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Geographic access to HIV pre-exposure prophylaxis (PrEP) in Atlanta, GA:
The role of geographic level and mode of transportation

By

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Master of Public Health

Global Epidemiology

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Abstract

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Background: Disparities in access to HIV pre-exposure prophylaxis (PrEP) are well documented in the United States. Geographic access has commonly been measured with drive time analyses. However, results likely vary based on geographic level (county, census tract, block group) and mode of transportation (driving vs. public transit).

Objectives: To explore the impact of varying the geographic level and mode of transportation on calculated travel times to the nearest PrEP provider. To define areas in the Atlanta Metropolitan Statistical Area (MSA) with limited access to PrEP providers ("PrEP deserts") and explore associated sociodemographic covariates.

Methods: Population-weighted centroids were obtained for Georgia counties, census tracts, and block groups. PrEP providers were sourced from a publicly available national directory. Travel times were calculated using Google maps API. We defined a PrEP desert as a one-way travel time greater than 30 minutes. We utilized the Brown-Forsythe test to compare median differences and ran multivariable logistic regressions for PrEP desert classification on sociodemographic variables.

Results: Drive times were significantly shorter than public transit times at the census tract and block group levels. There were no differences in median values between geographic levels. Over 30 percent of the Atlanta MSA population resided in a PrEP drive desert. Public transit data was missing for over 60 percent of the population yet in the more central 5-county metropolitan area for which data was available, over 75 percent resided in a PrEP public transit desert. Travel times were shortest in the urban center, and finer levels of geography revealed more nuanced patterns of access. Higher concentrations of Black, Latinx, and high school educated persons were associated with increased odds of PrEP desert classification.

Conclusions: Disparities between public transit and drive times were intensified outside the urban center, potentially indicating a need to improve public transit outside the city center. Finer levels of geography showed more subtle patterns in spatial access across space. However, when analyzing aggregate data, we found limited differences in travel measurements between geographic levels. Given transportation barriers faced by a majority of residents who rely on public transit, alternative options for PrEP access should be considered to improve access.

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INTRODUCTION

Context of HIV and PrEP in the United States

Despite a decline in new human immunodeficiency virus (HIV) diagnoses in the United States (U.S.) between 2012-2016, certain populations remain disproportionately affected (1). Racial disparities are staggering, with the rate of HIV infections eight times higher in black compared to white individuals (1). Men who have sex with men (MSM) account for the majority of new diagnoses among transmission risk groups (1, 2, 3), and the U.S. South carries the highest regional burden of HIV nationally (1, 4).

The advent of HIV pre-exposure prophylaxis (PrEP) with tenofovir disoproxil fumarate and emtricitabine represents a critical component of HIV prevention strategies for at-risk populations. In a large sample of men and transgender women who have sex with men, PrEP use was associated with a 44 percent reduction in the incidence of HIV (5). Further, an open-label randomized trial of PrEP use in MSM found an 86% reduction in incident HIV infections (6). Mathematical models predict that application of the Centers for Disease Control and Prevention (CDC) PrEP guidelines to 40 percent of eligible MSM would prevent over 30 percent of anticipated HIV infections among MSM in the U.S. (7).

Despite the promises of PrEP for HIV prevention, disparities exist related to PrEP access. Differential access to PrEP may occur for reasons ranging from individual healthcare provider comfort and patient insurance status (8), to cost (9, 10) and stigma (11). Although the annual prevalence of PrEP use in the U.S. increased by over 50 percent between 2012-2017, there was a disparity in scale-up across groups, with the

South having the lowest prevalence (12). State-level estimates of PrEP-eligible MSM reinforce the need to focus efforts on black MSM (BMSM) (13). It is estimated that five states (including Georgia) accounted for about 35 percent of BMSM with PrEP indications in the U.S. in 2015 (13). In Atlanta specifically, PrEP uptake was lower than expected in a cohort of BMSM despite high interest in initiating therapy (8, 9, 10).

Spatial access to PrEP providers may also contribute to disparities in uptake (4, 14-17). The PrEP Locator was developed in 2016 as an open-source, geolocated directory of medical providers who prescribe PrEP in the United States, in order to provide individuals with a single, comprehensive directory of service providers to help improve access (17). Recent spatial analyses revealed an uneven distribution of PrEP-providing clinics compared to HIV burden, with poorest access in the U.S. South, in counties with high proportions of residents living in poverty, and among people who lack health insurance or belong to a racial minority group (4). Siegler et al. (2019) defined "PrEP deserts" as census tracts with a one-way drive time of greater than 30 minutes from the nearest PrEP provider and found that location in the U.S. South and lower urbanicity were associated with increased odds of PrEP desert classification (18).

Geospatial Analyses

Geospatial analyses provide a useful tool for understanding disparities related to healthcare access. The concept of access may consider factors such as availability or volume of services, travel distance, accommodation, affordability, and utilization (19). The five most commonly used spatial accessibility measures include distance to the closest provider, number of services within a particular travel distance or time, mean distance to a specified number of providers, gravity models and two-step floating catchment area models (2SFCAM) (20). Distance-based measures address the minimum cost (distance or time) to reach a service, but do not account for population demands as more complex models like gravity models and 2SFCAM do (21, 22).

Selecting an appropriate spatial unit, or level of geography, is an important consideration for travel time analysis. Geographic levels are hierarchically related; census tracts are statistical subdivisions of a county, averaging about 4,000 inhabitants, while census block groups (block groups) are statistical divisions of census tracts, containing between 600 and 3,000 people (23). Travel time is typically calculated along the shortest path between the nearest service provider and a geographic unit's population-weighted centroid, or the central balance point (24). Census tracts are often selected for travel time analyses due to the availability of detailed socioeconomic, demographic and housing data which is often not available at finer geographic levels (20). However, this may not be an optimal level of geography to capture the potential variation within a metropolitan area of public transit times. Additionally, it has been shown that accessibility measured for smaller geographic units is less subject to aggregation error than larger units (20).

Geospatial access studies have focused on the impact of travel mode (20, 25-27), distance (28, 29, 30) and time (20, 31). In a national comparison of Euclidean (straight-line) versus road network (travel) distance, Boscoe et al. (2012) found that Euclidean distance was an adequate proxy for driving distance in nearly all geographic areas (32). Conversely, Eberhart et al. (2015) found that driving distances were significantly longer than Euclidean distance in Philadelphia (31).

Spatial disparities to care are associated with poorer health outcomes (28, 29, 30), and transportation barriers represent an important consideration in access to care (33). Individuals taking public transportation are thought to be disproportionately impacted by such barriers, as they face an increased travel time to care (25). Traditional geospatial analyses have mostly excluded public transit from consideration of access to care (18, 32, 34). This implicitly highlights disparities faced by persons in rural areas but does not address individuals within metropolitan areas that also face transit barriers.

Studies which have included public transit considerations often use complex, resource intensive methods which may not be easily reproduced in other geographic areas. The advent of general transit feed specification (GTFS) has made analysis of public transit time more accessible, with open-source information from transit agencies describing schedules, trips, routes and stops (35). Travel time research utilizing this data has consistently demonstrated that public transit times are much longer than drive times (19, 21, 25, 31, 36).

