the road network, and $\theta_{i,t}(N_i)$ denotes the opportunity cost of driving.

As the purpose of this paper is to study the impact of the structure of road networks on pollution, the first key partial derivatives here is

$$\frac{\partial \rho_{v,i,t}}{\partial N_i} = \frac{\partial \rho_{v,i,t}}{\partial Ci} \cdot \frac{\partial C_i}{\partial N_i} \tag{8}$$

The first term on the right hand side of Equation 8 represents the marginal impact of congestion on the pollution intensity of driving and therefore should be positive; i.e., more congestion leads to more pollution per unit of driving. The second term on the right hand side represents the marginal impact of the road network on congestion. Ultimately the sign of this term will depend upon which aspect of the road network we choose to quantify, but for illustrative purposes, consider a measure of how connected the network is, where larger values indicate a better connected road network. In this case we should expect a negative sign for this term since a better connected network offers more alternative routes between any two destinations and should decrease traffic congestion. For intuition on the connectivity of road networks, consider Figure 1.

Building upon the fundamental law of road congestion, we have to consider the impact of the structure of the road network on driving. The fundamental law of road congestion asserts that an increase in lane miles - no matter where in the network they occur - leads to an equiproportional increase in $VMT_{i,t}$. However, the fundamental law of road congestion is truly a consequence of adding lane miles to existing roads, and is not likely an accurate descriptor of adding lane miles to a road network in the form of new roads which alter the topology of the road network. Adding lane miles in the form of new roads can lead to better connected road networks which could potential decrease the level of congestion experienced in a given road network. And even if the fundamental law of road congestion does hold in the sense that the level of congestion, another very important consideration must be accounted for: the opportunity cost of driving. By improving the connectivity of a road network, even conditional on the same level of congestion, the time of a given trip will not increase, and in some cases it will actually decrease.

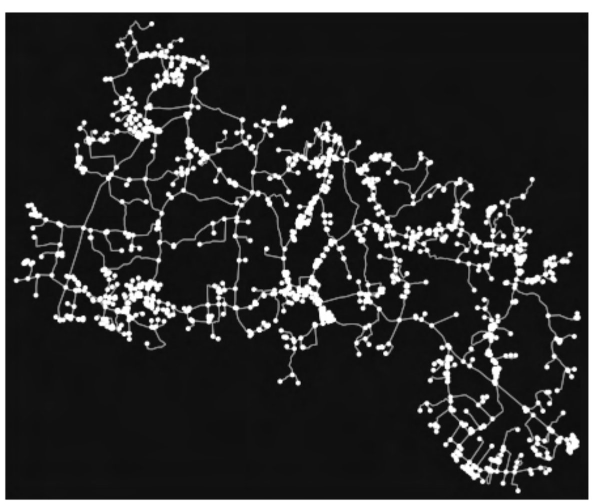
Thus we have that $VMT_{i,t}$ is a function of the structure of the road network via both congestion (C_i) and opportunity cost $(\theta_{i,t})$.

$$\frac{\partial VMT_{i,t}}{\partial N_i} = \left(\frac{\partial VMT_{i,t}}{\partial C_i} \cdot \frac{\partial C_i}{\partial N_i} \right) + \left(\frac{\partial VMT_{i,t}}{\partial \theta_{i,t}} \cdot \frac{\partial \theta_{i,t}}{\partial N_i} \right) \tag{9}$$

If we continue to that larger values of N_i correspond to better connected networks, all individual partials are negative, hence the two terms being added together are both positive and the overall sign for the partial derivative of vehicle miles travelled with respect to the structure of the road network is positive.

Given this, we can hypothesize the impact of road network structure on pollution as follows. First, by considering emissions we have that

Figure 1: An example of the road network of two different counties in Virginia. On the top is Arlington County, an example of a relatively dense, well-connected road network. On the bottom is Charles City County, an example of a relatively sparse network with fewer alternate routes available to drivers.



$$\begin{aligned}\frac{\partial E_{i,t}}{\partial N_i} &= VMT_{i,t}\left(\frac{\partial \rho_{v,i,t}}{\partial N_i}\right) + \rho_{v,i,t}\left(\frac{\partial VMT_{i,t}}{\partial N_i}\right) \\ &= VMT_{i,t}\left(\frac{\partial \rho_{v,i,t}}{\partial C_i}\cdot\frac{\partial \rho_{v,i,t}}{\partial N_i}\right) + \rho_{v,i,t}\left(\left(\frac{\partial VMT_{i,t}}{\partial C_i}\cdot\frac{\partial C_i}{\partial N_i}\right) + \left(\frac{\partial VMT_{i,t}}{\partial \theta_{i,t}}\cdot\frac{\partial \theta_{i,t}}{\partial N_i}\right)\right)\end{aligned} \tag{10}$$

Since we have a negative and a positive term, there is no clear prediction how an improvement in the structure of a road network ought to affect emissions.

Turning our attention to pollution stocks rather than flows, and assuming that a change in the structure of the road network occurs at time τ, we have that

$$\begin{aligned}\frac{\partial P_{i,T}}{\partial N_i} &= \left(\frac{\partial P_{i,T}}{\partial \rho_{v,i,t}}\cdot\frac{\partial \rho_{v,i,t}}{\partial N_i}\right) + \left(\frac{\partial P_{i,T}}{\partial VMT_{i,t}}\cdot\frac{\partial VMT_{i,t}}{\partial N_i}\right) \\ &= \left(\frac{\partial P_{i,T}}{\partial \rho_{v,i,t}}\cdot\frac{\partial \rho_{v,i,t}}{\partial C_i}\cdot\frac{\partial C_i}{\partial N_i}\right) + \left(\frac{\partial P_{i,T}}{\partial VMT_{i,t}}\cdot\left(\frac{\partial VMT_{i,t}}{\partial C_i}\cdot\frac{\partial C_i}{\partial N_i}\right) + \left(\frac{\partial VMT_{i,t}}{\partial \theta_{i,t}}\cdot\frac{\partial \theta_{i,t}}{\partial N_i}\right)\right) \\ &= \left[\sum_{t=\tau}^{T}(1-\delta)^{T-t}VMT_{i,t}\right]\left(\frac{\partial \rho_{v,i,t}}{\partial Ci}\cdot\frac{\partial C_i}{\partial N_i}\right) \\ &+ \left[\sum_{t=\tau}^{T}(1-\delta)^{T-t}\rho_{v,i,t}\right]\left(\left(\frac{\partial VMT_{i,t}}{\partial C_i}\cdot\frac{\partial C_i}{\partial N_i}\right) + \left(\frac{\partial VMT_{i,t}}{\partial \theta_{i,t}}\cdot\frac{\partial \theta_{i,t}}{\partial N_i}\right)\right)\end{aligned} \tag{11}$$

which extends our results on pollution flows to pollution stocks in the expected manner.

In the context of road networks, these partial derivatives will be represented using a series of topological indices which each describe a specific aspect of the structure of the road network. By the nature of the specificity of these topological indices, some will be better descriptors of the connectivity of road networks, serving as a better measure of network effects on congestion, while others will be better descriptors of the opportunity cost of driving. A detailed discussion of the topological indices used in this paper, and of topological indices in general, can be found in Section 4.

3 Traffic and Pollution

As we saw in the previous section, road network structure is the crux of congestion externality related tradeoffs. Denser, better connected networks increase the efficiency (and thus decrease the pollution intensity) of traversing the network, thereby reducing emissions conditional on a fixed quantity of vehicle miles travelled. The potential to reduce pollution is critical for several economic reasons, reasons as diverse and expansive as health, productivity, migration, and property values.

Knittel et al. (2016) used an IV approach to causally link pollution from driving to increased infant mortality, lower birth weights, and more premature births. Using the implementation of E-Zpass as a natural experiment, Currie and Walker (2011) found that decreased emissions due to decreased congestion at the toll plazas caused improved birth outcomes among mothers living near these toll plazas. Using superstition around the number four as a source of exogeneity and a license plate based driving ban in China, Zhong et al. (2017) also found a causal link between driving and air pollution, but further found that policy can significantly impact driving habits and, consequentially, pollution from driving.

Access to road network can also affect productivity. For instance, Shamdasani (2021) showed that in rural India, when farmers gained access to the road network, they were able to diversify their crop portfolios, growing higher return crops and improving their welfare. When access to the road network already exists, there are other means of increasing one's welfare. For instance, in Italy, Germani et al. (2021) found that pollution levels, to which driving contributes heavily, influence migration to other regions of the country with less air pollution in an effort to improve on welfare through health gains.

For those who remain stationary, traffic related pollution can affect property values as well. Using the fact that Iran began to produce more low grade gasoline as a consequence of sanctions, Amini et al. (2021) found that increases in air pollution led to decreases in house prices. Higgins et al. (2019) similarly found that increased pollution decreases house prices. They also found evidence of the tradeoff between location in the road network and pollution insofar as they found that while home owners value accessibility within road networks, the disamenity of air pollution can entirely offset gains from superior locations in the network.

One particularly interesting finding regarding decisions on where to live and pollution from driving was by Sider et al. (2013) who showed that those who emit the most pollution from driving tend to live in areas with the highest air quality. This raises the question of equity, and also further signifies the importance of policies aimed at reducing emissions from driving. But what can be done?

One simple mechanism for addressing emissions from driving is a fuel tax. Sipes and Mendelsohn (2001) found that driving is price inelastic as driving decreased only mildly in California when a tax on gasoline was implemented. Building on this, Spiller et al. (2014) confirmed the price inelastic nature of driving, but found that part of this reduction in driving is due to increased use of public transit. The authors provide support for recycling fuel tax revenues into public transit to increase this effect. This result confirms a paper by Anderson (2014) which used strikes by public transit workers to find that public transit substantially decreases traffic congestion, with delays increasing by as much as 47% while public transit services were unavailable. In addition to increased use of public transit, Bento et al. (2013) showed that fuel taxes also lead to increased carpooling. Inspired by the success of fuel taxes, Montag (2015) argues in favor of fuel taxes, but points out that fuel taxes need not be used in isolation and can instead be the basis of a more complete policy approach to reducing emissions from driving.

One potential complement for fuel taxes is to subsidize the purchasing of electric vehicles. However, as Holland et al. (2016) showed, subsidies can very quickly become too large and ultimately lead to deadweight loss. Compounding on this inefficiency is an equity issue. Electric vehicles do not emit pollution while they are being driven, but the electricity generated to power the vehicle does emit pollution. Since this pollution occurs elsewhere, a clear equity issue arises. Another downside of this approach is that it does not address congestion, and could potentially increase congestion due to the purchasing of additional/secondary vehicles.

Another potential complement to fuel taxes is congestion pricing. Congestion pricing has well founded theoretical support, e.g., (Arnott, 2013). But the evidence for congestion pricing does not end there. Tang (2021) found that the London Congestion Charge, which charged a fee to any driver entering the charge zone, significantly decreased traffic in the charge zone. With decreased traffic comes decreased pollution, but, per the authors' findings, a corresponding increase in property values due to the decreased traffic based congestion externalities.

Perhaps the most drastic means of reducing traffic is to preclude certain vehicles or drivers from driving altogether by implementing traffic bans. The aforementioned paper by Zhong et al. (2017) was an example of a study of a traffic ban. Han et al. (2020) similarly studied a traffic ban in China and found that it decreased pollution from driving and, consequentially, decreased mortality rates, most notably among older women. For a traffic ban implemented in Chile, Rivera (2021) implemented a fuzzy regression discontinuity design and found that the ban was successful in decreasing both traffic and pollution. Davis (2008) studied a license plate based traffic ban in Mexico City, but found a null result, i.e., the traffic ban did not reduce pollution levels in the city. In fact, drivers responded by increasing the number of vehicles used since an additional vehicle is one means of being able to drive on days when one's primary vehicle would not be permitted on the roads. Heading yet further in the wrong direction, Zhang et al. (2017) developed and empirically tested a theoretical model which showed that, in certain scenarios, license plate based traffic bans can actually increase emissions from driving. While increased driving and emissions is certainly a case of an unintended policy consequence, another example uncovered by Carrillo et al. (2018) is an increase in crime. By using the discontinuity of the border of the geographical area cover by the traffic ban, they found that crime increased substantially.

Given the price inelasticity of gasoline, the inefficiencies that can arise from subsidizing electric vehicles, and the potential for traffic bans to fail because they incentivize additional vehicle purchases, not to mention the series of equity issues that arise from many of these policy options, what else can be done? One remaining option which has yet to be explored in the literature is to optimize the structure of road networks.

The key requirement for the structure of road networks to affect pollution lies in the fact that the structure of road networks also affects the behavior of drivers. Daniel et al. (2009) created a model to study optimal driver behavior in road networks with known bottlenecks which cause excessive traffic congestion, demonstrating that changes to the structure of the network can indeed affect the behavior of drivers. Simulations performed by Tsekeris and Geroliminis (2013) supported having a larger, denser, mixed-use urban core which has optimized the proportion of land allocated to transportation, as this structure should reduce traffic congestion.

While not all cities can benefit from this approach, it certainly would seem to have potential in at least some situations, particularly, whenever a city is expected to experience rapid growth. Consider the case of a new, massive production facility or warehouse being built just outside of a small city. That city can expect substantial growth, and may even be required to immediately expand certain traffic related infrastructure as part of a bid to host this new facility. Planning how the city expands, as this paper will eventually show, has the potential to profoundly affect the contribution to pollution levels caused by traffic. Optimizing the structure of the road network is a critical component to experiencing lower levels of air pollution and a reduction in the disamenities caused by air pollution.

4 Road Networks

Broadly speaking, a road network is a representation of the roads in a given geographical region and the way in which they interconnect, represented by a network in which vertices represent intersections and edges represent road segments (Marshall, 2016). Since directionality is critical for determining how users can access different regions of the network, and since information such as the physical distance between locations within the road network determine optimal routes through the network, road networks can be more specifically represented as weighted multi-digraphs (Boeing, 2017b). In fact, the default means of constructing road networks as mathematical objects in the current leading software (OSMnx) is to convert a two lane road segment into two separate road segments, directed opposite of one another (Boeing, 2017a). The rationale for this is that once on a road segment, a driver cannot simple turn around in the middle of the road and change direction.

Before continuing further, it will be helpful to formally define a road network. Let $N = N(V, E)$ be a road network where V is the set of vertices/intersection of N, and E is the set of edges/road segments of N. In network theoretic terms, for two intersections v_i and v_j in $V(N)$ connected by a road segment allowing drivers to traverse from v_i to v_j, the edge $e = v_i v_j$ may be expressed more fully as the pair $e = (v_i v_j, I(e))$ where $I(e)$ represents the set of all additional information contained in the network data about the road segment represented by the edge e. Such data may include the length of the road segment, the speed limit along the road segment, the amount of traffic flow on the road segment, or any other pertinent information. To illustrate an example of a road network, consider the example of the road network of Hopewell, Virginia presented in Figure 2.

Representing a road network in such a way is particularly useful as it allows us to use network theoretic tools to assess various structural aspects of the the road network. By considering structural aspects of the network such as its connectivity, we can assess, for instance, how impacted drivers are when portions of the road network are subjected to closures due to disruptions such as traffic accidents, road construction, or inclement weather (Jenelius and Mattsson, 2015).

To do this, we need to condense the road network into a scalar which conveys some important fact about a given road network. This is done through the use of topological indices (Sakakibara et al., 2004). Topological indices are used widely throughout applied network theory, in fields ranging from the study of transportation networks (Sakakibara et al., 2004), to the study of social networks Qi et al. (2017), to computational chemistry (Prabhu et al., 2020). In the case of Sakakibara et al. (2004), topological indices were used to help study the vulnerability of different cities in the Hanshin region of Japan in the event of an earthquake by measuring how isolated within the

Figure 2: The road network of the city of Hopewell, Virginia. Edges in this network represent road segments, while vertices represent intersections. In this representation, data on direction is encoded into the edges and multiple edges between two vertices are stacked so that the visual representation is as clean as possible.

network each city in the region is.

An individual topological index will provide information on a single aspect of the network. While there are numerous topological indices, not all are relevant or applicable to every type of network. In this paper, only topological indices with clear economic interpretations in the context of road networks will be considered.

