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Features and Limitations of Cell Phone Mobility Data for Disaster Recovery Applications

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ABSTRACT

When studying justice-related questions while using mobility data, is it important to critically examine the data for bias, particularly geographic bias. This report reviews a single dataset of human mobility derived from app-based mobile GPS data. We compare to the census demographics associated with the census block group that the unique device id resides in. We compare mobility data to "ground truth" datasets at airports, hospitals and grocery stores. Each ground truth dataset also has its own sampling bias, making comparisons difficult. We found that Veraset, the mobility data providers explored in the study, recorded data from 595,370 Veraset users, which is 8.5 % of the estimated Houston Metropolitan Area population. There are 2,181 CBGs where the Veraset sample size is more than 5 % of the CBG population, and 836 CBGs where the Veraset sample size is less than 5 % of the CBG population. There was no significant difference in the sample size disadvantaged and non-disadvantaged census tracts. We note that while the Veraset samples appear to capture users spread across the Houston Metropolitan area, there may be poorer coverage of users from lower income populations. We also note an unusual drop in mobility data between the first and second month of the collected dataset. While human mobility datasets can be large in nature, device persistence is lacking and trend data is sparse. Good quality ground truth data is essential to calibrate mobility datasets.

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1. INTRODUCTION

Human mobility data has become more prolific and readily available for use in research. Applications include understanding how people move in space and time as part of their daily life, store visitation trends, traffic forecasting, urban planning [1], accessibility inequality [2, 3] and epidemic mitigation [4]. A 2021 Pew Report shows 97 percent of Americans own a cellphone and 85 percent own a smartphone [5]. People carry their phone with them wherever they go, generating a wealth of location data. Human mobility data can be used to track how people respond to a disaster by tracking preparation and evacuation behavior, as well as movements during the disaster.

Cellphone carriers are reluctant to share their data due to privacy issues. As a result, many datasets are collected from apps when the user has opted in to location sharing. Users who opt in to location data on an app such as WhatsApp might look very different demographically than users who have opted in for location data on GasBuddy or Bumble.

Several commercial companies, such as Veraset, SafeGraph and X-mode offer anonymized and aggregated cellphone location data, gathered from cellular networks and Global Positioning System (GPS). Raw trace data from GPS is aggregated by the data aggregation companies, but their methodology is not made public [6]. Each company has partnerships with thousands of different apps to share user location that is collected when the user is actively using the app. These partnerships are not shared publicly. Because of this and the sampling rate representing 5-10 percent of the population, each dataset shows different human mobility patterns for the same geography and time [7]. Partnerships are often growing and changing over time, as new ones are added, and others dropped. Historical datasets may not be sampling be the same devices over time, making longitudinal studies difficult. Sampling bias and representation across demographics for each city are not published. Researchers are encouraged to purchase multiple mobility datasets [7], however cost can be prohibitive.

2. BACKGROUND

Mobility justice as a field often incorporates mobility information with demographic indicators or other screening tools for vulnerability. Commonly used tools or sets of indicators in the United States context include the CDC Social Vulnerability Index[1], the Climate and Economic Justice Screening Tool[2], and the EJScreen tool[3]. Each of these tools provides a mapping of specific indicators of disadvantage to specific geographical areas, resulting in a policy-oriented mapping of which areas and communities are most vulnerable. The different mapping tools focus on different indicators associated with disadvantage particular to their domains.

Despite the end of formal racially discriminatory housing practices, many United States metropolitan statistical areas continue to exhibit racial segregation in housing, often corresponding to disparate income levels between racial groups [8, 9]. Studies of mobility practices in metropolitan areas sometimes therefore explicitly include or specifically examine the connection between mobility behavior during disasters (including COVID-19) and segregation or historical redlining practices [10, 11, 12]. Transportation and accessibility issues have a legacy in redlining practices. In Houston, a city with sprawling suburbs, residents from primarily poor and black neighborhoods experience longer travel times compared to individuals from non-poor and white neighborhoods when using public transit, even though their travel durations by driving are similar [2]. Compounded by poorer and black neighborhoods having lower rates of car ownership, urban accessibility is not equal. A study in Houston shows residents visit a median of nine locations five times or more in the period of one week [2].