There is an opportunity to leverage location-based analyses of public transit data available. However, few public health studies have compared results between geographic levels and modes of transportation. Apparicio et al. (2017) compared discrepancies in results using different distance types, aggregation methods and accessibility measures and found that distance types were similar with the exception of travel time by public transit and described measurement errors for census tracts in suburban areas of Montreal (20). In Atlanta, Dasgupta et al. (2016) found that traveling by public transportation took significantly longer than driving to the nearest HIV provider at the census tract level and noted longer travel times overlapped with areas of higher poverty (26). No studies have compared travel time results both between geographic levels and by mode of transportation, our aim here in assessing PrEP access in Atlanta, GA.

Aims

The goal of this thesis is two-fold – one methodologic and the other descriptive – and divided into three aims. The first aim is to explore the variation in results when measuring distance and time to the nearest PrEP provider at different geographic levels (county, census tract, and block group) and modes of transportation (driving versus public transit). Our goal is to identify the impact of geographic level and mode of transportation on measures of access. The second aim is to define areas in the greater Atlanta metropolitan area which have limited access to PrEP providers via driving (PrEP drive desert) and public transit (PrEP public transit desert). The third aim is to explore sociodemographic covariates which may be associated with increased odds of PrEP desert classification. By doing so, we may identify disparities in PrEP access and opportunities for improved service provision in the Atlanta area.

METHODS

Demographic and Geographic Methods

Geographic shapefiles and population-weighted centroids were obtained from the U.S. Census Bureau at the county, census tract, and block group levels for Georgia. We obtained data for PrEP providers from PrEP Locator, an open source, geolocated directory of medical providers who prescribe PrEP in the United States (17). PrEP Locator data were vetted through January 2019 and limited to Georgia, yielding a total of 52 PrEP providers for analysis.

Shapefile, population-weighted centroids, and PrEP Locator data were exported to ArcMap 10.7.1. Near tables were generated at each geographic level to determine origin-destination (OD) pairs, the closest PrEP provider to each population-weighted centroid. Travel distance and times between OD pairs were then generated using a Python code with repeated calls to the Google Maps application programming interface (API). Travel times were calculated based on 8am and 1pm departures, and average travel times were used for analysis.

Travel data were joined to demographic data from the 2013-2017 American Community Survey (ACS) 5-year estimates (ACS tables B01001, B01003, B02001, B03002, B08301, B15003, B17017, and B27010). We limited our analysis to the 29 county Atlanta Metropolitan Statistical Area (MSA) in order to gain insight about Atlanta and its surrounding communities. The distribution of travel time was determined for each geographic level and was then categorized based on Siegler et al.'s PrEP desert classifications (18). Due to a paucity of data on publicly acceptable public transit time to healthcare services, we uniformly categorized drive and public transit PrEP deserts as a one-way travel time greater than 30 minutes.

Due to a large proportion of missing public transit data in our sample, two datasets were created for analysis. The first dataset (referred to as the "full MSA dataset" in this paper) contains all observations in the Atlanta MSA, including those with missing transportation data, in order to determine the full distribution of data and understand the potential impact of public transit data missingness on analyses. This dataset was primarily used for descriptive purposes. The second dataset (referred to as the "study dataset") is comprised of the observations with complete (non-missing) transportation data at each geographic level. Due to the hierarchical, nested relationship between counties, census tracts, and block groups, if transportation data was missing from a county, all census tracts and block groups contained in that county were also removed from the dataset. The same stepwise process was then repeated for the remaining census tracts and affiliated block groups. The study dataset was utilized for all statistical analyses in order to adequately make comparisons between geographic levels.

Statistical Analysis

We described county, census tract and block group demographic and spatial characteristics using proportions, medians, interquartile ranges, means and standard deviations. To explore the variation in results when measuring distance and time to care at different geographic levels and modes of transportation (Aim 1), we calculated the median difference for each travel measure (drive and public transit distance, and drive and public transit time) between each geographic level, and the median difference in travel distance and travel time by mode of transportation for each geographic level. We utilized the Brown-Forsythe test to compare median differences. Next, we performed Spearman rank correlation analysis between each travel measure and mode of transportation. Local differences between public transit time and drive time were visualized using choropleth maps.

To define areas in the Atlanta MSA which have limited access to PrEP providers (Aim 2), we calculated the proportion of counties, census tracts and block groups (and their corresponding populations) which fall in different travel time categories. Data were displayed using choropleth maps. Of note, we used the full MSA dataset in order to visualize the entire geographic sample, including areas where public transit data is missing.

To determine sociodemographic variables associated with increased odds of being classified as a PrEP desert (Aim 3), we performed multivariable logistic regression on PrEP desert classification with multiple sociodemographic variables. Based on Siegler et al.'s 2019 analysis (18), we explored the association between the odds of PrEP desert classification for every five percent increase in population with a high school education, living in poverty, without health insurance, of African American race, of Hispanic/Latino ethnicity, and utilizing a car for travel to work (a proxy for vehicle ownership). All data analysis was completed in SAS version 9.4.

RESULTS

The full MSA dataset was comprised of 29 counties, 948 census tracts and 2597 block groups (Table 1). After excluding geographic units with any missing travel data, the study dataset was limited to five counties (Fulton, DeKalb, Gwinnett, Clayton and Cobb), and less than 50 percent of the original census tracts and block groups. Figure 1 displays a map of the Atlanta MSA, the five-county study area, PrEP providers in Georgia, and transit routes including Interstate 285 (I-285) and major public transit routes.

Aim 1

For the entire Atlanta MSA, drive distances and times were greatest at the county level compared with the census tract and block groups (Table 2). The median drive time was around 22 minutes for census tracts and block groups, while around 36 minutes at the county level. In the 5-county study dataset, these drive times became more similar at around 14 minutes at the census tract and block group levels and around 10 minutes at the county level. Public transit distance and times were lower at the county level (4.1 miles, 34.7 minutes) than the census tract and block group levels (nearly 6 miles, 46 minutes), regardless of dataset.

Using the 5-county study dataset we found no statistically significant difference in median travel distance ($F = 0.31$, $p = 0.59$) or travel time ($F = 1.37$, $p = 0.28$) by mode of transportation (Figure 2a) at the county level. Statistically significant differences were found in both distance and time at the census tract and block group levels. The median difference between public transit vs drive distance at the census tract level was 1.20 miles ($F = 41.70$, $p < 0.0001$), while the difference in drive versus public transit time was 32.24 minutes ($F = 206.93$, $p < 0.0001$). At the block group level, the median difference between drive versus public transit distance was 1.70 miles ($F = 115.05$, $p < 0.0001$), while the difference in drive versus public transit time was 31.40 minutes ($F = 436.65$, $p < 0.0001$). There were no statistically significant differences for any of the four travel measures between geographic levels (Figure 2b).

Table 3 presents results for Spearman rank correlations between all travel variables. With the exception of public transit travel measures, all variables were globally similar ($r_s > 0.90$, $p < 0.05$). Correlations were difficult to assess at the county level due to a small sample size ($n = 5$). Results were similar at the census tract and block group levels, and results are reported below for the block group. The strongest correlation was between drive distance and public transit distance ($r_s = 0.95$, $p < 0.05$), while the weakest correlation was between drive time and public transit time ($r_s = 0.81$, $p < 0.05$).