The first topological index presented is the mean edge betweenness centrality. Edge betweenness centrality has been used to identify critical road segments in terms of traffic flow and vulnerability to risks such as flooding (Casali and Heinimann, 2019; Tachaudomdach et al., 2021). In the context of a road network, edge betweenness centrality measures how critical each road segment is to traversing through the network in terms of the proportion of shortest paths between all pairs of vertices that pass through each road segment. Edge betweenness centrality assigns a value for to each road segment in the network. By considering the mean value over all road segments, we attain a measure of how important an average road is to efficiently traversing the network, i.e., how much travel disruption via detours would occur if an arbitrary road was closed somewhere in the network. The expression for the mean edge betweenness centrality of a network N is given by Equation 12 where $\sigma(s,t)$ is the number of shortest paths from s to t, and $\sigma(s,t|e)$ is the number of shortest paths from s to t which contain e. It is easy to see that this value is bounded between zero and one (note that it is just an average proportion).

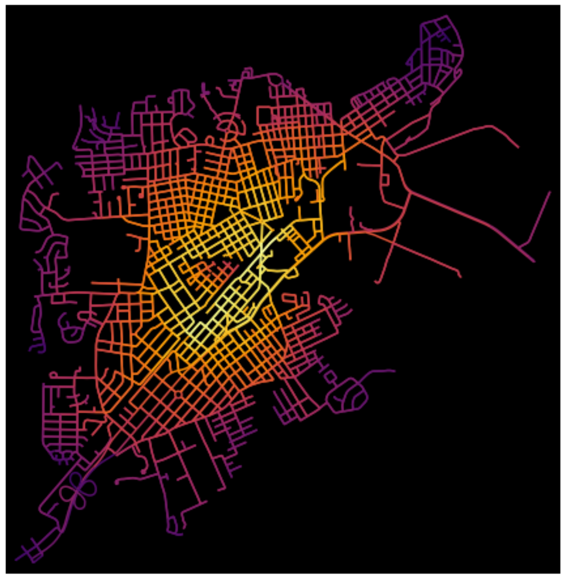
$$MEBC(N) = \frac{1}{|E|} \sum_{e \in E} \sum_{s,t \in V} \frac{\sigma(s,t|e)}{\sigma(s,t)} \tag{12}$$

To help improve intuition for edge betweenness centrality, consider Figure 3 which shows the road networks of Hopewell, Virginia and Fairfax County, Virginia where each road segment is colored according to its edge betweenness centrality. Brighter yellows represent the road segments with the greatest edge betweenness centrality and darker purples represent the road segments with the lowest edge betweenness centrality. In the case of Hopewell, the roads near the center of the city prove to be the most critical for efficiently traversing the road network. Notice that in the very center of the city there is a portion of the network that is relatively less connected and, consequentially, less critical for efficiently traversing the road network. In the case of the much larger road network of Fairfax County, the bright yellow streaks are Interstate 66, Interstate 95, and the Capital Beltway.

Since the goal is to determine the impact of road structure on ambient pollution levels, it is important to know how to interpret estimated regression coefficients for each topological index. In this case, road networks with a larger mean edge betweenness centrality should have a greater degree of disruption to the flow of traffic whenever some critical road segment is closed. Intuitively, this can be viewed as a measure of bottlenecks within a road network; a road network with a greater mean edge betweenness centrality is likelier to suffer from more bottlenecks. In particular, these bottlenecks should be characterized by long detours that make re-routing highly inefficient. This is because smaller values of edge betweenness centrality are assigned to road segments that lie on relatively few shortest paths between destinations while larger values of edge betweenness centrality are assigned to roads that lie on a large proportion of shortest paths between destinations. When many alternative routes exists, the likelihood of a specific road segment lying on a shortest path between a specific pair of locations in the road network is lower than when relatively few alternative routes exist. This is verified below in Figure 4. Since road closures are a common reality, we should expect that a road network structure characterized by a larger mean betweenness centrality should lead to greater disruption of travel and consequentially more pollution, and thus a positive regression coefficient.

The vertex/intersection analog of edge between centrality is called load centrality. Load centrality has been used to identify key intersections in transportation networks whose closure would significantly disrupt transportation flows, increasing transportation costs and times (Liu et al., 2019). Mean load centrality considers the average impact to travel across the network due to the closure of an intersection (and thus all incident road segments). The formula for mean load centrality is analogous to that of mean edge betweenness centrality. Mean load centrality is included in this

Figure 3: This figure shows the road networks for Hopewell, VA (top) and Fairfax County, VA (bottom). Road segments are colored according to their edge betweenness centrality - brighter yellows indicate road segments with the greatest edge betweenness centrality while darker purples indicate road segments with the lowest edge betweenness centrality.



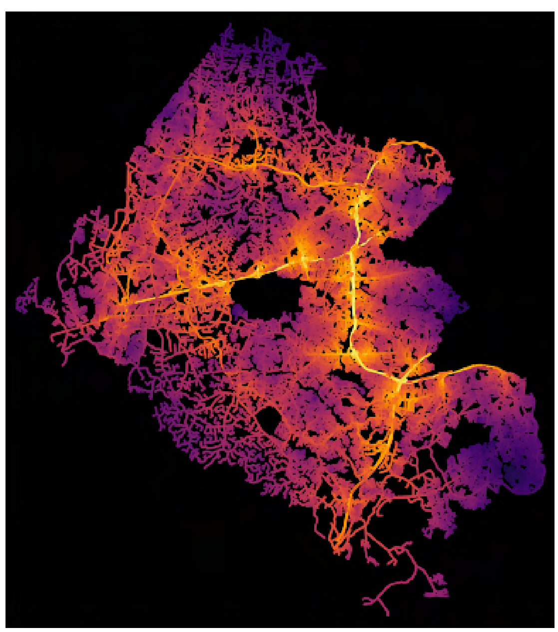
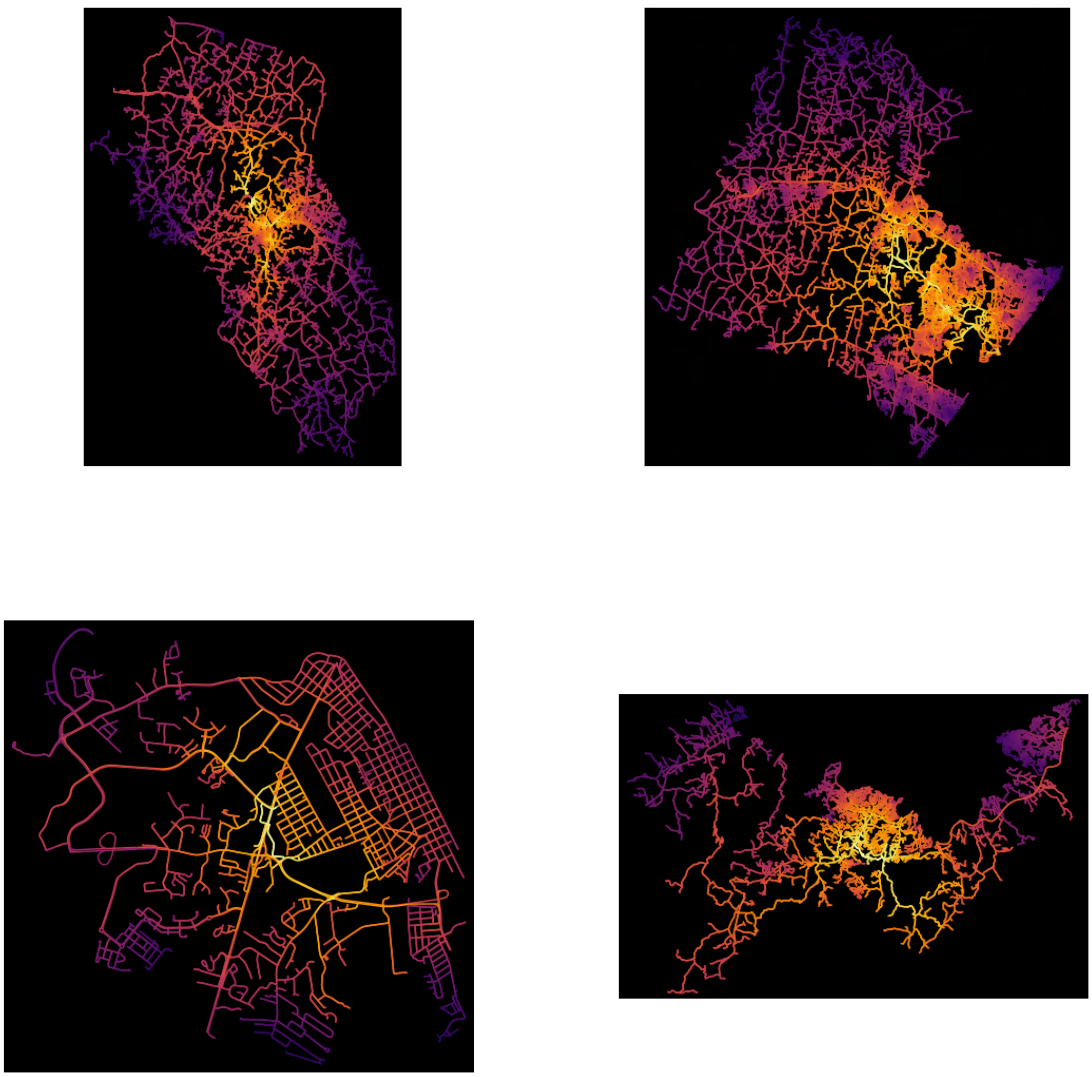


Figure 4: The top two municipalities (Fauquier County and Loudoun County, from left to right) are two municipalities with edge betweenness centralities below both the mean and median in the sample. These two counties offer many alternative routes and it is easy to see that the size of a detour created by a specific road closure will only ever be but so large. The bottom two municipalities (Fredericksburg (city) and Roanoke County, from left to right) are two of the municipalities with the largest mean edge betweenness centralities (each is greater than both the sample mean and median). It is easy to spot bottlenecks and the potential for long detours due to road closures in these two municipalities.



discussion for two reasons. First, to provide intuition into the difference in consequences between closing a road segment versus closing an intersection - namely that all incident road segments are effectively closed as well in the latter case (at least to through traffic). Second, we should expect similar results for these two topological indices.

$$MLC(N) = \frac{1}{|V|} \sum_{v \in V} \sum_{s \neq v \neq t \in V} \frac{\sigma(s,t|v)}{\sigma(s,t)} \tag{13}$$

As an alternative measure of the connectivity of a road network, designed specifically to look at the likelihood of additional routes being available to a driver, we have the percentage of three-way intersections. Since most intersections are either three or four-way intersections, three-way intersections come at the expense of four-way intersections, and so an increase in the proportion of three-way intersections implies a decreased presence of alternative routes available at intersections throughout the road network.

The final topological index considered in the main body of this text is circuity. Circuity is a measure of excess driving required to traverse a given route in the network. Circuity is defined as the ratio of the distances between locations in the network and the Euclidean distance between those same locations. Road networks with higher values for circuity require longer trips on average, thereby increasing the opportunity cost of driving. Formally, circuity is defined as follows where $d_N(u,v)$ denotes the minimum travel distance through network N between locations u and v, and $d_E(u,v)$ denotes the Euclidean distance between those same two locations.

$$Circuity(N) = \frac{\sum_{u,v \subseteq V(N)} d_N(u,v)}{\sum_{u,v \subseteq V(N)} d_E(u,v)} \tag{14}$$

5 Data

5.1 Road Networks

The explanatory variables of interest in this paper are a series of topological indices describing various structural aspects of municipal road networks. To compute these topological indices, road networks were obtained from OpenStreetMap (OSM) using the OSMnx module in Python (Boeing, 2017a). As road networks are multi-digraphs, this means that every road segment is directed from one intersection to another; recall that in the case of a two-way street, each road segment is represented as two distinct segments oriented in opposite directions.

Using this definition of a road network, we can represent a road network N as a $|V|\times|V|$ matrix $A(N)$, called the adjacency matrix of the road network, where the i^{th} row and the i^{th} column denote intersection i and where the element A_{ij} indicates whether or not a road segment exists from intersection i to intersection j with either a one (the road segment exists) or a zero (the road segment does not exist). Each topological index is then computed using the adjacency matrix $A(N)$ for each municipal road network.

5.2 Pollution Data

Data on pollution levels comes from the EPA Air Quality System. The pollutant considered in this study is particulate matter (PM2.5). This pollutant was chosen since gasoline, diesel, and electric cars are produce PM2.5 when in use. All observations on each day during the time period covered in this paper (January 1 to December 31, 2020) from every site in each municipality are averaged to create mean county level pollution data for each day that data was available. Due to the fact that EPA sites typically do not record data for all pollutants, this is the data that limits the geographical scope of this paper. The Commonwealth of Virginia was chosen because it offers consistent trans-

Figure 5: Summary statistics for pollution levels and the topological indices.

	Mean	SD	Min	Median	Max
Particulate Matter (PM2.5)	6.725	4.067	0.000	6.000	53.100
Edge Betweenness Centrality (Mean)	0.005	0.003	0.001	0.004	0.011
Load Centrality (Mean)	0.011	0.006	0.002	0.010	0.025
Circuity	1.092	0.033	1.041	1.087	1.186
Percent 3-way Intersections	0.556	0.031	0.492	0.558	0.638

portation policies (opposed to a multi-state study) and because Virginia offers diverse municipality types (cities are independent of counties in Virginia) and thus diverse road network structures, all existing within a relatively confined geographical area. Using EPA sites in Virginia which record pollution data of interest during the time frame of this study leaves us with 38 different cities and counties for which there is sufficient pollution data.

5.3 Weather Data

Since weather affects pollution levels, and since weather data varies over time, data for several pertinent weather variables from NOAA are included. The weather variables include temperature, wind speed, and precipitation. Observations of weather data are at the municipality-day level.

6 Methodology

6.1 Pollution Stocks

First we consider the impact of road network structure on pollution stocks based on Equation 11. Since myriad factors affect the pollution stock of a given municipality, e.g., the industrial composition of the municipality, and since the structure of the road network can affect, in this case, the industrial composition of the municipality through transportation costs, it is clear that the structure of the road networks is endogenous. For the same reason, it is also clear that we must control for municipal level heterogeneity with municipal level fixed effects. However, the structure of the road network over relatively short time scales (and in the case of this study) does not change. This means that we need to include two time invariant datum for each municipality in our regressions, which, unfortunately, leads to a colinearity problem. To address this, a Hausman-Taylor instrumental variables model is used.

The Hausman-Taylor model is a two-stage IV model which relies on both fixed and random effects to overcome the collinearity problem with the topological indices and the municipal level fixed effects (Hausman and Taylor, 1981). The model is specified as follows where $y_{i,t}^{p}$ denotes the stock of pollutant p in municipality i on day t, N_i denotes the road network for municipality i, $f_\tau(N_i)$ denotes the topological index τ of the road network N_i, the matrix $X_{i,t}$ contains the time varying controls, γ_i is a municipality level fixed effect, $\omega_{w(t)}$ is a week of year fixed effect, $\delta_{d(t)}$ is a day of week fixed effect, and $\varepsilon_{i,t}^{p}$ is the residual.

$$y_{i,t}^{p} = \theta f_\tau(N_i) + \beta X_{i,t} + \gamma_i + \omega_{w(t)} + \delta_{d(t)} + \varepsilon_{i,t}^{p} \tag{15}$$

The parameter of interest in this model is θ which tells us about the impact of road network structure on pollution stocks. In the stocks and flows model, $\theta f_\tau(N_i)$ comes from Equation 11. Per the motivating theory, the expected sign of theta is indeterminate, and in practice will depend upon which topological index we consider (recall Section 4). The magnitude of the effect of road network structure on pollution stocks, the parameter θ will not carry specific meaning given that topological indices are not exactly equivalent to the partial derivative from Equation 11 but merely an approximation of this. Thus, it will not be reasonable to interpret the magnitude of θ, only the sign and statistical significance.

6.2 Pollution Flows

In addition to considering pollution stocks, we also consider pollution flows. Since no papers to date consider the impact of road networks structure on pollution outcomes or use topological indices, it is highly important that results are robust in the sense that they are consistent for both pollution stocks and flows.