As noted in [13], the use of mobility data, which may include call records as well as GPS data provided via third party aggregators such as Veraset, Safegraph, and Cuebiq, has become a popular resource to model human behavior patterns during disasters such as pandemics and natural disasters response and recovery. Note that in this paper, we focus on app-based GPS data provided through Veraset.

In recent years, there has been a growing body of literature using mobility data to analyze Covid-19 transmission and its impact on human behavior. In [14], the authors combined mobility data with subway traffic patterns to identify essential services within an urban area, and in [15] the authors cross-reference mobility data with the CDC's Social Vulnerability Index to analyze the relationship between sociodemographic factors and stay-at-home behavior during lockdown. Similarily [16] evaluates the correlation between census block group income and physical distancing behaviors using SafeGraph mobility data, in particular examining trends in visitations to places such as supermarkets, hospitals, and parks. The authors note the limitations of not being able to evaluate the mobility data against traditional data sources. Veraset mobility data is used both in [17] to create Covid risk scores using agent-based modeling, and in [18] to create network graphs to analyze travel between Census Block Groups (CBGs) during the pandemic.

The need to critically examine mobility and location data, particularly for aggregator-based mobility data, was noted in [13]. In response to increased interest in using mobility data, there

[1]https://www.atsdr.cdc.gov/placeandhealth/svi/index.html
[2]https://screeningtool.geoplatform.gov/
[3]https://www.epa.gov/ejscreen

have been attempts to standardize analysis metrics [6] and evaluate the coverage and representativeness of cell phone data [19]. In [20], the authors note that mobility data under-represents children and seniors. In a correspondence letter, [21], it is noted that a correlation was found between mobility data and Covid transmission rates up to April 2020, but that correlation was weaker at later dates when the reduction in travel was less dramatic. This was also found in [22], where the Covid reproduction number and mobility proxies for change in travel were closely tied only for the heavily urban populations, where were large mobility samples, for the first 15 weeks of the pandemic. County-level comparisons were difficult due to lacking data on which portions of the population were represented in the sample of cell phone users.

Commercial mobility data aggregators clean, transform and extract GPS data with opaque methods and this prevents purchasers from identifying raw metrics. Making comparisons between counties with variability in socioeconomic status is difficult. Researchers found further validation and standardized frameworks for data generation are needed to better understand how to interpret mobility metrics [6]. Some papers have evaluated differences across mobility data aggregators, and have found that mobility metrics can vary between datasets. In [23], the amount of social distancing and distance travelled were compared across several mobility datasets, including SafeGraph, Facebook, and Google. The paper also reports high Pearson's correlation for PlaceIQ, Descartes Labs, Cuebiq, and SafeGraph mobility datasets between the overall population in large metropolitan areas and the number of unique devices in the dataset. In [7], the graph properties of networks constructed based on mobility data from Spectus, X-mode, and Veraset were compared at different spatial resolutions. The paper reported dissimilar results across the three datasets, highlighting the sensitivity of derived mobility metrics and analysis to the mobility data source and how it is processed.

Several studies reported Pearson's correlation between the population size and the mobile device population. In [24] found strong Pearson's correlation between Houston CBG population and the number of unique devices per CBG, but did note lower-income CBGs appeared to be under-represented in their data. We note this paper used similar data to what we present in this paper, however, the authors did not filter out CAIDs without a identified home in the Houston area, which may explain the differences in our results. In [25], the authors also found strong linear correlation between the county level population in Flordia and the Veraset sample size, but noted that there may be bias in the representativeness of the data for the Asian, White, Hispanic, and elderly population due to these variables being identified as signfificant covariates in their analysis. It was also found in [26] that at a country level, there was strong correlation between the Safegraph sample size and the country level population in Puerto Rico during Hurricane Maria. However, the study found some spatial bias in cell phone location data after Hurricane Maria when there was limited cell phone access due to infrastructure damage, and therefore did not include these time periods in their analysis. In [27] which examines the disparities in evacuation procedures during Hurricane Harvey in Houston using Cubeiq data, trip data was re-weighted based on Census population counts.