There was a similar overall pattern in the absolute difference between public transit time and drive time between geographic levels (Figure 3). At the county level, the absolute difference in travel time was lowest (< 15 minutes) in Fulton, DeKalb and Gwinnett counties, while > 30 minutes in Cobb and Clayton counties. At finer geographic levels (census tract and block group), we see the lowest absolute difference inside the I-285 and the highest in the northwest (Cobb county), southwest (Fulton county) and northeast (Fulton, DeKalb and Gwinnett counties). At the block group level, a finer level of geography allows us to notice patterns which didn't appear at the census tract level. For example, we see an area in northeast Gwinnett county and another in north Fulton county with lower travel time discrepancies than seen at the census tract level.

Aim 2

In the entire Atlanta MSA, 65.5 percent of counties (32.4 percent of the population) were categorized as PrEP drive deserts, meaning residents must drive more than 30 minutes to reach the nearest PrEP provider (Table 4). Nearly 30 percent of census tracts and block groups were categorized as PrEP drive deserts. Drive times were shortest inside and adjacent to I-285, as well as in parts of some southeast counties (Butts, Lamar, Morgan and Newton) (Figure 4). Drive times were longest (> 60 minutes) in the south (Meriwether county), southwest (Heard and Carroll counties), northwest (Bartow and Cobb counties) and north (Pickens county). Again, finer levels of geography reveal more nuanced patterns in access.

Though over 50 percent of geographic units (60 percent of the population) were missing public transit data in the full MSA dataset, a sizable proportion (>30 percent) were still categorized as PrEP public transit deserts (Table 4, Figure 5). Public transit time was missing for the majority of geographic units outside of I-285, representing over 3.2 million people (Figure 5). In the 5-county study dataset, 60 percent of counties and around 70 percent of census tracts and block groups were categorized as PrEP public transit deserts (Table 4). Public transit times were shortest in the urban center and became longer as location extended outside I-285 (Figure 5). Again, finer levels of geography allow for visualization of patterns not apparent at the county level.

Aim 3

Several demographic characteristics were associated with increased odds of PrEP desert classification in a multivariable logistic regression model (Table 5). We were unable to complete regression analysis at the county level due to a small sample size (n = 5). Overall patterns were consistent between the census tract and block group levels, so adjusted odds ratios are reported below for the block group level. For both drive time and public transit time, there were positive associations between PrEP desert classification and increases in high school educational attainment (drive: AOR = 1.20; 95% CI = 1.01, 1.41; public transit: AOR = 1.24; 95% CI = 1.13, 1.36), African American population (drive: AOR = 1.21; 95% CI = 1.11, 1.32; public transit: AOR = 1.09; 95% CI = 1.05, 1.13) and vehicle ownership (drive: AOR = 1.61; 95% CI = 1.23, 1.99; public transit: AOR = 1.31; 95% CI = 1.22, 1.40). There was a negative association between PrEP desert classification and an increase in population living in poverty (drive: AOR = 0.84; 95% CI = 0.70, 0.99; public transit: AOR = 0.82; 95% CI = 0.75, 0.89). For public transit time only, there was a positive association between PrEP desert classification and an increase in Hispanic/Latino population (AOR = 1.25; 95% CI = 1.15, 1.36).

DISCUSSION

Using publicly available data on PrEP providers in Georgia, we examined the variation in travel time results at three geographic levels and two modes of transportation, defined areas of the Atlanta MSA which have limited access to PrEP providers and explored sociodemographic covariates associated with limited PrEP access. We found significant differences in travel time based on mode of transportation at the census tract and block group levels, however aggregate differences were not found between geographic levels for any travel measures. With the exception of public transit travel time, all travel variables were globally similar to each other in correlation analyses. Over 30 percent of the Atlanta MSA population must drive longer than 30 minutes to reach the nearest PrEP provider, and in the 5-county Atlanta metropolitan area, over 75 percent of the population must travel longer than 30 minutes using public transportation. Travel times were lowest inside and around I-285 (referred to locally as “inside the perimeter”), and finer levels of geography revealed more nuanced patterns of access across space. Finally, several sociodemographic correlates were associated with PrEP desert classification.

Aim 1

We found significant differences in public transit and drive time. Within the 5-county greater Atlanta metropolitan area, over three quarters of the population who rely on public transportation must travel greater than 30 minutes to the nearest PrEP provider, while only five percent experience drive times exceeding 30 minutes. This is consistent with several other studies comparing public transit time to drive time. Commute times to

HIV care providers were three times higher for public transportation users in Atlanta (25) and similarly long in Philadelphia (31). Public transit times were also significantly longer than drive times for analyses done in Albuquerque (19). This is an important finding when considering that people with longer travel times are less likely to be retained in care (27) or access their medications (33), and using public transit has been associated with lower rates of HIV care attendance in Atlanta (25).

When examining aggregate data, we found no significant difference in median travel time measures between geographic levels in the 5-county greater Atlanta metropolitan area. We know that measuring access is influenced by the accessibility measure used, type of distance and aggregation method (20). While the census tract has traditionally been used for the availability of detailed demographic data, we posited that a finer level of geography may be more suitable for urban travel time analysis. Most previous studies have not compared travel time findings between geographic levels. We found that for the 5-county greater Atlanta metropolitan area, there is negligible difference in travel time results between the census tract and block groups. This suggests that beyond the census tract, finer levels of geography may not provide additional value for travel time analysis.

With the exception of public transit time, all travel variables were highly correlated. This finding is consistent with analysis done by Apparicio et al. (2017), who compared six distance types (including shortest network time by foot, bike, car and public transit) for travel time calculation in Montreal and found that measures were globally similar with the exception of public transit time (20). This finding confirms that measuring public transportation is complex and must consider factors such as the unequal distribution of public transit systems across the study area, as we clearly see from an abundance of missing public transit data outside the perimeter in our study.

Aim 2

A large proportion of the Atlanta MSA population face long commute times to the nearest PrEP provider regardless of mode of transportation. We see that the majority of PrEP providers in Georgia are located inside the perimeter and southeast of the Atlanta MSA. This is similar to the distribution of HIV providers in Atlanta, concentrated in north and central Atlanta (25). For the entire Atlanta MSA, about 30 percent of the population lives in a PrEP drive desert. It is critical to highlight that public transit data was missing for over half of the MSA (the majority located outside the perimeter), representing roughly 3.2 million people. This highlights the inherent disparity of public transit access in suburban areas and reiterates the uncertainty of measurements found in these areas where public transit is often scarce (20). Even so, we found that over 75 percent of residents in the 5-county greater Atlanta metropolitan area reside in a PrEP public transit desert.

Unlike when examining aggregate data, the level of geography matters when visualizing local differences in access on a map. We found that drive times were lowest in and around the perimeter and public transit times lowest in the urban center. This is consistent with previous studies which found HIV provider supply to be higher inside the perimeter for both travel modes, and lower if traveling by public transit (26). We see the largest disparity in public transit vs. drive time in southwest Fulton County, northwest Cobb County and northeast DeKalb, Fulton and Gwinnett counties. Travel time disparity was lowest in the city center, similar to findings from a health access study in Helsinki, Finland (36). It is clear from our maps that the county level is not sufficient for observing the nuanced differences in PrEP access across space, and that as you utilize finer levels of geography these differences become more evident. These results highlight the reality that access to PrEP (among other health services) is highest in the urban center, and that finer levels of geography enable a more detailed understanding of spatial disparities.