To determine the impact of road network structure on pollution flows, a first differenced model of pollution stocks is used. The model is specified as follows where $\Delta y_{i,t}^{p}$ denotes the change in the pollution stock of pollutant p in municipality i on day t, N_i denotes the road network for municipality i, $f_\tau(N_i)$ denotes the topological index τ of the road network N_i, the matrix $X_{i,t}$ contains the time varying controls, γ_i is a municipality level fixed effect, $\omega_{w(t)}$ is a week of year fixed effect, $\delta_{d(t)}$ is a day of week fixed effect, and $\varepsilon_{i,t}^{p}$ is the residual. The first differenced model still includes the municipal level fixed effect to account for local emissions from sources other than transportation, e.g., power plants. manufactories, etc. Because the municipal level fixed effect is included, a Hausman-Taylor approach is again used to estimate θ, the parameter of interest.

$$\Delta y_{i,t}^{p} = \theta f_\tau(N_i) + \beta X_{i,t} + \gamma_i + \omega_{w(t)} + \delta_{d(t)} + \varepsilon_{i,t}^{p} \tag{16}$$

7 Results and Discussion

7.1 Pollution Stocks

We begin with the results for pollution stocks. Estimates of θ for each pollutant-topological index combination can be found in Table 1.

The first topological index described in this paper was mean edge betweenness centrality, a measure of how important road segments are to efficiently traversing the road network. Assuming that the mean edge betweenness centrality of a road network is a much better descriptor of network connectivity than the opportunity cost of driving (which is the intention behind choosing this topological index), the expected sign of θ is positive. We find a positive and statistically significant result for mean edge betweenness centrality, indicating that more bottlenecks in road networks leads to higher levels of pollution, potentially through increased congestion. Conditional on this topological index being a much better descriptor of network connectivity than the opportunity cost of driving, this result conforms with theoretical expectations. I.e., road networks in which roads are more likely to have bottlenecks at critical junctures for efficiently traversing the network are less efficiently designed and contribute to higher pollution levels.

Mean load centrality, a vertex analog of edge betweenness centrality, had very similar results to mean edge betweenness centrality. The expected sign of θ was again positive since all we have done is change our focus from the importance of road segments to the importance of intersections for efficiently traversing the road network. We again find a positive and statistically significant result. The consistency between the edge and vertex based notions of centrality provides credibility to the use of these topological indices as a measure of the structure of municipal road networks.

The third topological index discussed was the percentage of three-way intersections in the network. Similar to the previous two topological indices, this was chosen with the expectation that it is a better predictor of network connectivity than the opportunity cost of driving. This result again confirms the model, as we have a positive and statistically significant estimate.

The final topological index mentioned earlier in the paper was the circuity of the network. Circuity was chosen as a viable candidate for a better descriptor of the opportunity cost of driving than network connectivity. Given this, we should expect a negative value for θ, and this is precisely what we see. Drivers are likely driving less in more circuitous networks due to the higher opportunity cost of driving, thereby leading to lower levels of pollution stocks.

Altogether, these results indicate two key takeaways. First, relevant topological indices can be used as reliable measures of the structure of a road network. Second, we have established sound evidence that the structure of municipal road networks has an effect on ambient pollution levels.

Table 1: Estimated values of θ for each pollutant-topological index pair from the Hausman-Taylor model for the impact of road network structure on pollution stocks. *** denotes statistical significance at the 1% level, ** denotes statistical significance at the 5% level, and * denotes statistical significance at the 10% level. There are $N = 2,915$ observations included in the regressions. Robust standard errors are provided in parentheses.

	Fine Particulate Matter			
Mean Edge Betweenness Centrality	303.776**			
	(150.425)			
Mean Load Centrality		120.496**		
		(59.668)		
Percentage of 3-Way Intersections			12.421**	
			(6.151)	
Circuity				-14.425**
				(7.143)
Temperature	0.012	0.012	0.012	0.012
	(0.012)	(0.012)	(0.012)	(0.012)
Precipitation	-0.611***	-0.611***	-0.611***	-0.611***
	(0.101)	(0.101)	(0.101)	(0.101)
Wind Speed	-0.130***	-0.130***	-0.130***	-0.130***
	(0.018)	(0.018)	(0.018)	(0.018)

7.2 Pollution Flows

Next we turn our attention to pollution flows. Our theoretical framework suggests that we should expect to see the same signs for θ in these models that we expected to see in the case of pollution stocks. Results are presented in Table 2.

Mean edge betweenness centrality yet again presented a positive and statistically significant estimate of θ, confirming that a greater presence of bottlenecks lead to higher pollution levels, likely through increased congestion. For the intersection analog, mean load centrality, we also see the same effect. This consistency further validates the credibility of the results and of the use of appropriate topological indices for measuring the connectivity of road networks.

The percentage of three-way intersections again was positive and statistically significant. This consistency further validates the use of topological indices, the model, and the plausibility of increased congestion from less robustly connected road networks leading to higher levels of pollution stocks.

Finally, the estimate for circuity is positive and statistically significant. In the pollution stocks regression, we observed a negative and statistically significant result. However, the opposite sign estimated in the pollution flows regression is not necessarily a contradiction. In fact, a strong economic argument can be made that this coefficient should be positive for pollution flows. The negative estimate found in the pollution stocks regression indicates that drivers have reached a lower equilibrium level of driving in municipalities with more circuitous road networks. But in the short run commitments are much less flexible and the opportunity cost of driving may be much lower. Thus, in the short run, we should expect increased vehicle miles travelled as a consequence of driving more circuitous routes between locations in the road network since traversing these routes requires more driving, not less.

Table 2: Estimated values of θ for each pollutant-topological index pair from the Hausman-Taylor model for the impact of road network structure on pollution flows. *** denotes statistical significance at the 1% level, ** denotes statistical significance at the 5% level, and * denotes statistical significance at the 10% level. There are $N = 1,789$ observations included in the regressions. Robust standard errors are provided in parentheses.

	Fine Particulate Matter			
Mean Edge Betweenness Centrality	51.593**			
	(25.979)			
Mean Load Centrality		23.310**		
		(11.738)		
Percentage of 3-Way Intersections			70.435**	
			(35.467)	
Circuity				5.289**
				(2.663)
Temperature	-0.080***	-0.080***	-0.080***	-0.080***
	(0.0117	(0.017)	(0.017)	(0.017)
Precipitation	-0.654***	-0.654***	-0.654***	-0.654***
	(0.170)	(0.170)	(0.170)	(0.170)
Wind Speed	-0.121***	-0.121***	-0.121***	-0.121***
	(0.027)	(0.027)	(0.027)	(0.027)

8 Mechanism Validation

In the previous section, it was shown that the structure of a road network has an impact on pollution stocks and flows, and the nature of this relationship was described for each of the four topological indices considered in this paper. However, these results were interpreted within the context of an assumed framework. In this section it is shown that the four topological indices are indeed satisfactory measures of either congestion or of the opportunity cost of driving.

To do this, a measure of congestion and a measure of average commute times will each be regressed against each of the topological indices. Specifically, a separate regression is run for each pair $(y_i^m, f_\tau(N_i))$ of mechanism and topological index. The two mechanisms, congestion and the opportunity cost of driving, are represented here by the ratio of drive times during peak traffic to drive times during free flow traffic and the mean commute time, with data coming from the Bureau of Transportation Statistics and Census Bureau, respectively. Due to data availability on the mechanisms measures, the geographical area considered here consists of 51 of the largest metro areas in the United States. Road networks are again obtained using OSMnx. Controls include population, the per capita annual number of public transit rides, and an indicator for whether or not each metro area is a capital. Density, as a measure of urban form, is again used as an instrument. The IV regressions are specified as shown in Equation 17. Summary statistics for the data can be found in Table 6.

$$y_i^m = \theta f_\tau(N_i) + \beta X + \varepsilon_i^m \tag{17}$$

Figure 6: Summary statistics for the topological indices, mechanisms, and controls for the cross section of metro areas used in this section.

	Mean	SD	Min	Median	Max
Mean Edge Betweenness Centrality	0.002	0.001	0.000	0.001	0.005
Mean Load Centrality	0.004	0.002	0.001	0.004	0.014
Circuity	1.047	0.019	1.012	1.043	1.089
Congestion	1.093	0.031	1.050	1.080	1.170
Mean Commute Time	27.884	3.657	21.400	27.500	37.700
Density	5768.510	5005.294	1123.000	4256.000	29298.000
Capital	0.314	0.469	0.000	0.000	1.000
Trips	34.218	38.159	3.300	23.400	229.800
Ln(Populaton)	14.854	0.824	13.862	14.676	18.143

Results from the mechanisms models confirm the assumptions made about what the topological indices are describing and can be found in Table 3.

Beginning with the congestion models we see that both mean edge betweenness centrality and mean load centrality lead to larger congestion ratios. As these two topological indices are used to measure the presence of bottlenecks in road networks, and since bottlenecks should lead to more congestion, we can confirm that higher levels of mean edge betweenness centrality or mean load centrality cause higher levels of pollution through increased congestion from a greater presence of bottlenecks.

Turning our attention to the mean commute time models, we see that there is a statistically significant effect attributable to circuity. Since circuity was intended to be a measure of the opportunity cost of driving, we can confirm that the lower levels of pollution stocks observed in municipalities with more circuitous road networks can be explained by less driving occurring as a consequence of greater commute times. Similarly, the higher levels of pollution flows observed in municipalities with more circuitous road networks can be explained by drivers having fixed commitments in the short run, commitments which require greater time spent driving and thus higher levels of vehicular emissions.

Table 3: Estimated values of θ for each mechanism-topological index pair from the IV model for the impact of road network structure on pollution inducing mechanisms. *** denotes statistical significance at the 1% level, ** denotes statistical significance at the 5% level, and * denotes statistical significance at the 10% level. There are $N = 51$ observations in each cross section. Robust standard errors are provided in parentheses.

	Congestion Ratio			ln(Mean Commute Time)		
Mean Edge Betweenness Centrality	29.017***			-74.879		
	(5.919)			(67.074)		
Mean Load Centrality		8.717***			-31.823	
		(3.097)			(28.812)	
Circuity			-0.842			3.265*
			(0.557)			(1.888)
Capital	-0.004	-0.002	0.011***	0.057***	0.059***	0.011
	(0.004)	(0.005)	(0.003)	(0.014)	(0.017)	(0.016)
ln(Public Transit)	0.004	0.005	0.003	0.063***	0.065***	0.076***
	(0.017)	(0.015)	(0.013)	(0.003)	(0.005)	(0.012)
ln(Population)	0.033***	0.030***	0.018***	0.053*	0.049*	0.093***
	(0.010)	(0.010)	(0.003)	(0.027)	(0.028)	(0.002)
Constant	0.547***	0.596***	1.694***	2.423***	2.494***	-1.720
	(0.108)	(0.111)	(0.580)	(0.512)	(0.544)	(2.045)

9 Conclusion

Transportation is among the leading causes of air pollution. The structure of road networks affects transportation patterns and thus affects air pollution. Assuming the fundamental law of road congestion, a simple theoretical framework of the contribution of transportation to air pollution stocks and flows was used to make predictions about the indirect effect of the structure of road networks through transportation on air pollution stocks and flows.

In order to determine the effect of road network structure on air pollution stocks and flows, a theoretical framework for the effect of the structure of road networks was developed. Several topological indices were used to describe the structure of municipal road networks. Using the definitions of the different topological indices, predictions were made as to the expected sign of the point estimate of the effect of the structure of the road network on air pollution stocks and flows. Using these topological indices with Hausman-Taylor models using a measure of urban form as an instrument, we found that road network structure does indeed affect air pollution stocks and flows in a way which conforms to our theoretically derived hypotheses.

To confirm that the topological indices used really were measuring what they were claimed to be measuring, and to confirm the economic explanations offered for the mechanisms explaining the observed effects of road network structure on pollution stocks and flows, additional IV regressions were run in which measures of congestion and of the opportunity cost of driving were regressed against the topological indices over a cross section of 51 of the largest metro areas in the United States. Results from these regressions further confirmed that the topological indices are valid measures for what they were used to measure, specifically that they were valid measures of congestion and of the opportunity cost of driving.

Beyond identifying that the structure of road networks affects air pollution stocks and flows, and that while appropriate topological indices can be useful descriptors of the structure of road networks, the choice of topological index is critical, one final limitation must be addressed. Generalizing these results is unmistakably dependent upon the intention behind urban design. Generalizing these results to other (North) American cities should be reasonable, though verification of this would be useful. However, given that the urban form of North American cities is much more car-centric than the urban form of other cities, generalizing these results to cities outside of North America is likely a mistake, and certainly inadvisable without empirical verification.

For this reason, the most apparent policy implications for this work are twofold. The first major policy implication lies in the design of new or rapidly expanding urban(izing) areas in North America. Consider the case of a small city or even a rural/suburban area gaining a massive distribution center for some large company. Rapid expansion of this municipality is likely to ensue. With this rapid expansion comes increased traffic, increased emissions, and decreased air quality. Designing the expansion of this municipality in a pollution minimizing manner can reduce some of the costs of the new distribution center (worse air quality and correspondingly worse health outcomes), thereby leading to a better economic outcome from this new facility.

Extending this to perhaps a more practical policy implication of this work, cities which straddle rivers could benefit from the construction of additional bridges which connect the distinct sides of the city. If a single bridge were to be closed, the spillover effects would ripple across large portions of the city, increasing congestion. Conversely, the construction of an additional bridge could have spillover effects which decrease congestion throughout nearby portions of the city. However, as observed in our results, this congestion effect could potentially be outweighed by the corresponding change in the opportunity cost of driving arising from a better connected road network.

A second major policy implication of this research pertains to the design of cities insofar as how economic concepts can affect optimal urban design. Specifically, in order to reduce vehicular emissions in car-dominated cities, road networks should be designed in a manner which reduces bottlenecks and the opportunity cost of driving. This means that, in direct contradiction of the fundamental law of road congestion, additional highway lane miles can potentially be used to reduce congestion - the key here is that these additional lane miles must be created in a manner which increases the connectivity of the road network, i.e., additional lanes miles must be created in a manner which eliminates bottlenecks. If this is successfully done then increased lane miles could very well lead to reduced congestion and, by extension.

Finally, to conclude with a pithy synopsis of the results of this paper, bottlenecks are bad.