There has been some prior work using mobility data to analyze the impact of Winter Storm Uri. [24] identify critical points of interest using maximum entropy and Lagrangian relation methods to construct a network representing mobile travel. In [28], the authors use a combination of 311 service calls, mobility data, cell phone location data, and demographic data to compare the behavior patterns of Houston residents during the power outage versus the month prior. The study used statistical metrics such as one-way ANOVA and trip clustering to evaluate the extent of power outages and food accessibility, and found that storm impacts were more severe in low-income and neighborhoods with high minority populations. Using similar datasets, along with social media network network data, [29] determined that the heterophily in hazard-exposure between census tracts led residents to temporarily relocate between tracts during the event.

3. METHODS

3.1. Study Area

3.1.1. History

This study focuses on the deep freeze climate event that occurred in Houston, TX in February, 2021. We looked at census and cellphone data within the Houston Metropolitan Statistical Area (MSA), which consists of Austin, Brazoria, Chambers, Fort Bend, Galveston, Harris, Liberty, Montgomery and Waller counties.

Houston is the only major city in North America which does not regulate land use and is known for its lack of traditional zoning [30]. The absence of zoning has contributed to housing segregation, environmental justice concerns, gentrification and displacement, and disparities in access to amenities and services. Rapid and unplanned urbanization including in hazardous area leads to high vulnerability and exposure of individuals and communities to extreme weather conditions(Cardona et al., 2012). During the post-World War II era of highway expansion and affordable single-family homes in the suburbs, Houston started witnessing housing segregation concentration of minority populations in certain areas due to historical redlining practices. Suburbanization and car-centric development led to lower investment in the public transportation sector and members of the population unable to afford cars could not access essential services. Smiley and Hakkenberg [31] found that while socioeconomic status was the primary driver of the temporal change in Houston's urbanization, the social dynamics associated with spatial disparities in urbanization relate primarily to race, regardless of socioeconomic status.

3.1.2. Climate Hazard

On February 10-20, 2021, a deep freeze impacted the entire state of Texas with many counties experiencing wind chill values below zero. It was the coldest winter storm for Texas since December 1989. The deep freeze was caused by a multitude of factors, including the negative Arctic Oscillation (AO) and the polar vortex. AO is a back-and-forth shifting of atmospheric pressure between the Arctic and the mid-latitudes of the north Pacific and north Atlantic. With a negative AO, a weaker jet can dip further south, enabling outbreaks of Arctic air into the mid-latitude regions. The polar vortex is an extensive coverage of low pressure and cold air surrounding Earth's poles. It was weakened, allowing warm air to flood into the Arctic and polar air to sink down into the mid-latitude.

At its height, 10 million people lost power, with most widespread outages occurring on February 16th. During this time, people lacked warmth and the ability to cook food. The freeze also caused water pipes to burst and some hospitals had to be closed as a result. Sleet and freezing rain also made roads hazardous to travel.

More than two out of three Texans (69 percent) lost electricity at some point during Winter Storm Uri for an average of 42 hours, while almost half (49 percent) lost access to running water for an average of more than two days, according to a report from survey conducted by the Hobby School of Public Affairs at the University of Houston. Nearly one-third of people reported water damage in their home. Survey and power outage data for individual neighborhoods indicated that Black and Hispanic residents may have experienced longer and more severe outages [32].

A timeline of weather events and impacts on energy supply is shown below which was compiled using news and weather reports.