Aim 3

Geographic access to PrEP and other health services have been associated with a variety of sociodemographic factors including poverty, educational attainment, racial minority group status, and access to health insurance. Our analysis found that residing in a PrEP desert was significantly and positively associated with belonging to a racial minority group, increases in high school educational attainment and access to a vehicle. Racial minority groups have consistently been found to have lower access to PrEP and other health services (4, 33, 37). In their national study of PrEP access, Siegler et al. found that increases in high school education and minority group population were associated with decreased odds of PrEP desert classification, opposite findings to ours (18). Our trend in educational attainment could be explained by suburban areas, where levels of education tend to be higher. Longer commute times to HIV care in Atlanta were previously associated with low vehicle ownership, opposite to our findings (25). This discrepancy could be related to our measure of vehicle ownership, as we used travel mode to work as a proxy.

We found that higher population rates of poverty were associated with lower odds of PrEP desert classification. This was surprising given opposite findings from other access studies (4, 18, 26, 33). Again, this trend could potentially be explained by suburban areas, where levels of poverty tend to be lower than urban areas. We did not find significant associations between PrEP desert classification and uninsured status as reported in the national study (18). This could potentially be explained by local differences in health insurance policies, particularly whether or not a state expanded Medicaid coverage. Our regression analysis reiterates the need for further exploration of sociodemographic factors in access to health services.

Limitations

This study has several limitations. We created our study dataset in order to run statistical analyses between geographic levels. Because this dataset was mostly limited by missing public transit data, we ultimately lost a lot of drive time data, particularly at longer travel times. This could certainly represent a source of selection bias, as the full MSA dataset contains observations with complete drive time data and incomplete public transit time data. Travel time data was limited to 8am and 1pm departures, which could result in under or overestimation of transit accessibility given travel times vary according to time of departure (35). Further, we did not account for the influence of transit stops, transfers, walking distance and travel speeds (35, 36). By using a single point (population-weighted centroid) in each geographic unit to measure access, we may be missing subtle findings related to access (18).

Travel time is only one measure of access, and we did not consider other influences such as acceptability, availability, affordability and appropriateness of services (8, 19). Additionally, some individuals may choose to access medical care in locations relative to other services, not necessarily their place of residence (18, 31). We limited PrEP providers to the state of Georgia, and for some geographic units the nearest PrEP provider could have been located in a bordering state. Additionally, PrEP Locator may not capture all PrEP providers, or may overestimate the availability of PrEP providers. Finally, this analysis may not be generalizable to other geographic areas, particularly rural contexts.

Public Health Implications

The present study demonstrates that utilizing finer levels of geography yields the benefit of visualizing more subtle patterns in local spatial access across space. However, when analyzing aggregate data, we found limited differences in travel measurements between the census tract and block group levels. We highlight disparities between public transit time and drive time which were intensified outside of the perimeter, reiterating the need to improve and expand the public transit system in suburban Atlanta. A large proportion of residents must travel greater than 30 minutes to reach the nearest PrEP provider, regardless of mode of transportation. This highlights the need to expand alternative options for PrEP access such as telehealth and home-based follow up visits like PrEP at Home, which has been widely accepted in pilot studies (14). Finally, important sociodemographic factors may contribute to disparities in PrEP access, and the public health community must consider these when planning interventions to improve access.

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Tables

Table 1. Characteristics of geographic sample.

	Full MSA Dataset[a]		Study Dataset[b]	
Geographic level	Geographic units, N	Population, N	Geographic units, n (%)	Population, n (%)
County	29	5286728	5 (17.2%)	3365297 (63.7%)
Census tract	948	5272828	433 (45.7%)	1989233 (37.7%)
Block group	2597	5286728	1104 (42.5%)	1857296 (35.1%)

[a]Dataset comprising the 29 county Atlanta Metropolitan Statistical Area (MSA), including observations with missing transit data.
[b]Dataset where all geographic observations have complete transit data.

Table 2. Univariate statistics for distance and travel time between population-weighted centroid and nearest PrEP provider, by geographic level.

	Full MSA Dataset[a]				Study Dataset[b]		
Travel measure[c]	N	Missing n (%)	Mean (SD)	Median (IQR)	N	Mean (SD)	Median (IQR)
County centroid	29				5		
Drive distance		0 (0.0%)	24.2 (14.9)	21.9 (15.0, 33.8)		6.3 (5.2)	3.7 (3.4, 7.5)
Public transit distance*		24 (82.8%)	8.9 (8.5)	4.1 (3.9, 11.7)		8.9 (8.5)	4.1 (3.9, 11.7)
Drive time		0 (0.0%)	35.2 (16.1)	35.5 (25.3, 45.2)		14.1 (8.5)	9.7 (7.8, 18.3)
Public transit time*		24 (82.8%)	43.9 (24.3)	34.7 (27.2, 50.5)		43.9 (24.3)	34.7 (27.2, 50.5)
Census tract centroid	948				433		
Drive distance		0 (0.0%)	13.2 (11.4)	9.7 (4.5, 18.8)		5.7 (4.6)	4.4 (2.3, 7.8)
Public transit distance*		511 (53.9%)	8.5 (8.7)	5.7 (2.4, 11.5)		8.2 (8.1)	5.6 (2.4, 11.4)
Drive time		0 (0.0%)	23.9 (13.8)	21.5 (13.5, 32.9)		14.6 (7.8)	13.8 (8.3, 19.8)
Public transit time*		511 (53.9%)	51.7 (36.3)	46.2 (26.3, 64.0)		50.9 (35.2)	46.1 (26.2, 63.8)
Block group centroid	2597				1104		
Drive distance		1 (<0.1%)	13.5 (11.8)	9.7 (4.6, 18.7)		5.7 (4.4)	4.5 (2.3, 8.0)
Public transit distance*		1384 (53.3%)	9.6 (10.3)	6.6 (2.8, 12.6)		8.4 (8.1)	6.2 (2.6, 11.4)
Drive time		1 (<0.1%)	24.3 (13.9)	21.7 (13.8, 33.0)		14.8 (7.6)	14.0 (8.8, 19.9)
Public transit time*		1384 (53.3%)	55.8 (44.2)	48.1 (30.0, 67.9)		50.7 (35.2)	45.4 (28.8, 63.7)

[a]Dataset comprising the 29 county Atlanta Metropolitan Statistical Area (MSA), including observations with missing transit data.
[b]Dataset where all geographic observations have complete transit data.
[c]Distance in miles, travel time in minutes.
*Public transit measures represent the limiting factor between datasets

Table 3. Spearman rank correlations between alternative travel measures and mode of transportation, by geographic level[a,b].

Geographic level	**Census tract**				**Block group**			
Travel measure	Travel distance		Travel time		Travel distance		Travel time	
Travel mode	Drive	Public transit	Drive	Public transit	Drive	Public transit	Drive	Public transit
Census tract								
Distance (drive)	1.00							
Distance (public)	0.95	1.00						
Travel time (drive)	0.93	0.90	1.00					
Travel time (public)	0.86	0.89	0.82	1.00				
Block group								
Distance (drive)					1.00			
Distance (public)					0.95	1.00		
Travel time (drive)					0.94	0.89	1.00	
Travel time (public)					0.86	0.89	0.81	1.00

[a]Using study dataset where all geographic observations have complete transit data.
[b]Correlations not available at the county level due to small sample size (n = 5).
All coefficient values significant at the p = 0.05 level.

Table 4. Proportion of population by travel time from population-weighted centroid to nearest PrEP provider, by geographic level.