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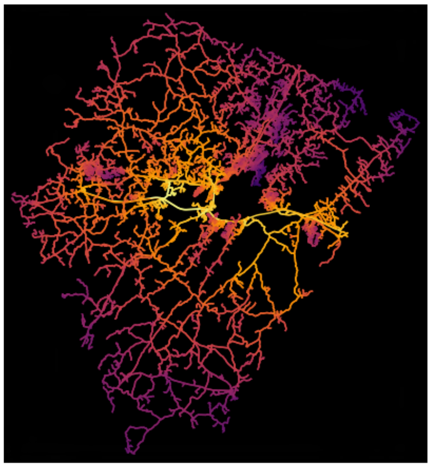
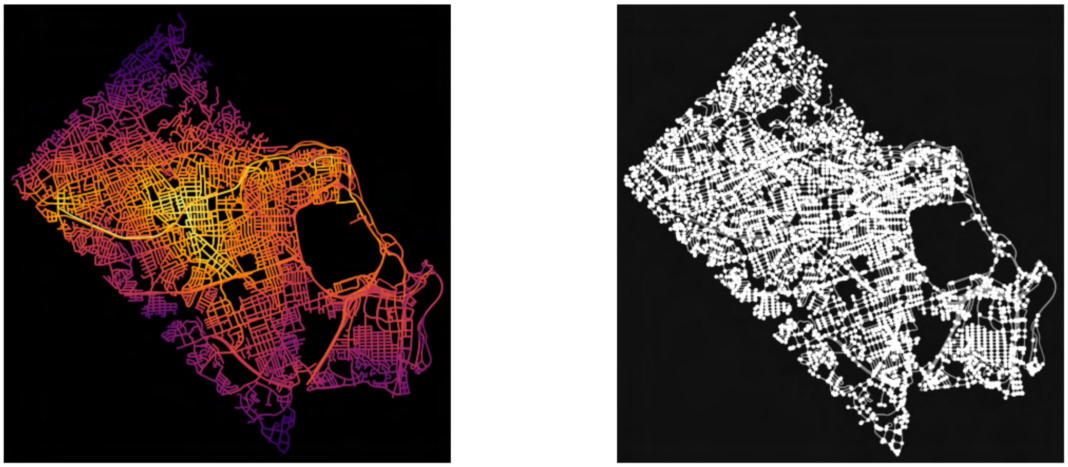
A Virginia Municipality Road Networks

Albemarle County

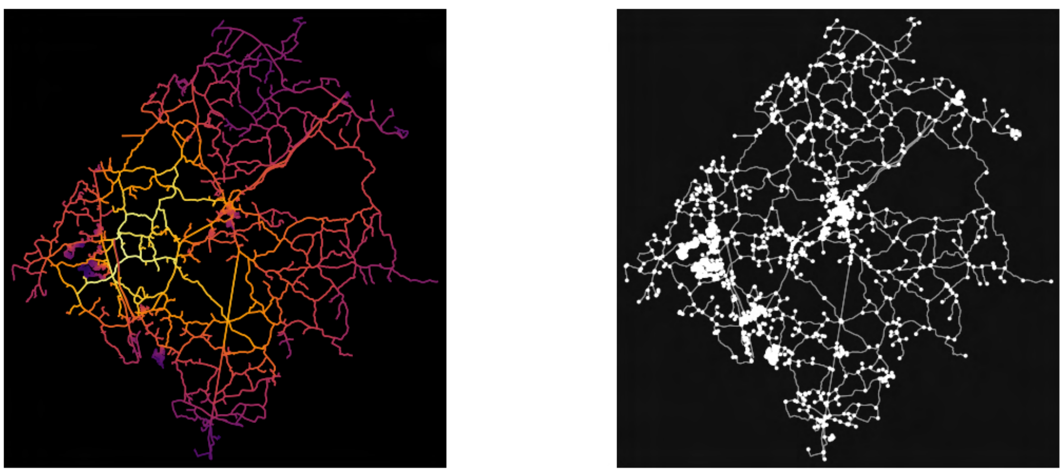



Alexandria

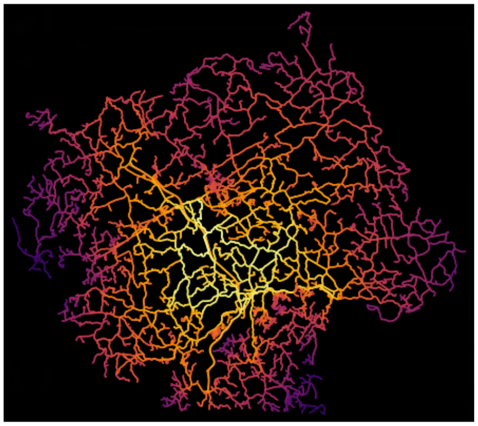

Arlington County

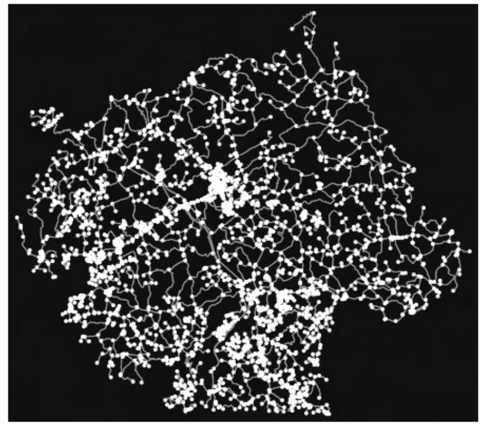


Caroline County

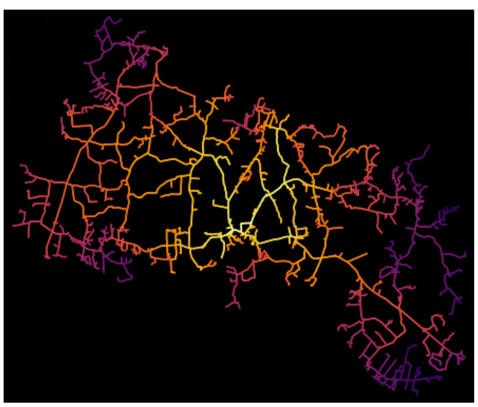


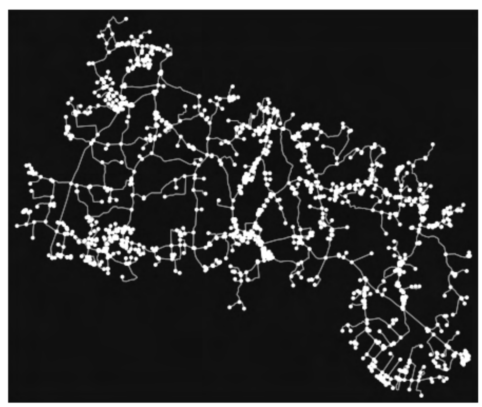
Carroll County



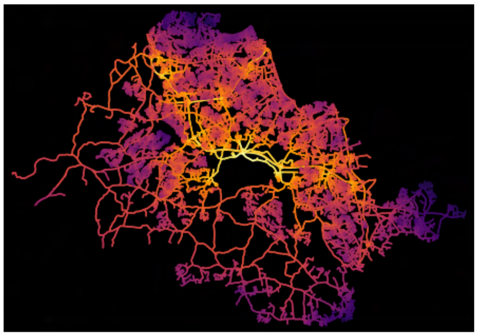


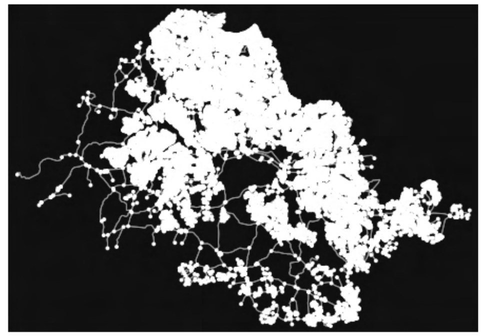
Charles City County



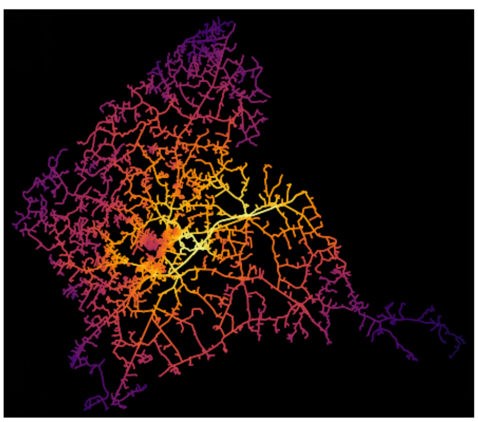


Chesterfield County

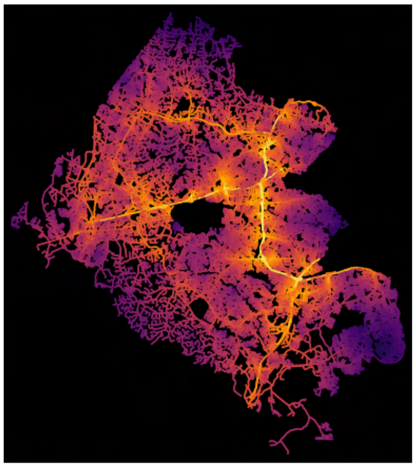
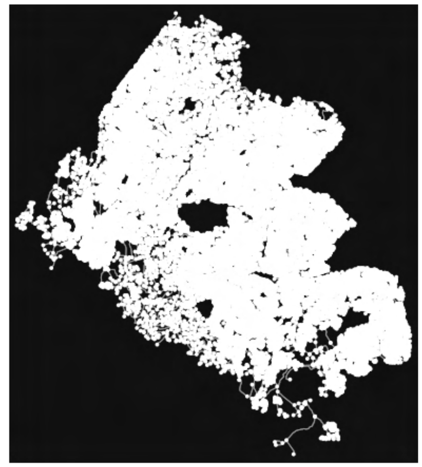




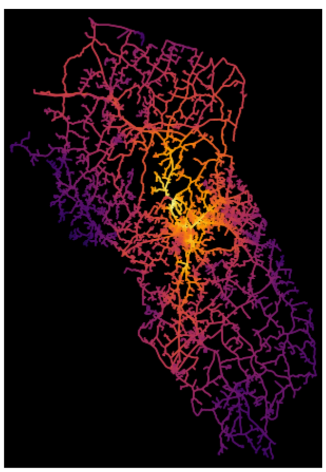
Culpeper County



Fairfax County

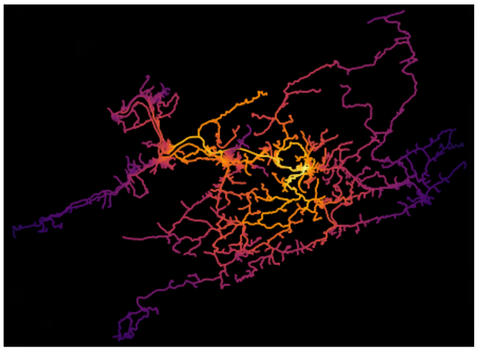
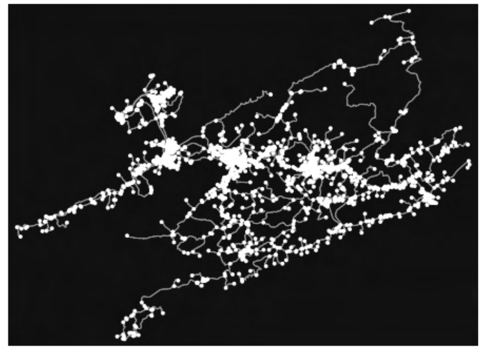
Fauquier County




Frederick County

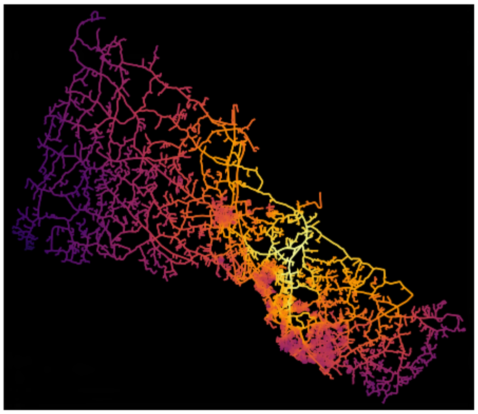
Fredericksburg

Giles County

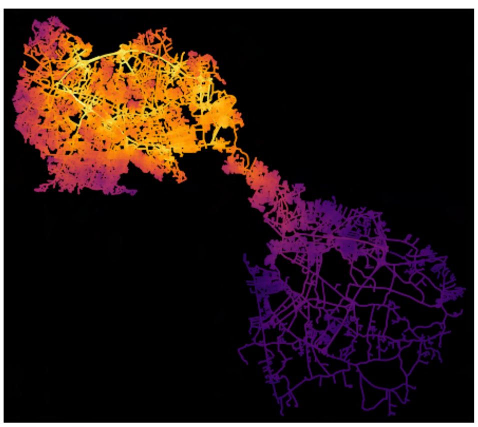



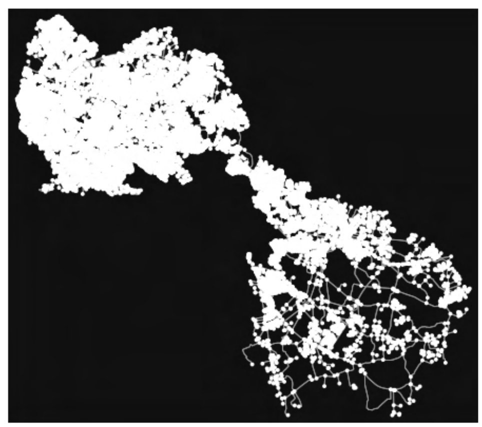
Hampton


Hanover County

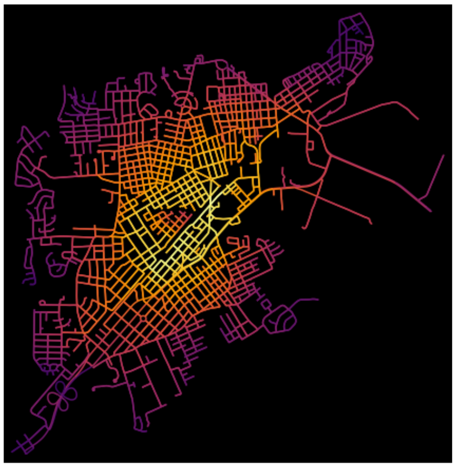


Henrico County

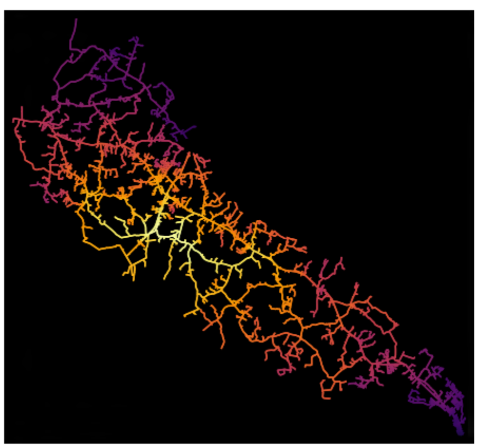
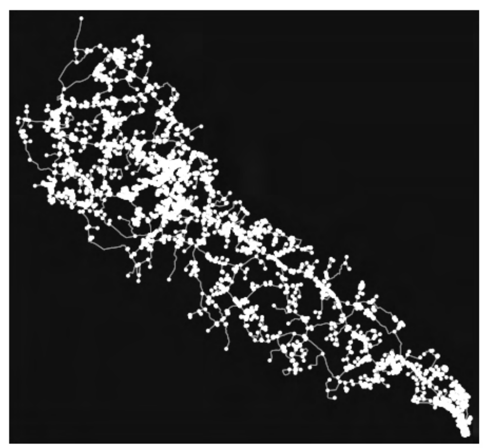