- Wednesday February 10 – Cold air moves into Texas bringing sleet and freezing rain; road conditions are hazardous; Houston not yet impacted.
- Thursday February 11 – Icy precipitation in Houston; ERCOT anticipates record-breaking demand due to storms; schools close.
- Friday February 12 – Governor issues disaster declaration for all of Texas.
- Saturday February 13 – Winter Storm Warning issued (no precipitation in Houston); 38 gas plants statewide shut down due to cold.
- Sunday February 14 – Storm hits, snow falls and temperatures plummet Sunday night; some areas in the region experience single-digit temperatures and Wind chill pushes these even lower; the National Weather Service Office-Houston issues Hard Freeze Warnings and the first Wind Chill Warnings.
- Monday February 15 – Temperatures hit record low for Feb 15 of 17 degrees Fahrenheit, and temperatures remain below freezing in some parts of the state; ERCOT blackouts, both rolling an unplanned, begin; at least 2 million Texas households are without power, including 1.4 million CenterPoint customers in the Greater Houston area; later, ERCOT announces the power grid was minutes from a statewide outage; H-E-B grocery stores limit purchases of propane tanks (2 per transaction) and water (2 gallons or 2 multi-packs per trip), and stores close early.
- Tuesday February 16 – Winter storm continues with wind chill and hard freeze warnings and temperatures around 13 degrees in Houston; at least 4.5 million customers in Texas are without power. Walmart closes its stores.
- Wednesday February 17 – More snowfall and winter advisory is issued; many grocery stores shelves are empty and people are struggling to find food; statewide, 3 million Texas households do not have electricity, including 1.39 million CenterPoint customers; by late Wednesday, the number of CenterPoint customers without power drops to 675,000.
- Thursday February 18 – Snow has stopped but temperatures remain low; in the afternoon, CenterPoint Energy reports that only 30,000 customers are without power; later Abbott announces power has been restored to most Texas homes; during an emergency meeting, the Texas Public Utility Commission passes a new rule, effective immediately, which dictates that transmission and distribution companies like CenterPoint cannot cut customers' electricity for more than 12 hours at a time.
- Friday February 19 – Power been restored to 1.39 million CenterPoint customers while 700,00 customers remain without power; ERCOT returns to normal operations at 10:36 a.m. and ceases rolling blackouts; 15 million people statewide lose access to clean water.

- Feb 20 (Sat)– Freeze warning ends at 9am.

3.2. Human Mobility Data

The Veraset mobility data used for this study was purchased in 2023. Cell phone location data was captured beginning December 1, 2020, two months prior to the event, through February 28, 2021, one week after the event ended. According to Veraset, their data samples 6 percent of the US population. Cellphone devices are given a unique ID to maintain anonymity, and the home location of the device is given at the Census Block Group (CBG) spatial scale to protect user privacy.

CBGs are spatial regions delineated by the US Census Bureau, and are updated after each Census. The boundaries for each CBG are drawn using an automated process that sets CBG boundaries using a mixture of visible barriers (e.g. roads, streams) and non-visible barriers (e.g. property lines, city borders). The CBGs are not determined based on population count, and some CBGs may include zero residents. The average CBG in the Houston Metropolitan area has roughly 1600 residents according to the 2020 Census [4] .

The Veraset data was provided for the entire United States, however for the purpose of this analysis, we limited our analysis to trips to destinations within the Houston Metropolitan area. For all analysis, we treat the time period from December 1, 2020 to Feb 9, 2021 as the baseline period where user behavior is not impacted by a climate event. The period from Feb 10, 2021 to Feb 20, 2021 is treated as the climate event period. We note that the precise dates for the baseline may vary when analyzing specific infrastructure sectors depending on the temporal resolution and availability of the ground truth data.

A ’trip’ in the Veraset data is captured and logged in the dataset when:

- The user is actively using an app that Veraset has partnered with to gain location information.
- The user has not opted out of location information sharing on that particular app.
- The user is located at a point of interest while actively using the app.

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The Veraset data used for this analysis includes the visitation data only, rather than raw movement data. To create visitation data, Veraset runs an algorithm to convert the raw GPS data provided by their partnered apps to a point of interest, such as a facility location[33]. Based on the GPS data logged while an app is in use, a trip is logged for that cell phone device at the point of interest over a certain period of dwell time. The Veraset algorithm determines the point of interest by taking a cluster of GPS location points, and using a canonical density-based DBSCAN clustering algorithm to merge the raw GPS data with the polygon associated with a point of interest. Often there are several possible points of interest that the clusters could be associated with due to

[4] https://www.census.gov/newsroom/blogs/random-samplings/2011/07/what-are-census-blocks.html

’jumpy’ GPS pings, and in these cases Veraset applies a machine learning algorithm to identify the most likely location.

Trips with low horizontal accuracy are discarded from the visitation dataset. To protect user privacy, Veraset uses a proprietary machine learning algorithm to identify locations that are most likely residential homes. If a home is detected, Veraset removes the address, and the location name is set to ’home’.