	Full MSA dataset[a]					
Geographic level	**County**		**Census tract**		**Block group**	
Travel time	N (%)	Population (%)	N (%)	Population (%)	N (%)	Population (%)
	29 (100%)	5286728 (100%)	948 (100%)	5272828 (100%)	2597 (100%)	5286728 (100%)
Drive time to nearest PrEP provider, minutes						
0-15	4 (13.8%)	2431695 (46.0%)	284 (30.0%)	1299289 (24.6%)	768 (29.6%)	1337691 (25.3%)
16-30	6 (20.7%)	1139745 (21.6%)	382 (40.3%)	2217924 (42.1%)	1056 (40.7%)	2170415 (41.1%)
31-60	17 (58.6%)	1681462 (31.8%)	270 (28.5%)	1695668 (31.2%)	734 (28.3%)	1714719 (32.4%)
61-90	2 (6.9%)	33826 (0.6%)	12 (1.3%)	59947 (1.1%)	38 (1.5%)	63173 (1.2%)
91-120	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
>120	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Missing	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	1 (<0.1%)	730 (<0.1%)
Public transit time to nearest PrEP provider, minutes						
0-15	0 (0.0%)	0 (0.0%)	39 (4.1%)	133105 (2.5%)	95 (3.7%)	139800 (2.6%)
16-30	2 (6.9%)	1612474 (30.5%)	91 (9.6%%)	331239 (6.3%)	208 (8.0%)	307095 (5.8%)
31-60	2 (6.9%)	1493399 (28.2%)	165 (17.4%)	753137 (14.3%)	497 (19.1%)	807458 (15.3%)
61-90	1 (3.4%)	259424 (4.9%)	97 (10.2%)	523502 (9.9%)	277 (10.7%)	515342 (9.7%)
91-120	0 (0.0%)	0 (0.0%)	26 (2.7%)	149491 (2.8%)	70 (2.7%)	161414 (3.1%)
>120	0 (0.0%)	0 (0.0%)	19 (2.0%)	121258 (2.3%)	66 (2.5%)	140019 (2.6%)
Missing	24 (82.8%)	1921431 (36.3%)	511 (53.9%)	3261096 (61.8%)	1384 (53.3%)	3215600 (60.8%)

[a]Dataset comprising the 29 county Atlanta Metropolitan Statistical Area (MSA), including observations with missing transit data.

Table 4 (continued).

	Study dataset[b]					
Geographic level	**County**		**Census tract**		**Block group**	
Travel time	N (%)	Population (%)	N (%)	Population (%)	N (%)	Population (%)
	5 (100%)	3365297 (100%)	433 (100%)	1989233 (100%)	1104 (100%)	1857296 (100%)
Drive time to nearest PrEP provider, minutes						
0-15	3 (60.0%)	2417795 (71.8%)	237 (54.7%)	964758 (48.5%)	616 (55.8%)	959661 (51.7%)
16-30	2 (40.0%)	947502 (28.2%)	180 (41.6%)	928943 (46.7%)	446 (40.4%)	806429 (43.4%)
31-60	0 (0.0%)	0 (0.0%)	16 (3.7%)	95532 (4.8%)	42 (3.8%)	91206 (4.9%)
61-90	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
91-120	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
>120	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Missing	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Public transit time to nearest PrEP provider, minutes						
0-15	0 (0.0%)	0 (0.0%)	39 (9.0%)	133105 (6.7%)	95 (8.6%)	139800 (7.5%)
16-30	2 (40.0%)	1612474 (47.9%)	91 (21.0%)	331239 (16.7%)	207 (18.8%)	306000 (16.5%)
31-60	2 (40.0%)	1493399 (44.4%)	165 (38.1%)	753137 (37.9%)	474 (42.9%)	760431 (40.9%)
61-90	1 (20.0%)	259424 (7.7%)	97 (22.4%)	523502 (26.3%)	242 (21.9%)	449774 (24.2%)
91-120	0 (0.0%)	0 (0.0%)	25 (5.8%)	143120 (7.2%)	48 (4.4%)	113935 (6.1%)
>120	0 (0.0%)	0 (0.0%)	16 (3.7%)	105130 (5.3%)	38 (3.4%)	87356 (4.7%)
Missing	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)

[b]Dataset where all geographic observations have complete transit data.

Table 5. Logistic regression[a] on PrEP desert classification with demographic correlates[b], by geographic level[c].

Correlates	PrEP drive desert AOR (95% CI)	PrEP public transit desert AOR (95% CI)
Census tract		
% with high school education: 5% increase	1.82 (1.17 - 2.84)	1.56 (1.24 - 1.97)
% living in poverty: 5% increase	0.85 (0.53 - 1.35)	0.66 (0.54 - 0.81)
% without health insurance: 5% increase	0.59 (0.28 - 1.25)	0.99 (0.77 - 1.27)
% African American: 5% increase	1.21 (1.00 - 1.48)	1.07 (0.98 - 1.16)
% Hispanic: 5% increase	1.17 (0.67 - 2.04)	1.34 (1.10 - 1.62)
% Vehicle ownership, 5% increase[d]	2.55 (1.41 - 4.59)	1.67 (1.40 - 2.00)
Block group		
% with high school education: 5% increase	1.20 (1.01 - 1.41)	1.24 (1.13 - 1.36)
% living in poverty: 5% increase	0.84 (0.70 - 0.99)	0.82 (0.75 - 0.89)
% without health insurance: 5% increase	0.91 (0.74 - 1.12)	0.99 (0.90 - 1.09)
% African American: 5% increase	1.21 (1.11 - 1.32)	1.09 (1.05 - 1.13)
% Hispanic: 5% increase	1.14 (0.96 - 1.36)	1.25 (1.15 - 1.36)
% Vehicle ownership, 5% increase[d]	1.61 (1.23 - 1.99)	1.31 (1.22 - 1.40)

[a]Using study dataset where all geographic observations have complete transit data.
[b]Using variables from the 2013-2017 ACS 5-year summary (Tables B01001, B01003, B02001, B03002, B08301, B15003, B17017, and B27010).
[c]Unable to run regression at county level due to small sample size (n = 5).
[d]Percent of workers age 16 years and older who report driving to work, used here as a proxy for vehicle ownership.

Figures

Figure 1. Map of geographic area, PrEP providers and major transit routes.