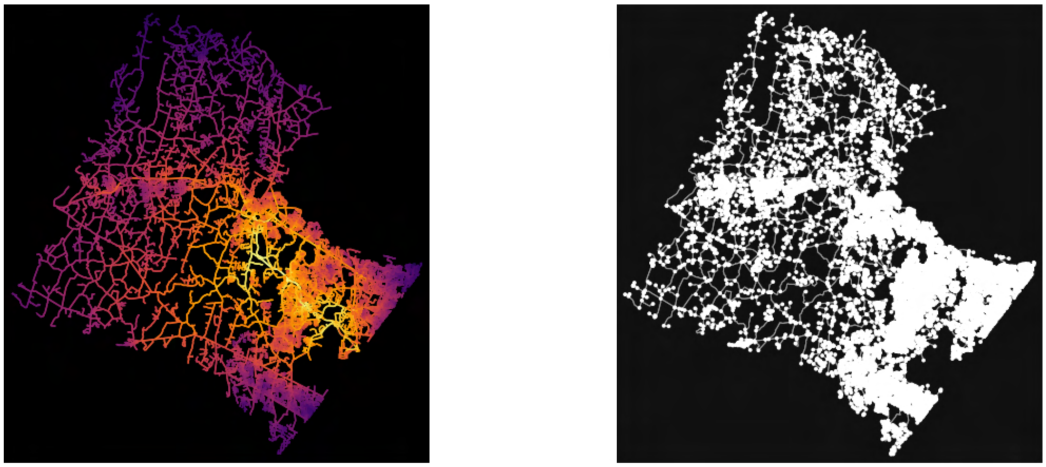
Hopewell



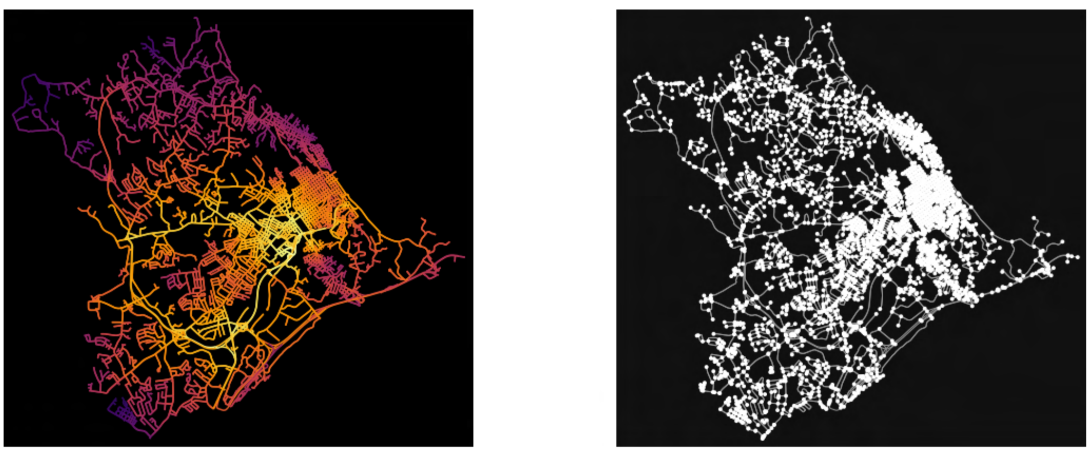

King William County

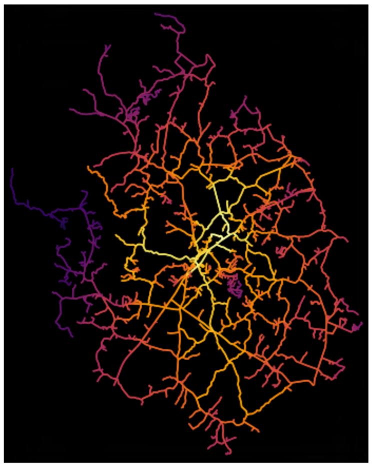
Loudoun County

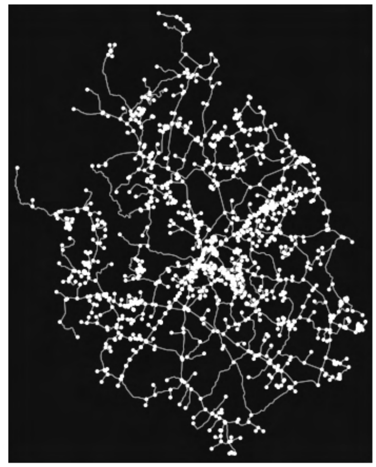


Lynchburg

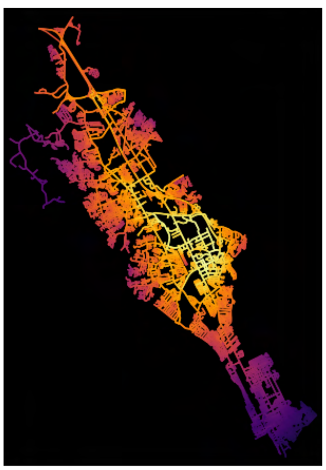


Madison County



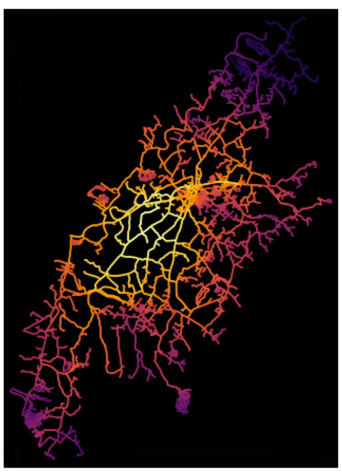


Newport News

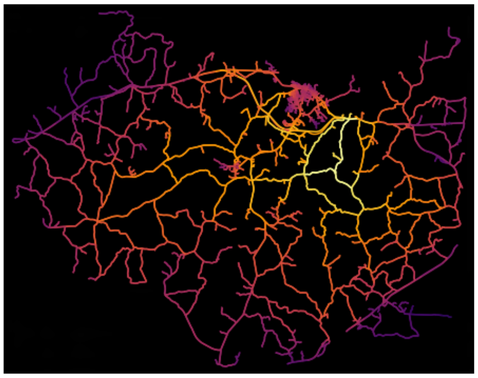
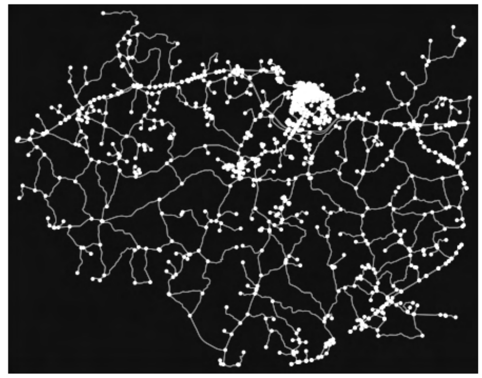