Note that a ’trip’ simply means the user had used an app while at a particular location. The Veraset data does some cleaning to cluster multiple GPS pings into a single trip at one location, but we have observed cases in the dataset where if the user is in a single location for an extended period of time, such as a work location or home, the data set will include multiple ’trips’ at the same location.

For each trip, Veraset provides the following data:

- Device ID (referred to as CAID) - a hash string linked to a specific mobile device
- Timestamp
- Dwell Time
- Location Name - For businesses, the location name is the business name. For identified homes, the location name is set to ’home’.
- Street Address - This information is not provided for identified homes.
- City
- State
- Zip Code
- NAICS Code - Business are tagged using the 2017 NAICS code values.
- Census Block Group - provided using the 2010 Census Block Map

3.3. Preprocessing

3.3.1. Limiting Data to Trips taken by Houston Residents

The purchased Veraset data includes mobile device data covering the entire United States during the time period of interest. We preprocessed the visitation data to capture the movement patterns of Houston residents. To do this, we first restricted the Veraset data to only include trips to Houston metropolitan area census block group (CBG) codes. The set of Houston metropolitan area CBGs was determined based on the 2020 Census Metropolitan area definition files [5]. Because the Veraset trip data was tagged using the 2010 Census Block map, after identifying the set of 2020 CBGs spanning the Houston area, we identified the corresponding set 2010 CBGs that

[5] https://www.census.gov/geographies/reference-files/time-series/demo/metro-micro/delineation-files.html

provided the same coverage (the process for reconciling 2010 and 2020 Census data is further detailed in the next section).

We then created a list of Veraset users who have taken at least one trip to a location tagged as a 'home' in the dataset - given that we already filtered the data to only include Houston area trip destinations (including trips to users' homes), this implies the user is most likely a Houston resident. Any trips taken by users who are not identified as Houston residents were removed from the data. Figure 3-1 compares the distribution of total trips taken by users with tagged homes in the Area of Interest (AOI) versus users without tagged homes in the AOI. From the figure, it is clear that while many users have been removed due to not having an identified home, most of these users had fewer than 5 trips logged during the dataset period. We suspect these users are either visitors to the AOI, or infrequent app users. Trips taken by users without homes in the AOI are overall less likely to provide interesting information on infrastructure visits. For all subsequent analysis in this paper, we limit our dataset to only include users with homes in the AOI.

After filtering, the mobility data includes trip data for 594,136 unique Veraset users (with unique Device IDs) who took 14,724,767 trips over the full dataset time period. The total number of trips taken per day by users with homes in the AOI is shown in Figure 3-2. On average, 163,608 trips were taken daily across all Veraset users with homes in the AOI.