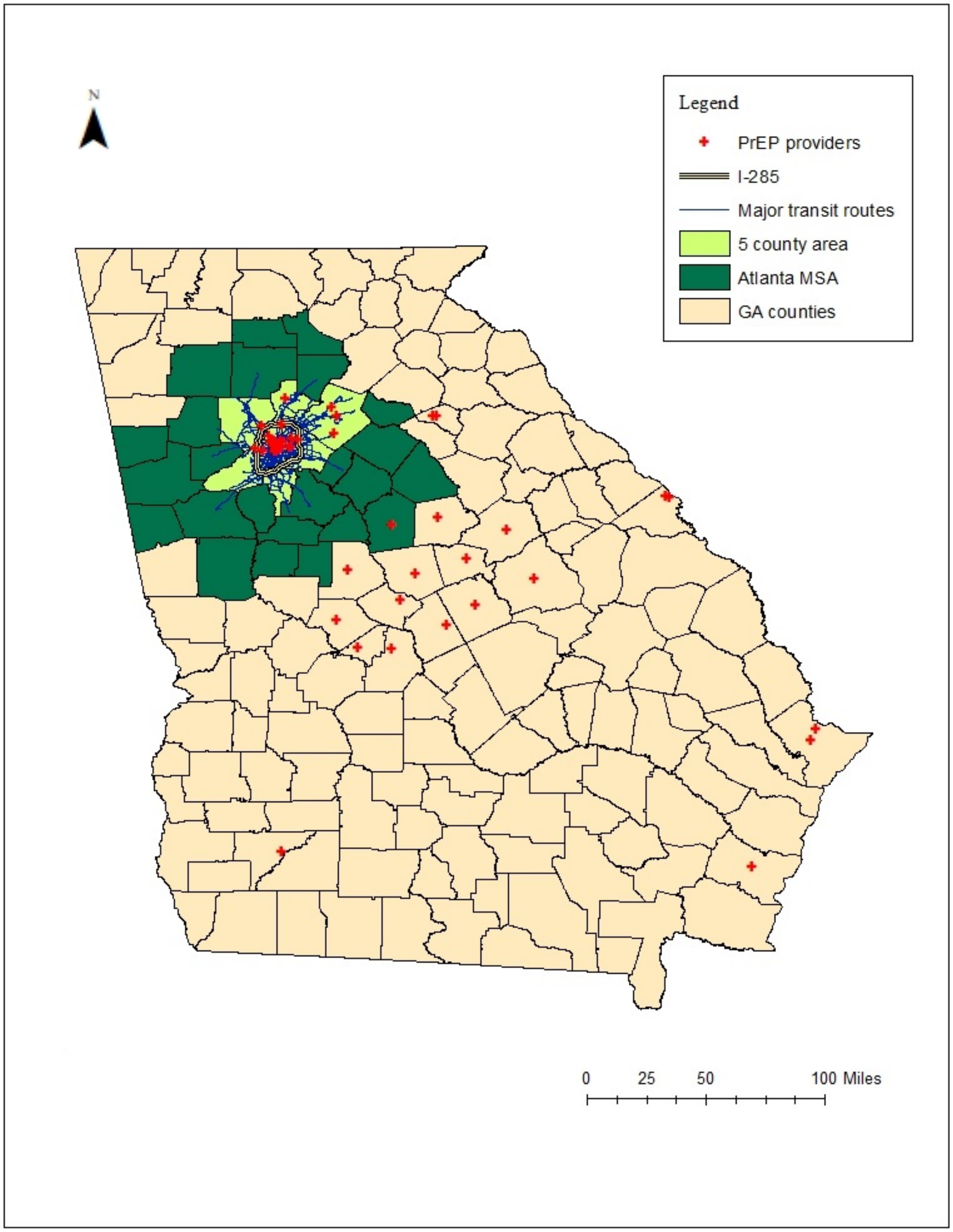
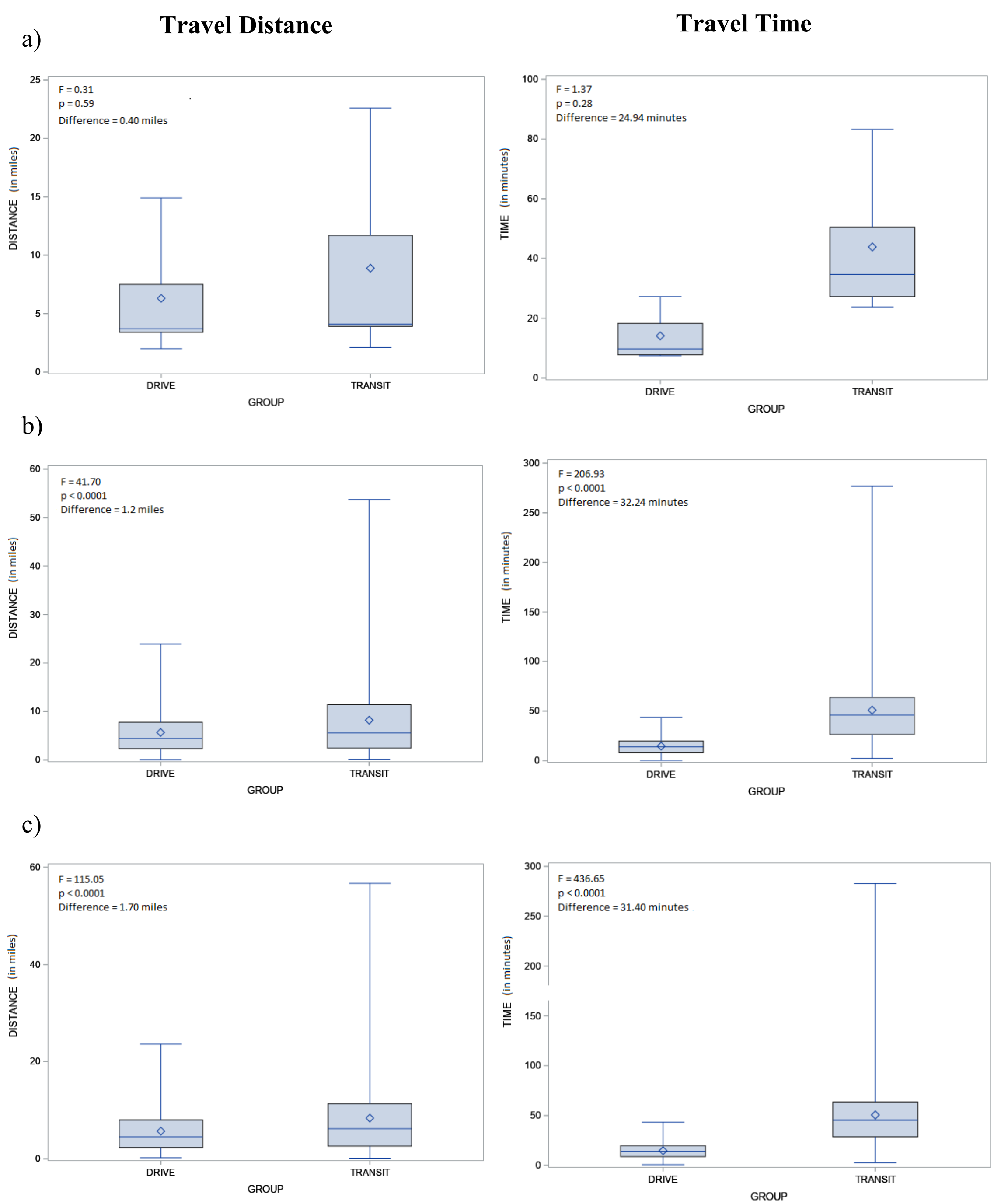


Figure 2a. Median difference[a] in travel distance and time between mode of transport, by geographic level. a) county b) census tract c) block group

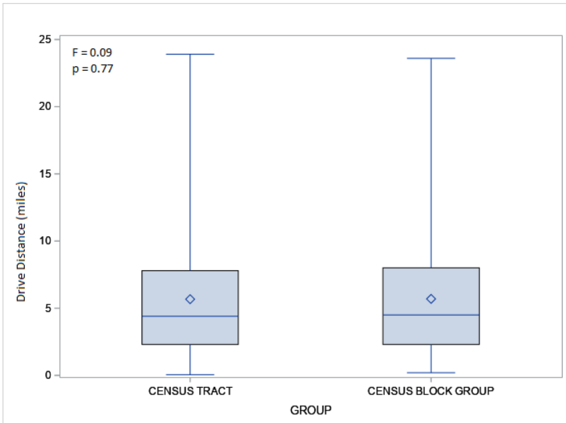


[a]Brown and Forsythe's test for ANOVA.