Norfolk

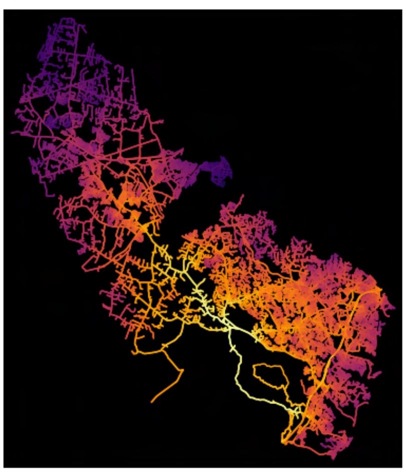

Page County



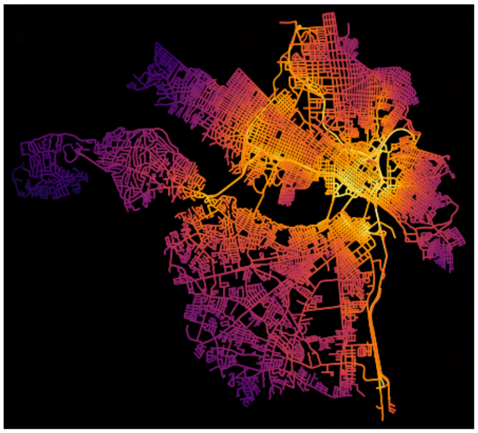

Prince Edward County

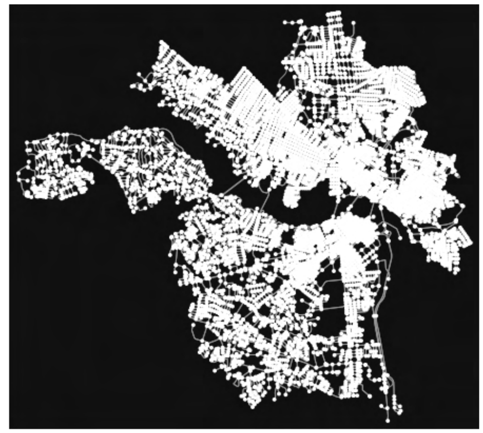
 

Prince William County

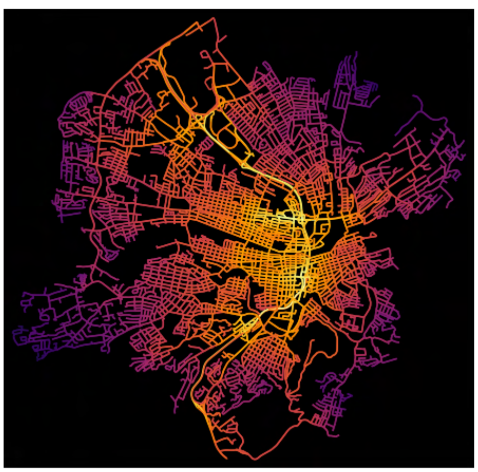
 

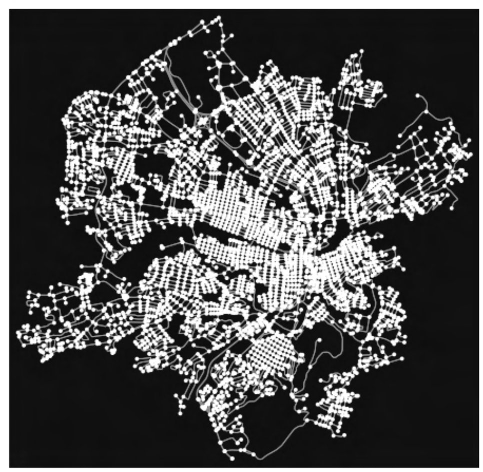
Richmond



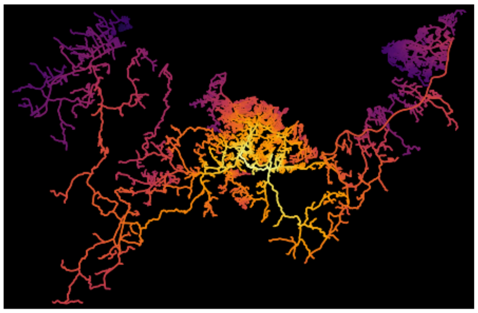


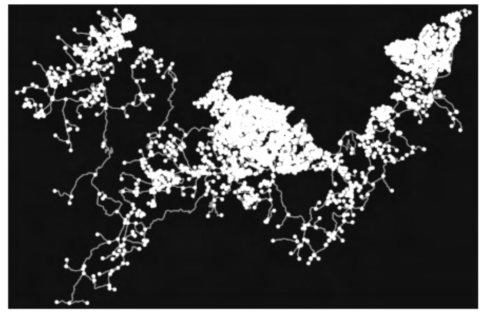
Roanoke



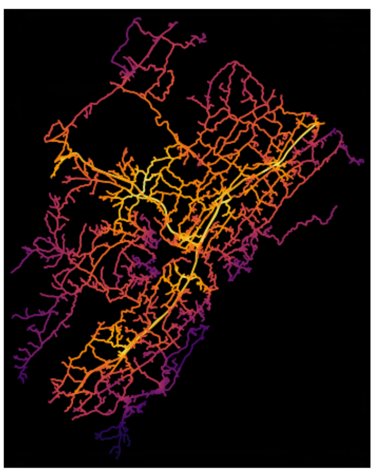


Roanoke County

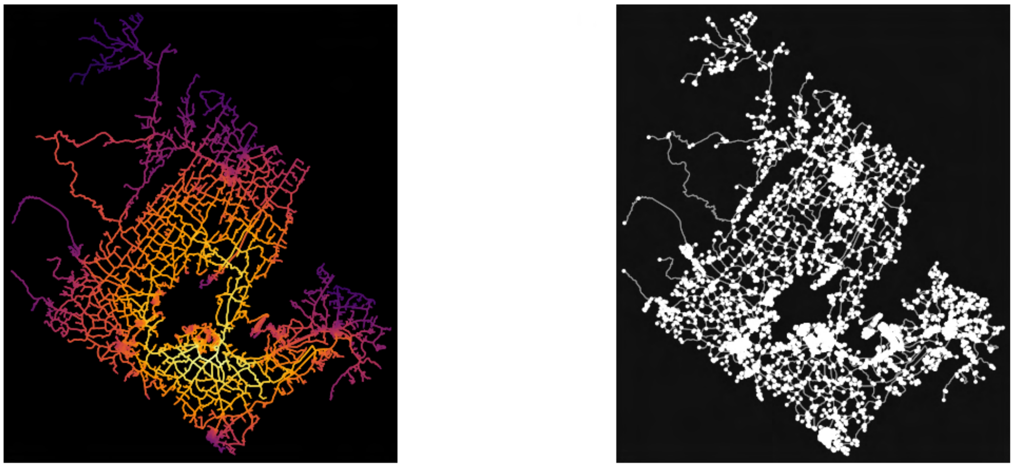




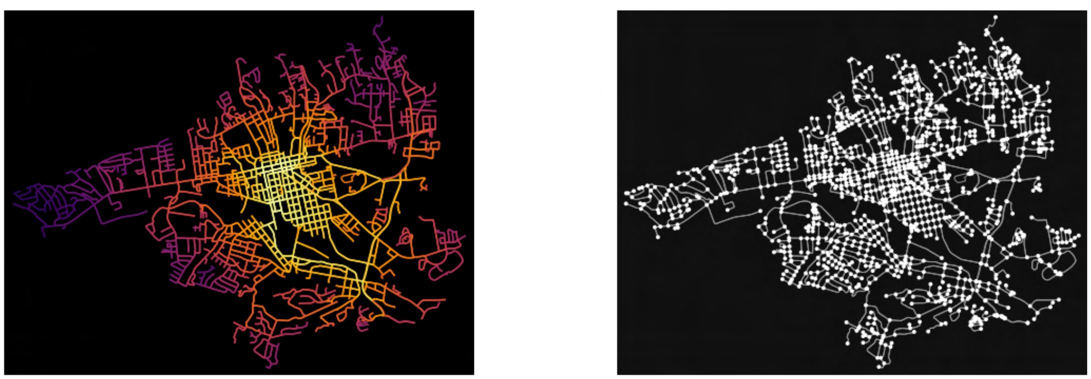
Rockbridge County



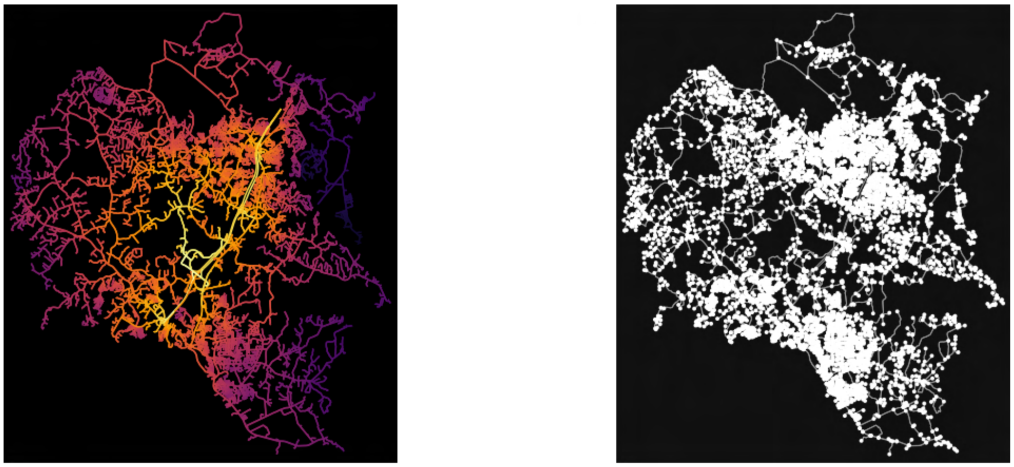
Rockingham County



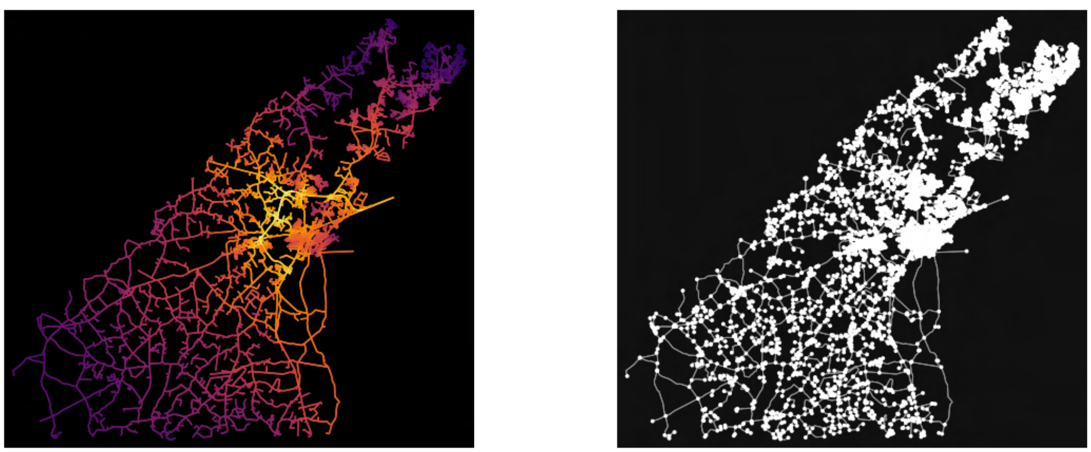
Salem



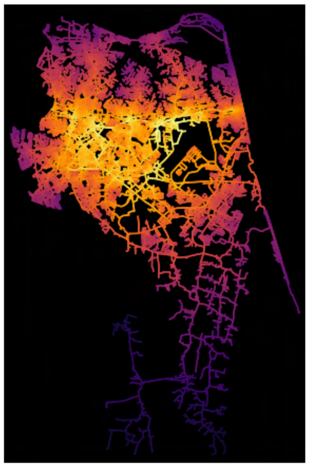
Stafford County



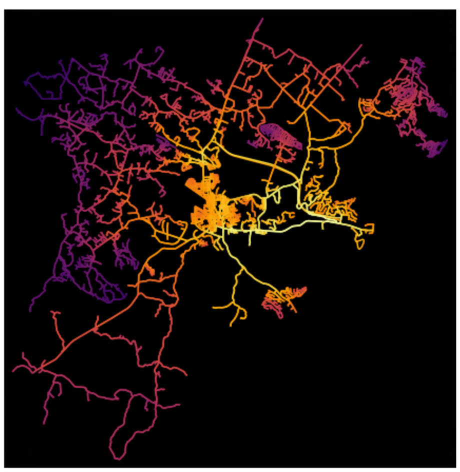
Suffolk

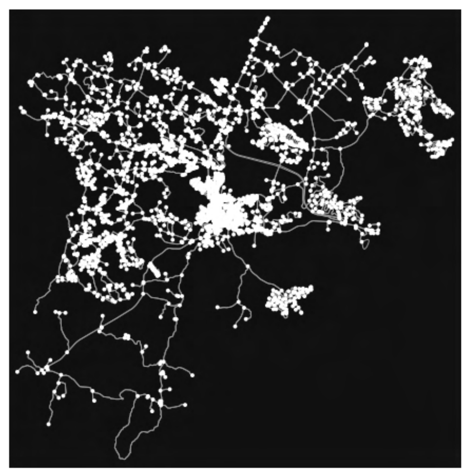


Virginia Beach



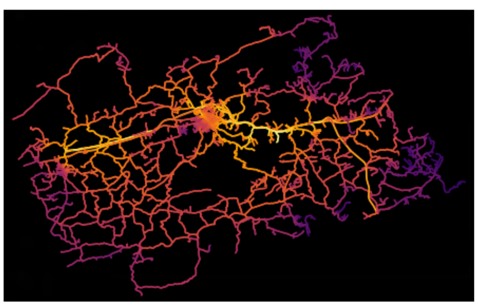
Warren County

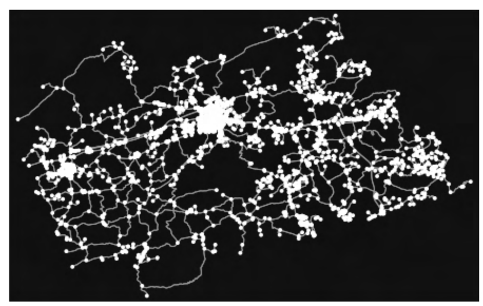




Winchester

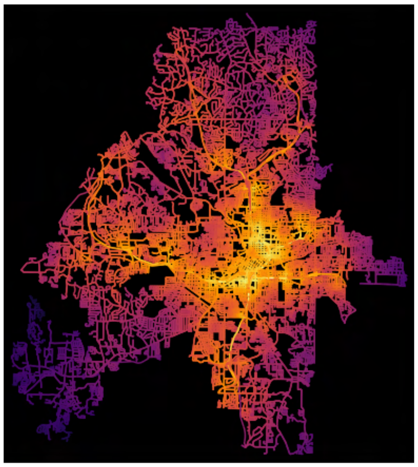
Wythe County



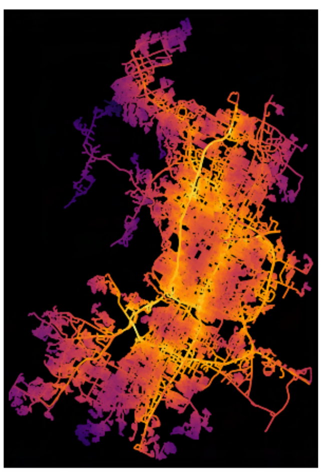


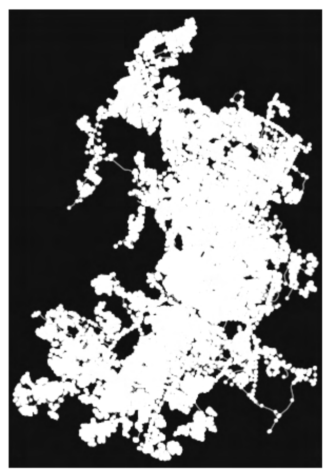
B Large Metro Area Road Networks

Atlanta, GA

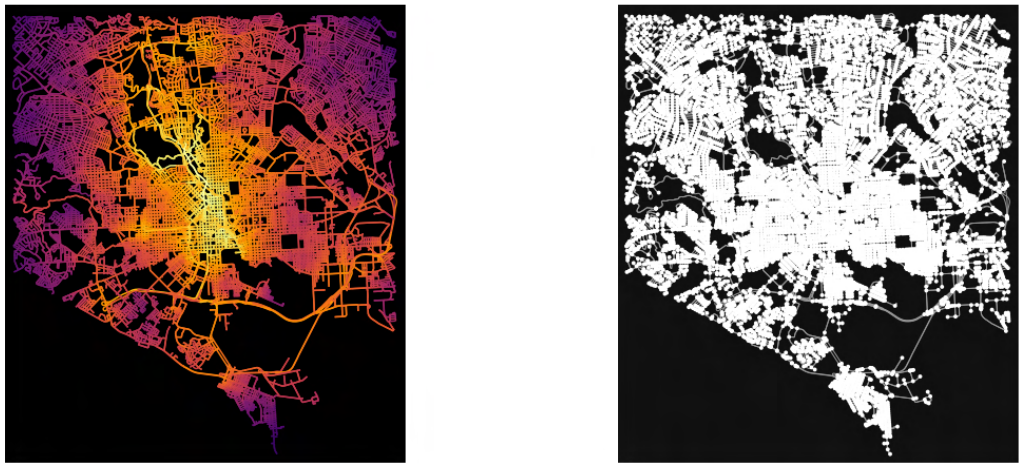


Austin, TX

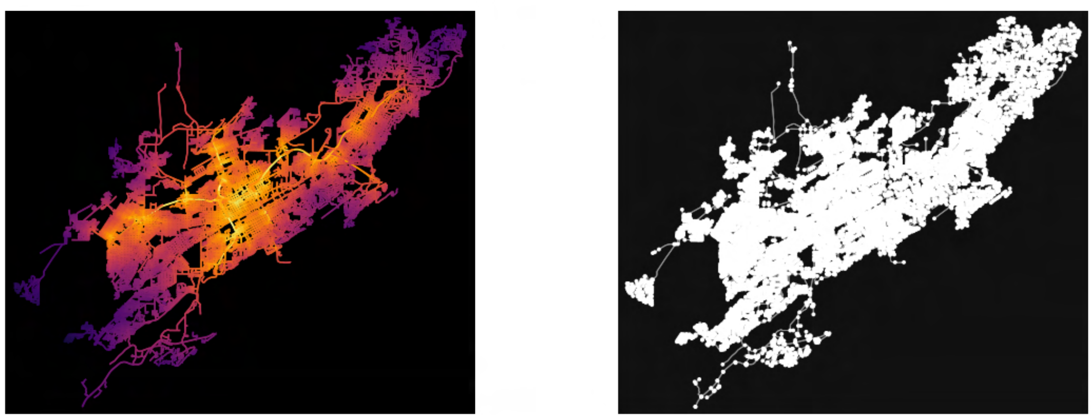




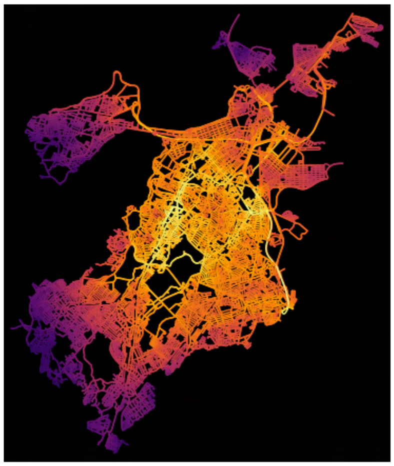
Baltimore, MD



Birmingham, AL

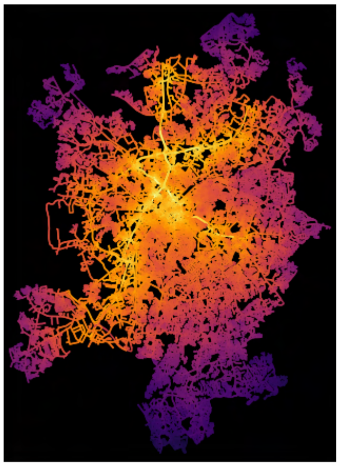


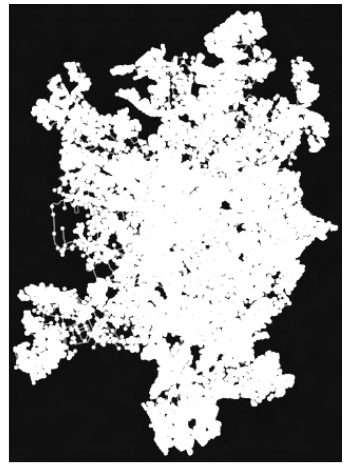
Boston, MA



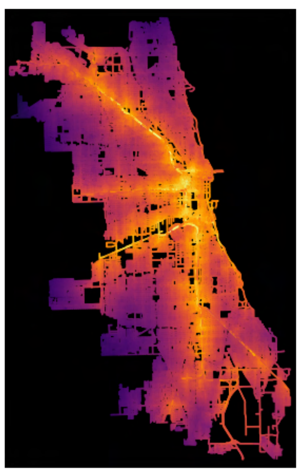

Buffalo, NY


Charlotte, NC

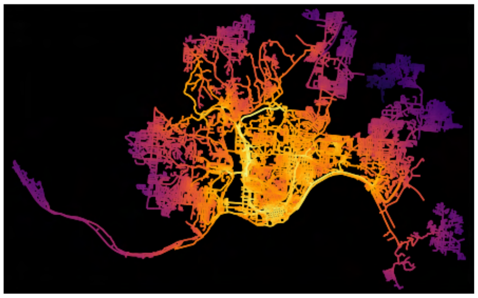


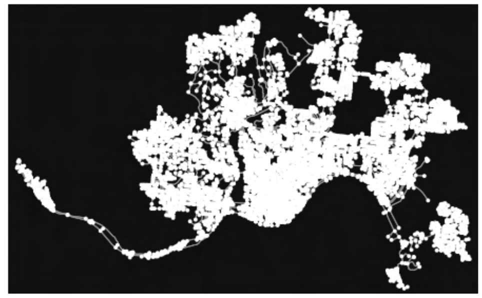


Chicago, IL

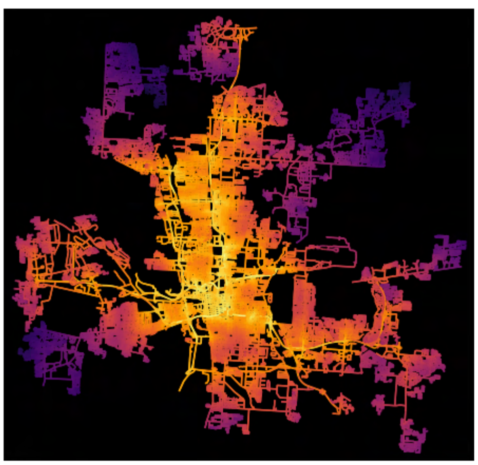


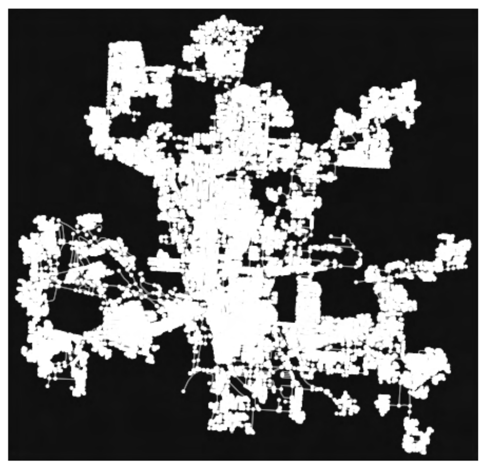
Cincinnati, OH



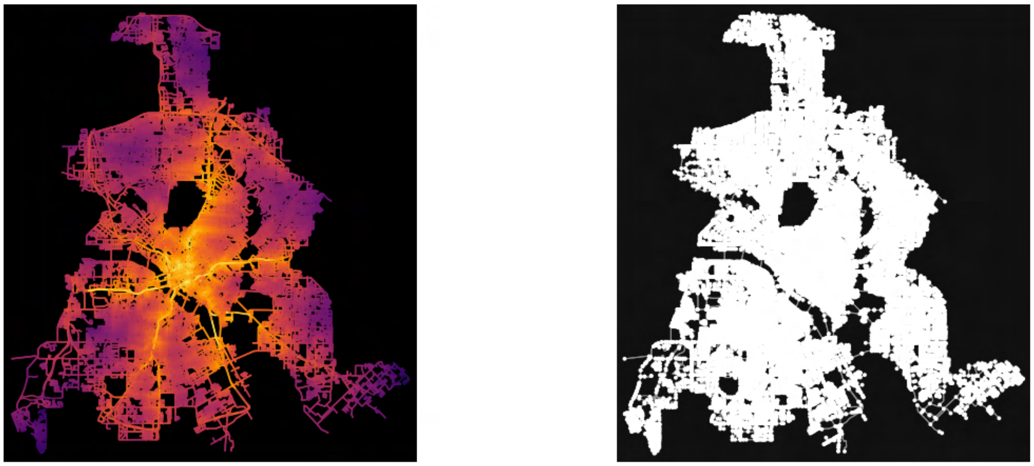


Columbus, OH

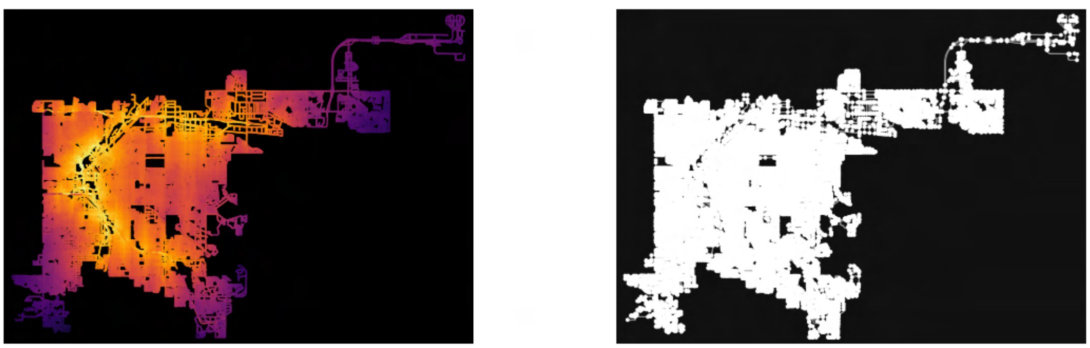




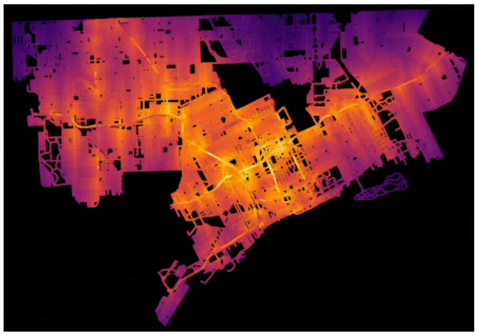
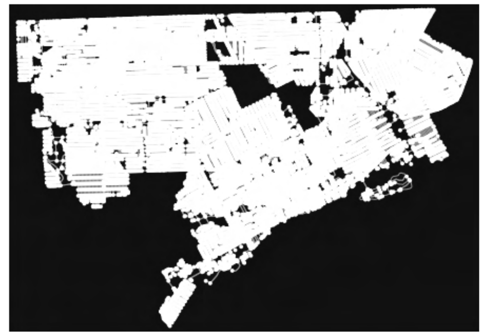
Dallas, TX