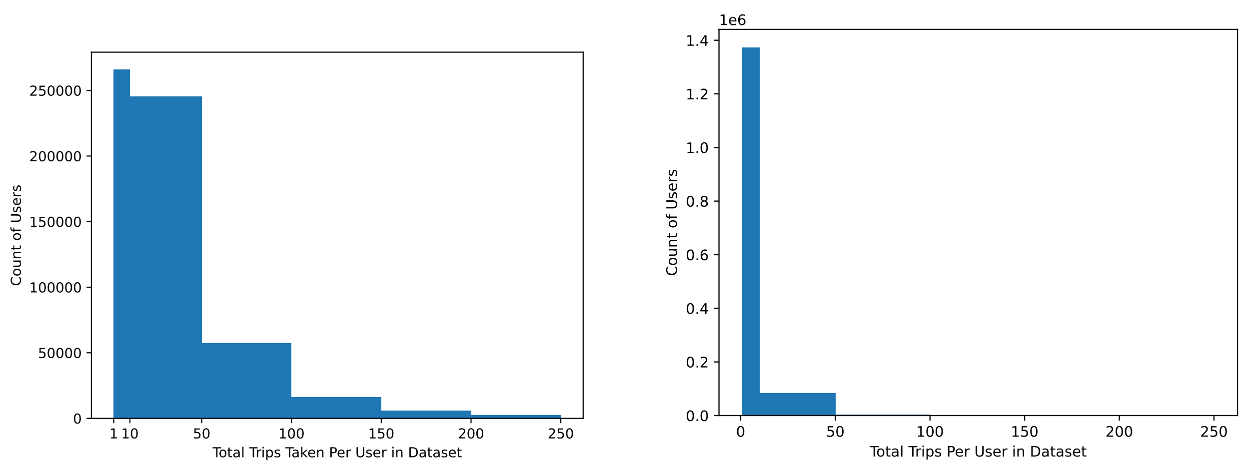

Figure 3-1 Distribution of total trips taken by individual users for the full dataset period, November 30, 2020 to February 28, 2021. (*Left*) Total trips taken by users with homes in the AOI. (*Right*) Total trips taken by users without homes (according to the data) in the AOI.

Our analysis relies in part on the accuracy of Veraset's software in flagging user homes, which we unfortunately cannot verify as we do not have access to raw movement data. We identified a few cases where it is clear that Veraset's software has incorrectly labeled user homes. There are 4 Houston area Census Block Groups (CBGs) that, according to the 2020 Census, have zero residents - these are CBGs that are located in business districts such as the major airports, or are primarily offshore. In addition, we identified 19 CBGs where the number of Veraset users in our dataset with homes located in the CBG was greater than the overall CBG population. Most CBGs with zero population or inflated Veraset homes are based out of business districts so we suspect that in many cases shift workers mistakenly had their work location identified as a home from the Veraset software.

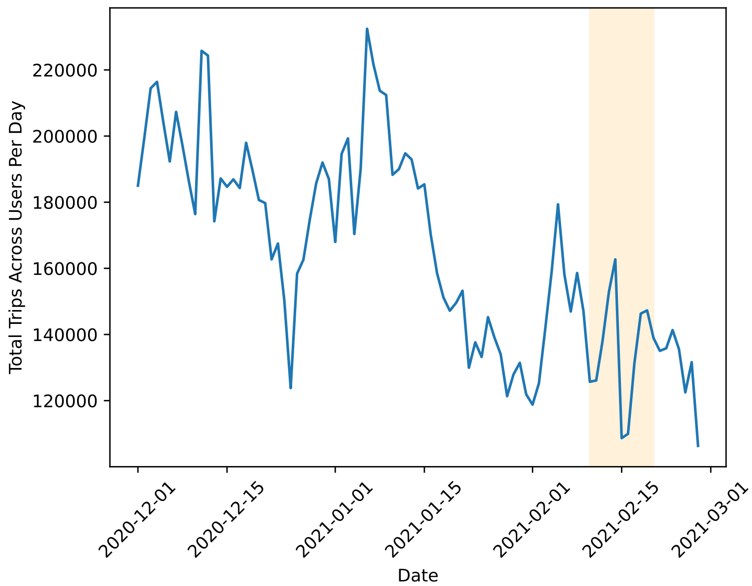

Figure 3-2 The total number of trips taken per day by Veraset users with homes in the Houston Metropolitan area. The highlighted section indicates the power outage time period.

Trips taken by users with mislabeled homes still provide value on number of visits to infrastructure services, so we include them in our analysis. However, for any maps that were produced for this report, we exclude homes from CBGs with zero population. We also excluded data for CBGs with inflated Veraset home counts in the demographic analysis section.

3.3.2. Estimating Population Counts using 2020 Census Data

Although the dataset period covers late 2020 through early 2021, Veraset tagged the CBG for each trip based on the 2010 Census map. This presented a challenge for the study on population and demographic representation, where we compare the Veraset data against the population counts according to the 2020 Census.

To accurately capture demographic trends, our analysis needed to use the 2020 Census as our ground truth rather than 2010 Census data, as there was considerable population and demographic shift between the two censuses. However, between 2010 and 2020, there were considerable changes to the assigned ID's and boundaries between CBGs, which posed an issue when trying to reconcile the Veraset data with the Census data. The Houston Metropolitan area used for this analysis spans 3021 CBGs according to the 2010 census block map, and 4154 CBGs according to the 2020 Census Block map. Given that the Veraset data was coded using the 2010 Census, we then needed to either (1) convert the Veraset data so that trip destinations were coded using the 2020 Census Block id rather than 2010, or (2) convert the 2020 Census data such that population estimates are being aggregated over the CBGs defined according to the 2010 Census map rather than the 2020 Census map.