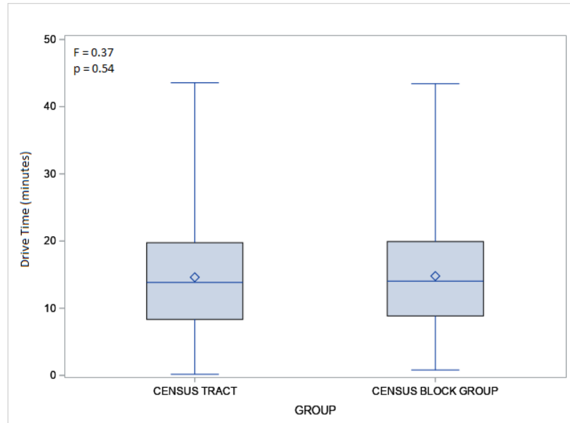
Figure 2b. Median difference[a] for each travel measure between geographic levels[b].
a) drive distance b) drive time c) public transit distance d) public transit time

Travel Distance **Travel Time**

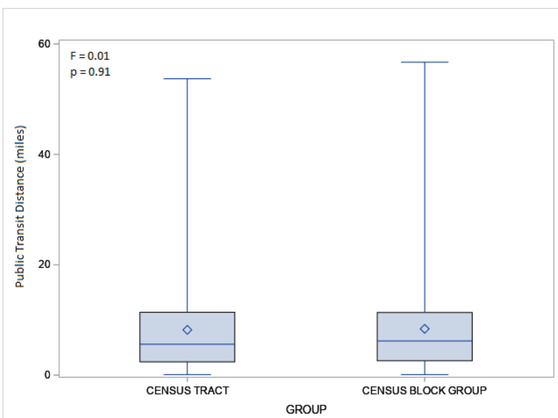
a)



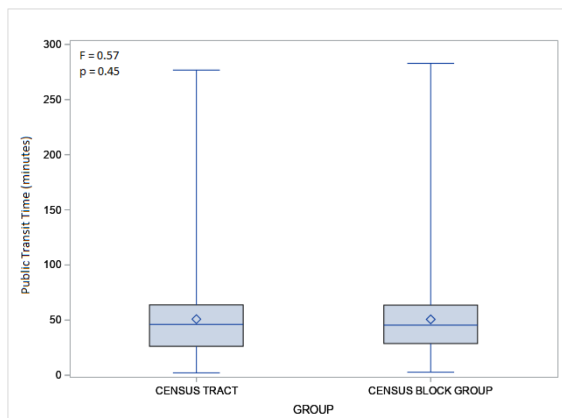
b)



c)



d)



[a]Brown and Forsythe's test for ANOVA
[b]County level excluded due to small sample size (n = 5)

Figure 3. Local differences between public transit and drive times, by geographic level.
a) county, b) census tract, c) block group

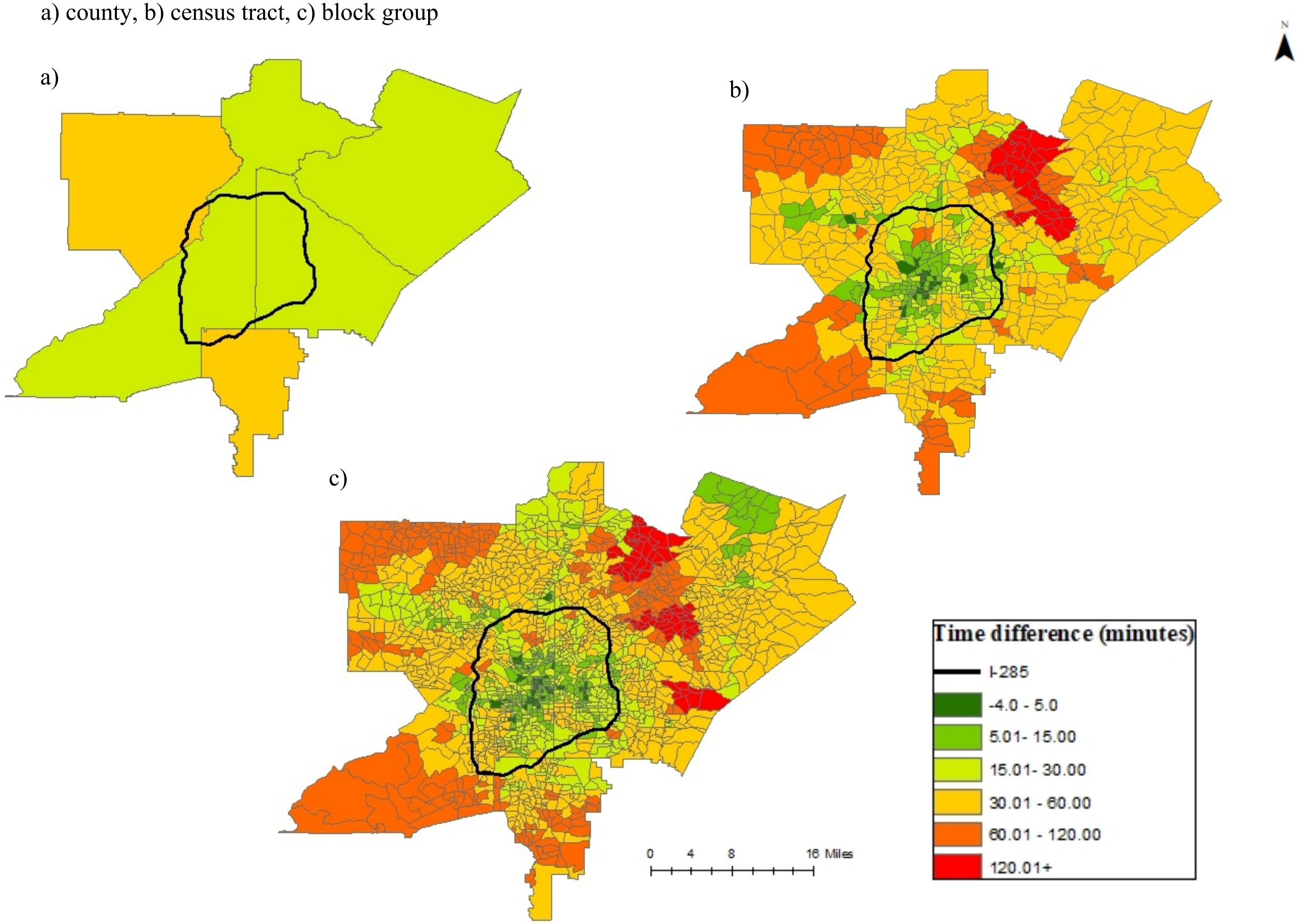


Figure 4. Drive time from population-weighted centroid to nearest PrEP provider, by geographic level.
a) county, b) census tract, c) block group