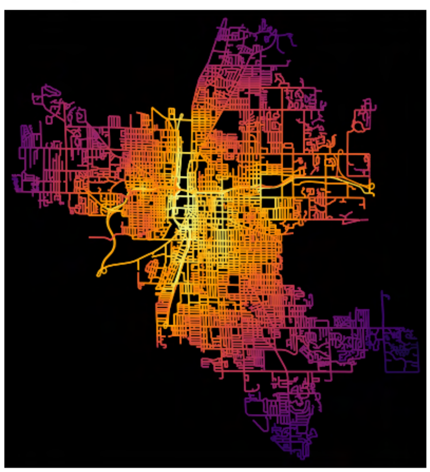
Denver, CO



Detroit, MI

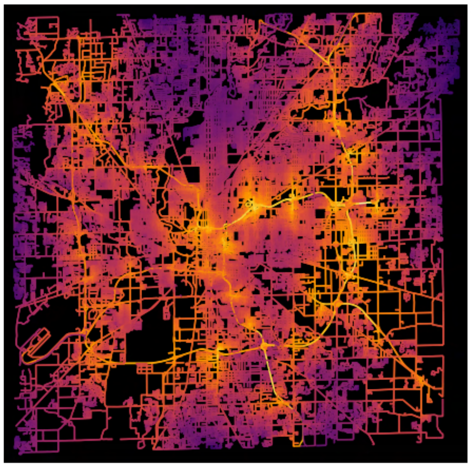
Grand Rapids, MI

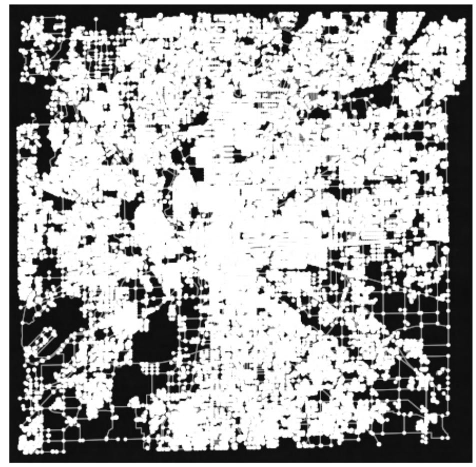



Hartford, CT

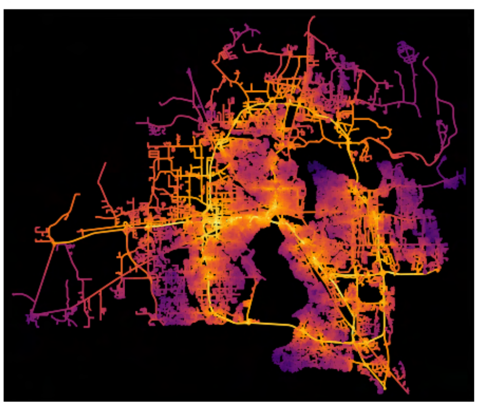
Houston, TX

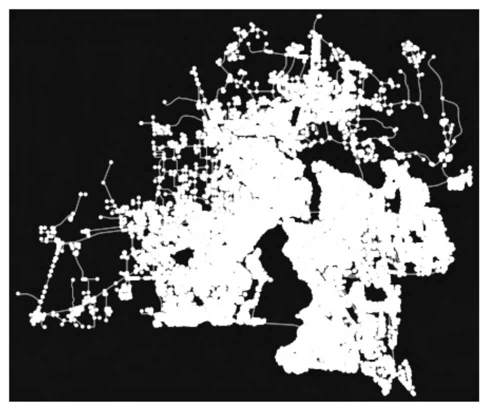
Indianapolis, IN



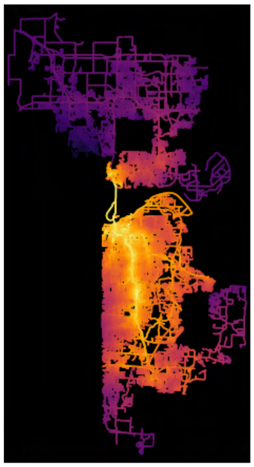


Jacksonville, FL

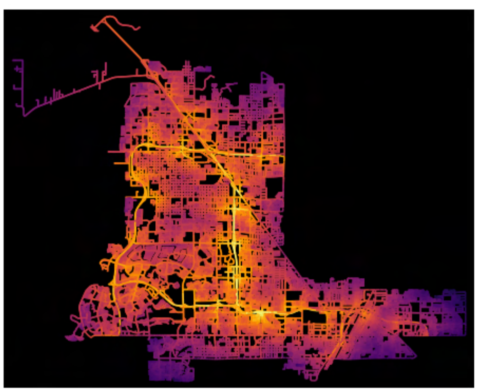




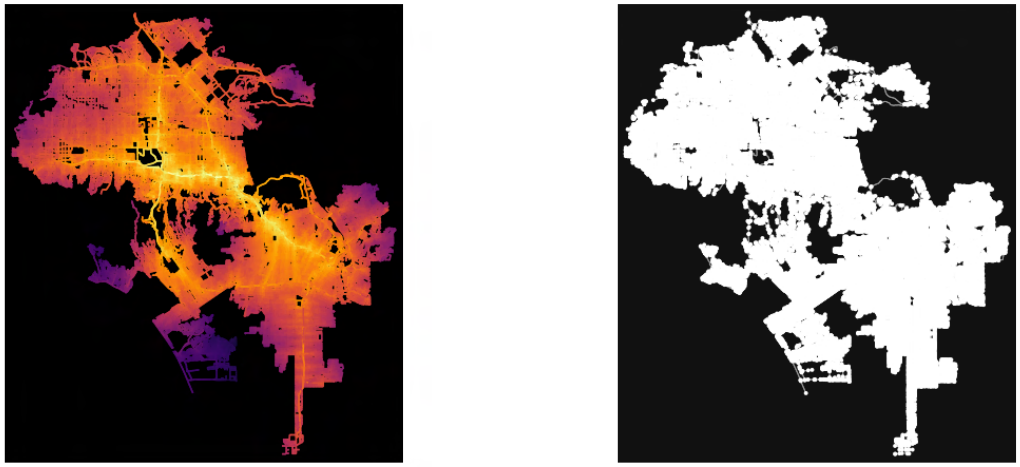
Kansas City, MO

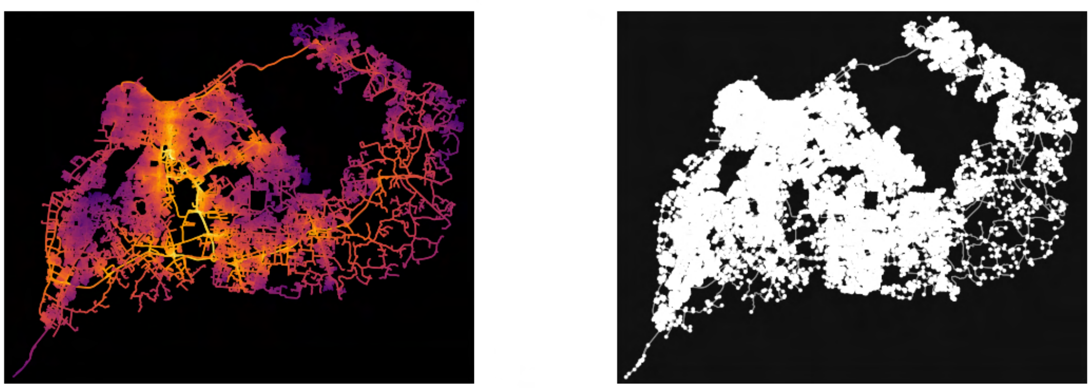
Las Vegas, NV

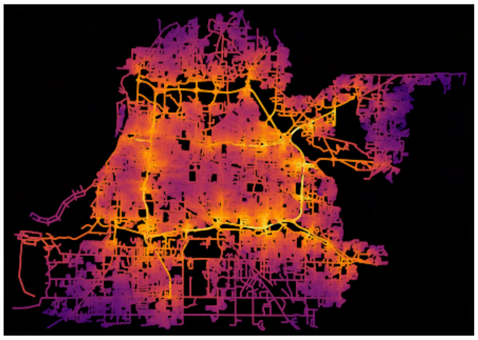
Los Angeles, CA

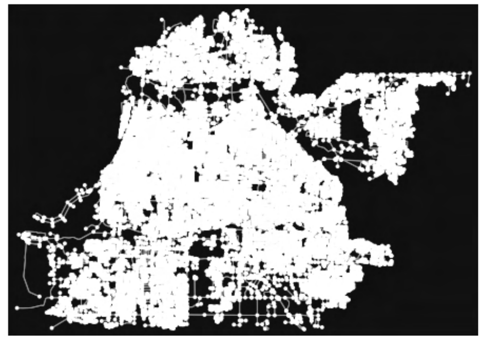


Louisville, KY

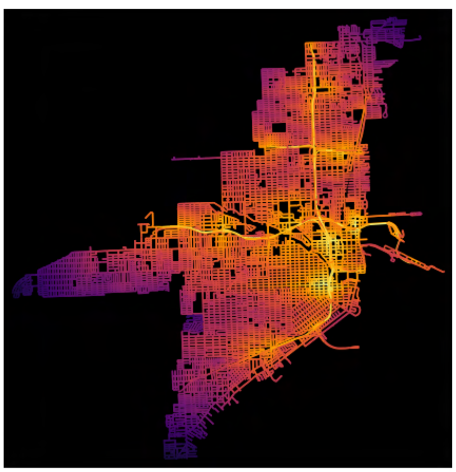


Memphis, TN





Miami, FL



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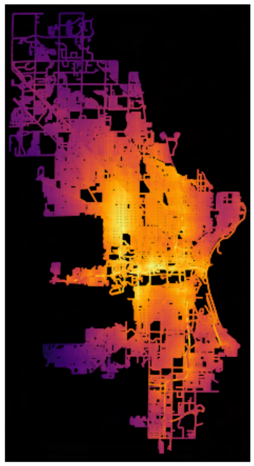
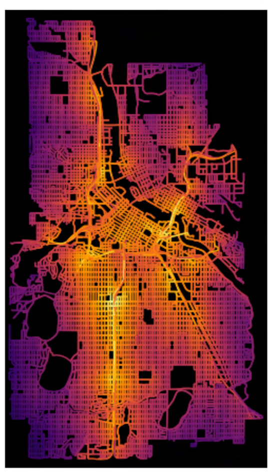
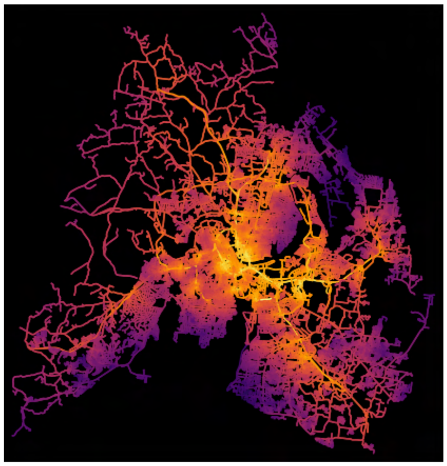
 

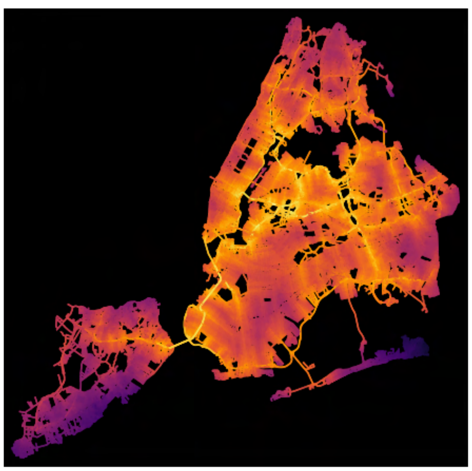
Minneapolis, MI

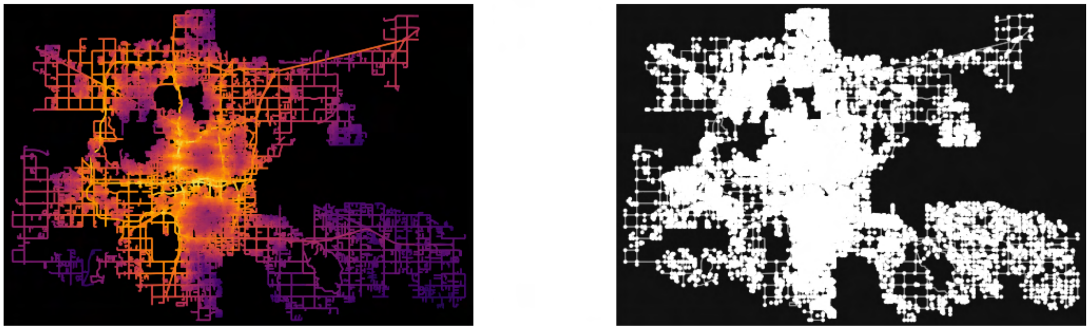
Nashville, TN



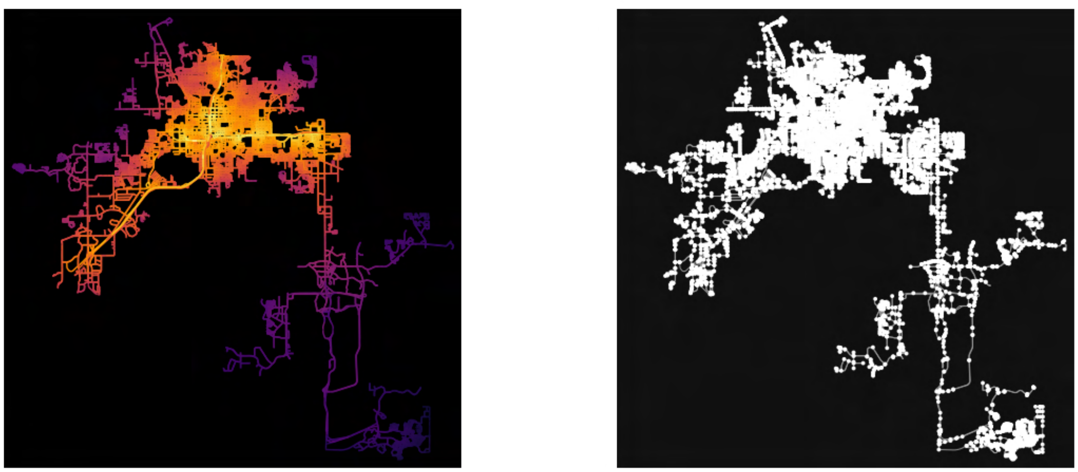
New York, NY



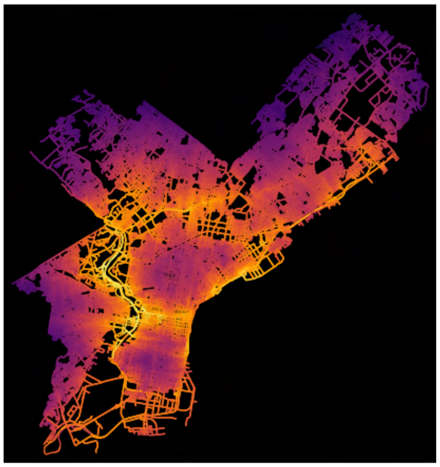
Oklahoma City, OK



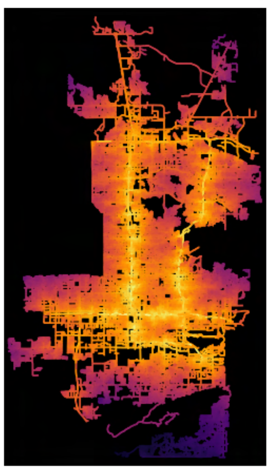
Orlando, FL



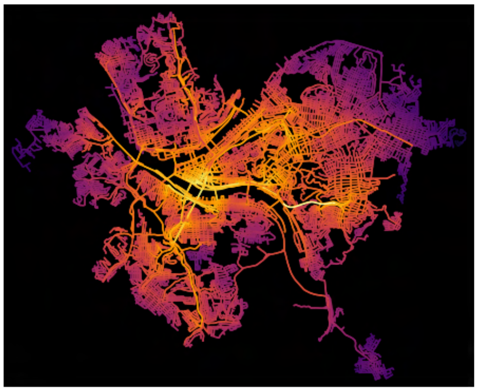
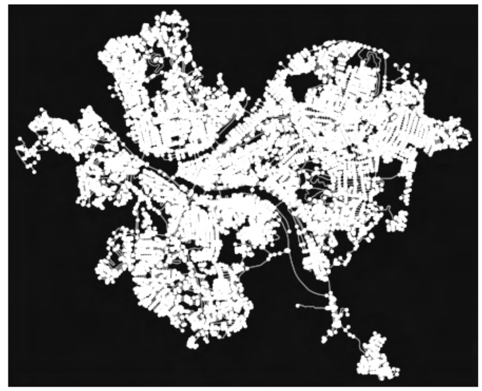
Philadelphia, PA