We found that approach (1) was not possible due to the fact that Veraset did not provide us with exact street address for trips to homes . While there are many ways to identify the CBG associated with a street address based on both the 2010 and 2020 Census, we cannot directly use them with the entire Veraset data for this reason.

We instead relied on option (2), and estimated the population over each 2010 CBG geographical region based on the 2020 Census population count. Note that we use the terms '2010 CBG' and '2020 CBG' to refer to Census Block Groups whose geographic region is defined by the 2010 Census map and 2020 Census map respectively. To estimate the population, we performed the following steps:

1. Overlay the 2010 and 2020 CBG maps in QGIS [6].
2. Based on the maps, estimate the overlap between each 2020 CBG and any intersecting 2010 CBGs as a fraction of the total 2020 CBG area.
3. Estimate the population over each 2010 CBG as a weighted sum of the Census population of intersecting 2020 CBGs, with the weights equal to the fraction overlap.

To illustrate this, we provide a few hypothetical examples:

- Case 1: A CBG does not change from 2010 to 2020 - the percentage overlap between 2010 and 2020 is 100%. The estimated population, over the 2010 CBG boundary, is therefore just the population (from the 2020 Census) for the corresponding 2020 CBG.
- Case 2: Two 2010 CBGs (CBG A and CBG B) were joined together to create a single CBG in 2020. The 2020 CBG population is 1000. The overlap between the 2020 CBG and CBG A is 70%, and the overlap between the 2020 CBG and CBG B is 30%. Therefore the estimated population for CBG A is $(0.7)(1000) = 700$, and the estimated population for CBG B is $(0.3)(1000) = 300$.
- Case 3: A 2010 CBG was split into three 2020 CBGs. The three 2020 CBGs have population counts of 400, 500, and 600 according to the 2020 Census. The estimated population over the 2010 CBG region is therefore $400 + 500 + 600 = 1500$.

In the actual data, the overlap between 2010 and 2020 CBGs were more complex. To simplify the analysis, we ignored cases where the polygon overlap between a 2010 and 2020 CBG was less than 5% of the 2020 total CBG area.

To further illustrate the approach with an actual example from the Veraset data, we show how the population was estimated over the 2010 CBG with GEOID 481576744001(the GEOID is the identification number for the CBG). To reiterate, we are estimating the number of residents living in the region identified as GEOID 481576744001 according to the 2010 Census map, based on the population counts taken in the 2020 Census. From the 2010 to 2020 Census, GEOID 481576744001 has been split into 8 separate 2020 CBGs. Some of those 2020 CBGs also overlapped with other 2010 CBGs. Table 3-1 details how much of the total population for each intersecting 2020 CBG was allocated to GEOID 481576744001 based on percent overlap. The total estimatedpopulation for GEOID 481576744001, is simply the sum of all entries in the right-hand column of the table above, 8459.

[6] https://qgis.org/en/site/

2020 GEOID	Overlap with 481576744001 as Fraction of 2020 CBG area	2020 Population	Population assigned to 481576744001
481576744013	1.000000	2644	2644
481576744014	0.209080	2387	499
481576744015	0.295437	1536	454
481576744024	1.000000	1119	1119
481576744023	0.853915	510	435
481576744012	1.000000	1188	1188
481576744021	0.468295	829	388
481576744022	0.231402	882	204
481576744011	1.000000	1528	1528

Table 3-1 Example of weighting-based method to estimate CBG population over a CBG region from the 2010 Census maps, based on population data gathered from the 2020 Census. The example provided is for the 2010 CBG with GEOID 481576744001. The total population for the 2010 CBG region, GEOID 481576744001 is the sum of all entries in the right-hand column.

This approach assumes that the population is uniformly distributed across the CBG, which is generally not true, particularly for CBGs that contain both more rural and urban populations. However, given that for 90% of the 2020 CBGs, either the entire 2020 CBG has been part of a single CBG in 2010, or the CBG remained the same between 2010 and 2020, we believe that the overall population counts are reasonable and this weighted aggregation approach is only necessary for the remaining roughly 10% of cases.