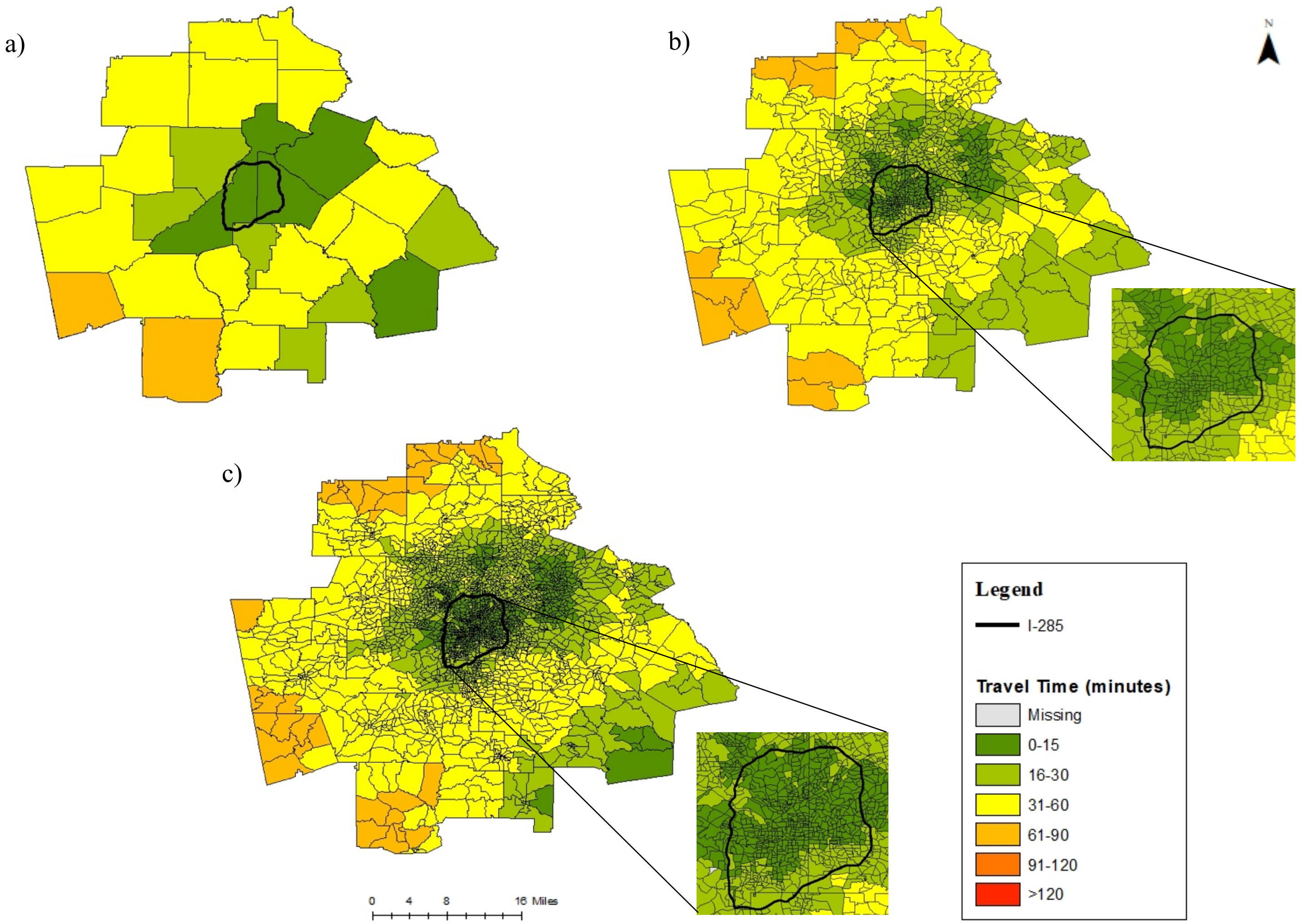
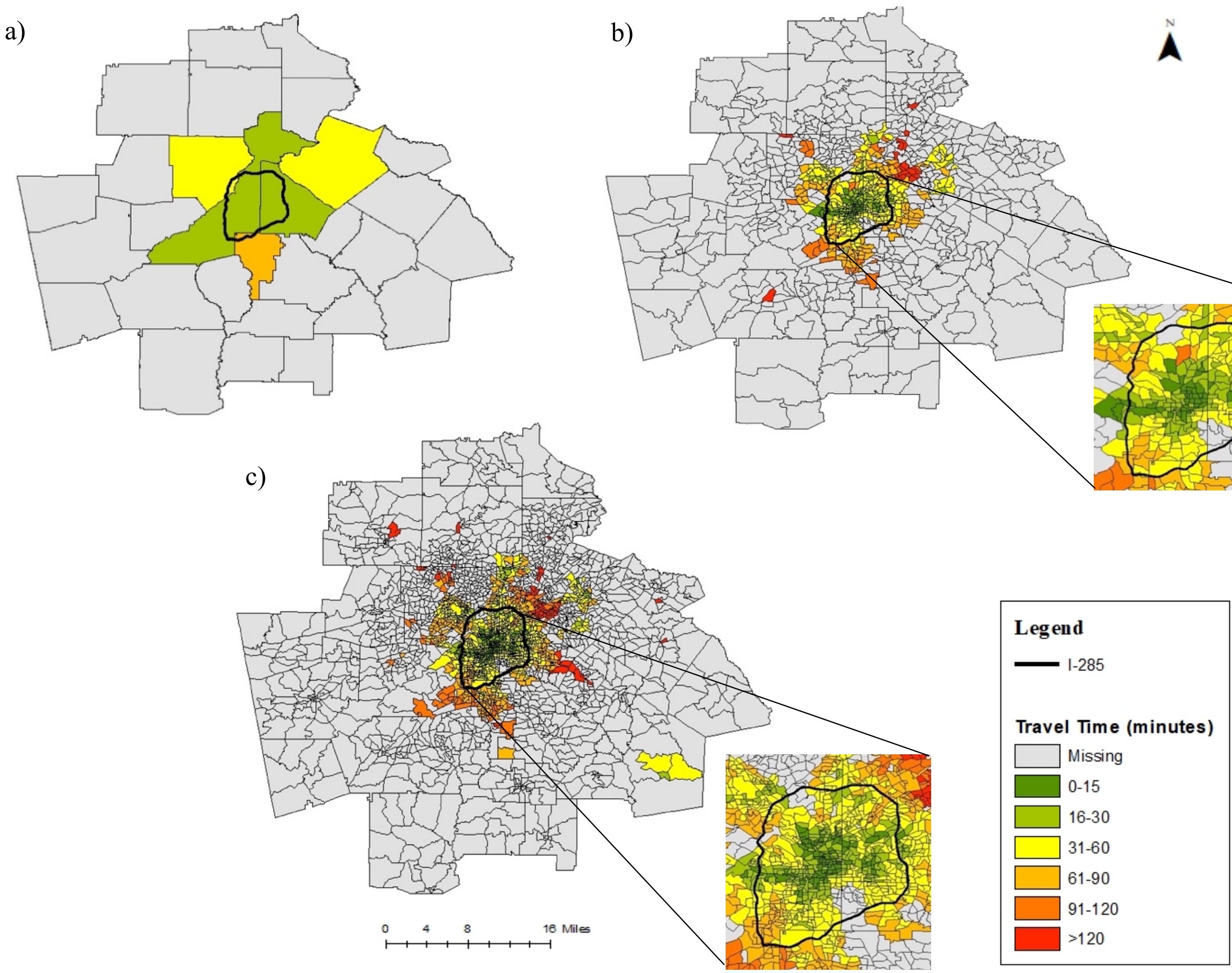


Figure 5. Public transit time from population-weighted centroid to nearest PrEP provider, by geographic level.
a) county, b) census tract, c) block group



*Population with missing data:
3.2 million