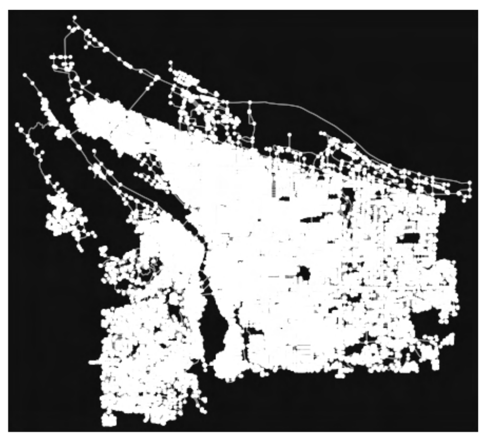
Phoenix, AZ



Pittsburgh, PA

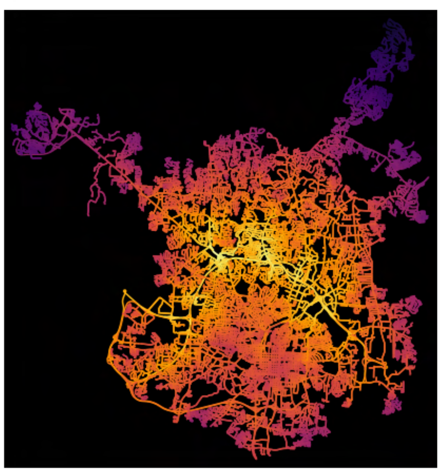



Portland, OR

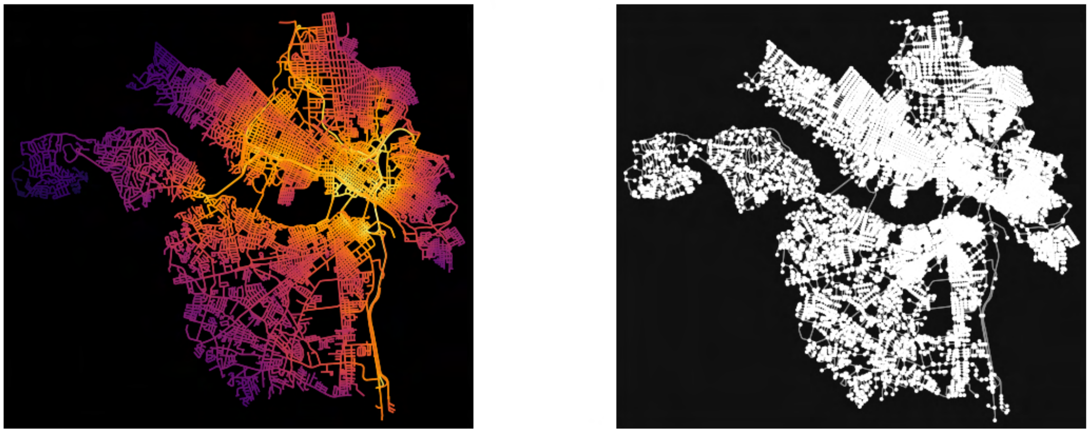



Providence, RI

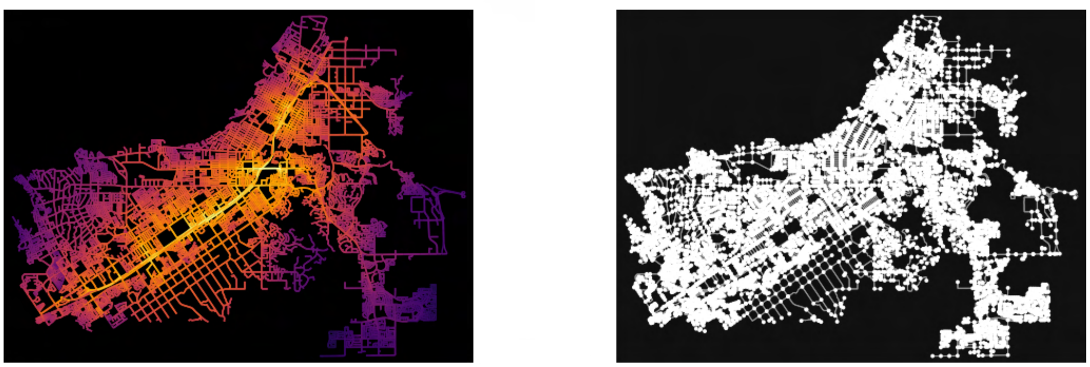
Raleigh, NC



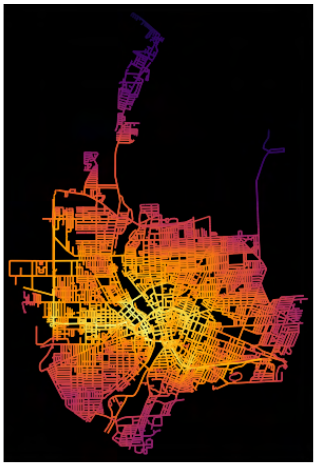
Richmond, VA



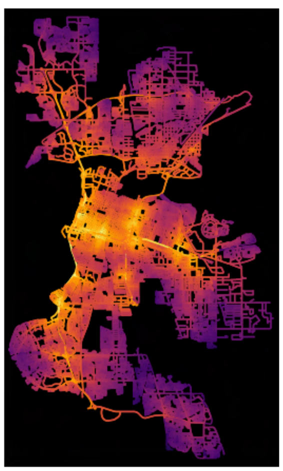
Riverside, CA



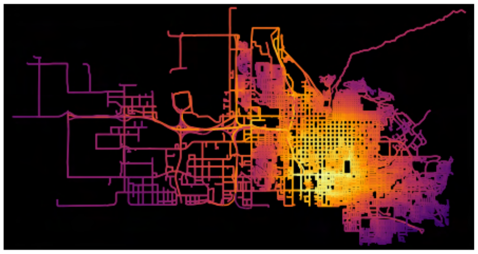
Rochester, NY

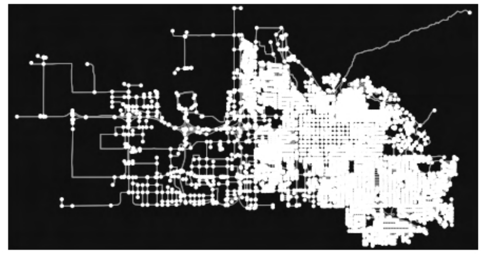


Sacramento, CA

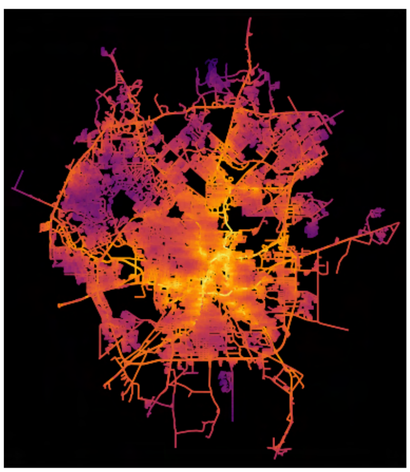


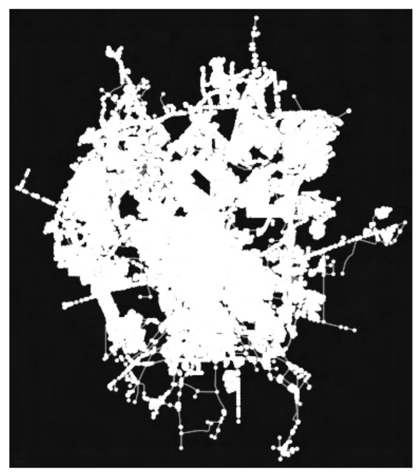
Salt Lake City, UT



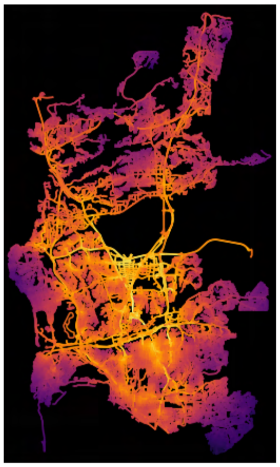


San Antonio, TX

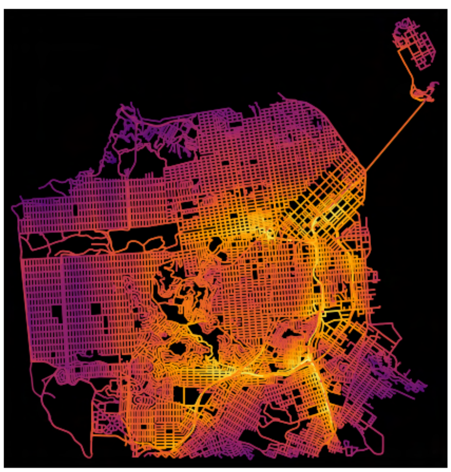




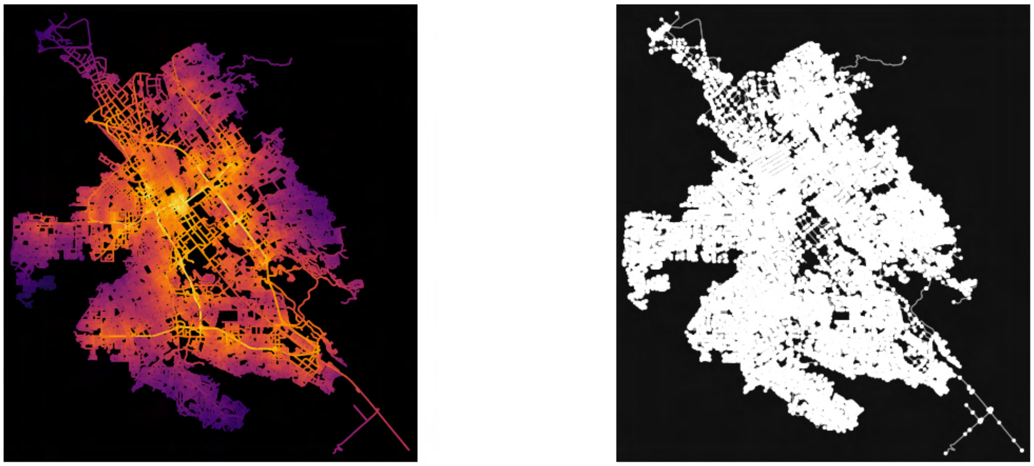
San Diego, CA



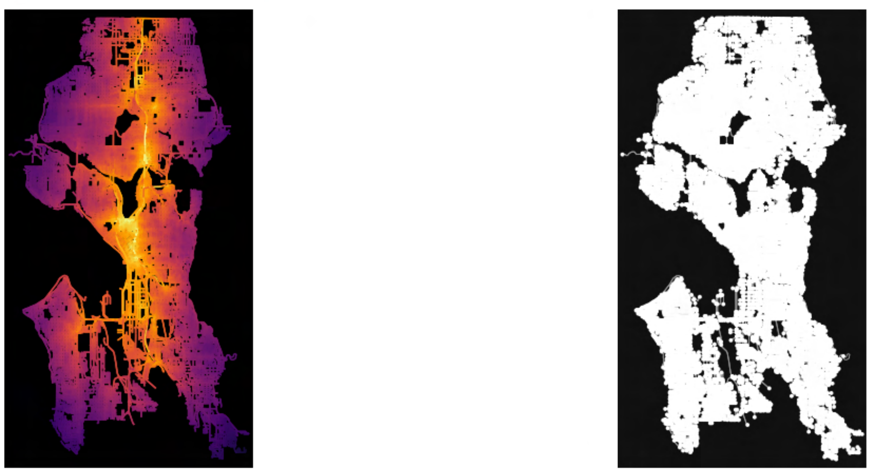
San Francisco, CA



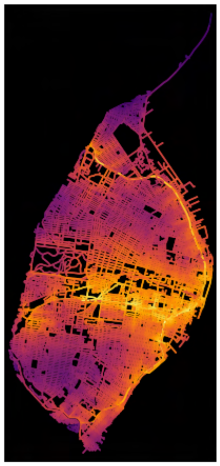
San Jose, CA

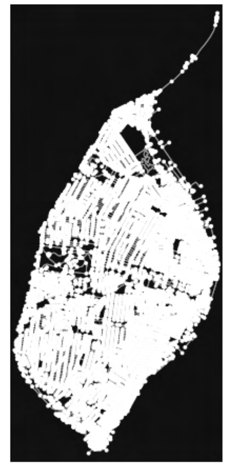


Seattle, WA

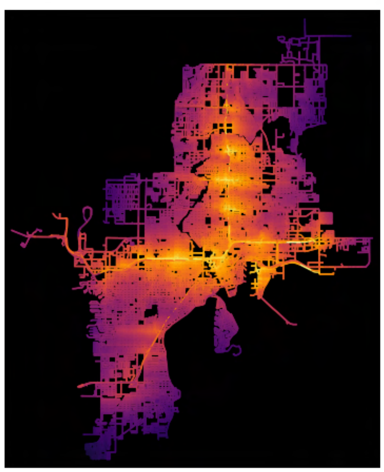


St. Louis, MO

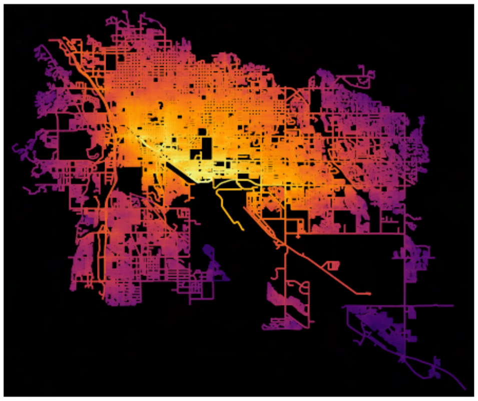


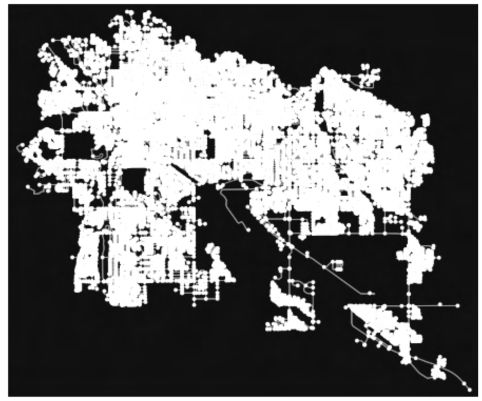


Tampa, FL

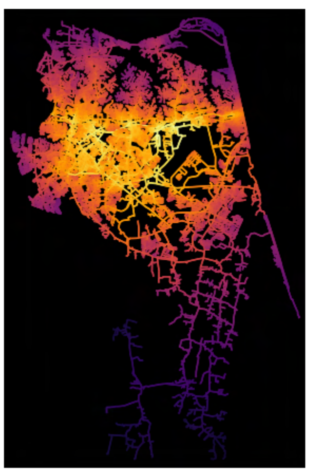


Tucson, AX





Virginia Beach, VA



Washington, DC