The use of 2010 Census groups also results in a few Census block groups with unusually large population sizes. The average Census block group contains 600 to 3,000 residents. According to the 2020 Census, the maximum 2020 CBG resident population in the Houston Metropolitan area was 12,769. With the weight-based aggregation scheme, the maximum estimated 2010 CBG population was 63,744. The CBG with maximum population size was a 2010 CBG, GEOID 481576729001, which had been split in 2020 into 17 separate CBGs, most likely due to the large population between 2010 and 2020.

Note that the 2010 Census map was used for all analysis in this paper where trips are grouped by CBG, and for any map images generated. Any CBG population values listed in this paper have been approximated using the weighted aggregation scheme outlined in this section.

3.4. Ground truth datasets

To validate the mobility data, and determine whether temporal variations in the data are noise or are indicative of real-world trends, we found datasets that either served as ground truth or as a second sampled dataset to compare the mobility data against. We were unable to directly access visitation data for more service sectors. The data was either tracked but private (e.g. grocery chains), difficult to track during the pandemic due to curbside access only (e.g. libraries), or not directly tracked (e.g. hospitals, airports). Working against these limitations, we found approximate ground truth resources, or secondary sampled datasets, for a few service sectors such as groceries, hospitals, and airports as detailed in the sections below.

We also compared total population counts for Veraset users against the 2020 Census and DOE identification of disadvantaged communities. In addition, because we analyzed total trips to major sports arena because these were larger events with precise population accounts during major games.

For future analysis, we will want to consider trips to other key infrastructure services, particularly services utilized during power outage events. Examples of services that have been considered when examining social infrastructure access during disasters [34] include:

- communications
- emergency logistics
- evacuation
- finance
- food
- fuel
- medical services
- medications
- restoration
- safety
- security
- shelter
- transportation
- waste management
- water

Each service in this list is provided by specific facilities, such as grocery stores (for food) or cell phone towers (for communications).

3.4.1. Census Data

The census data used for this analysis was obtained from the US Census Bureau 2020 American Community Survey (ACS), which provides 5-year summary tables for the Houston Metropolitan Statistical Area at the Census Block Group level [35]. Demographic data from the Census that was compared against the Veraset data in this analysis include race, age, Veteran status, SNAP enrollment, and income level. As discussed in the previous section, because the Veraset mobility data identified destination addresses using the 2010 Census, we adjusted the 2020 Census data to estimate the demographic data over each 2010 CBG geographic region.

3.4.2. DOE Disadvantaged Communities

The Department of Energy has generated a list of 368 Census tracts in the United States that are considered 'disadvantaged' based on a combination of 36 burden indicators that reflect energy burden, environmental and climate hazards, fossil dependence, and socioeconomic vulnerabilities [36]. Note that a Census tract is a set of Census Block groups. A tract is identified as a disadvantaged community (DAC) if is ranked in the 80th percentile of the cumulative sum of the 36 burden indicators and if at least 30 percent of households in the tract are classified as low income. The geographic distribution of all DACs in the US is shown in Figure 3-3. Note that one potential limitation of the DOE DAC labels is that Census tracts were determined to be disadvantaged based on the 2010 Census data rather than the 2020 Census, and therefore may not accurately reflect the population and demographics in 2021.

In our preliminary evaluation of Houston, we found that 30 percent (2.12 million) of Houston's population (7.02 million) lives in a disadvantaged tract. The distribution of low income, minority population, linguistically isolated population, and unemployed population percent across the tracts of Houston is depicted in Figure 3-4. The distribution of disadvantaged communities facing high energy burden, food desert, transportation burden and outages are shown in the Figure 3-5.

In this analysis, we separate Veraset data for users with homes in disadvantaged and non-disadvantaged tracts to examine differences in mobility patterns between the two groups. We also compare the representation of users from disadvantaged and non-disadvantaged tracts in the Veraset data.

3.4.3. Airports

For airports, the intent was to determine how well the mobility data reflected travel through the airport each day.

Monthly passenger counts are available for the major Houston airports [7]. The BTS data only included the two busiest airports in the Houston area, IAH and HOU. This ground truth Houston airport data, for December 2020-Feb 2021 was 2.37 million, 2.04 million, and 1.73 million

[7] Houston airport data.

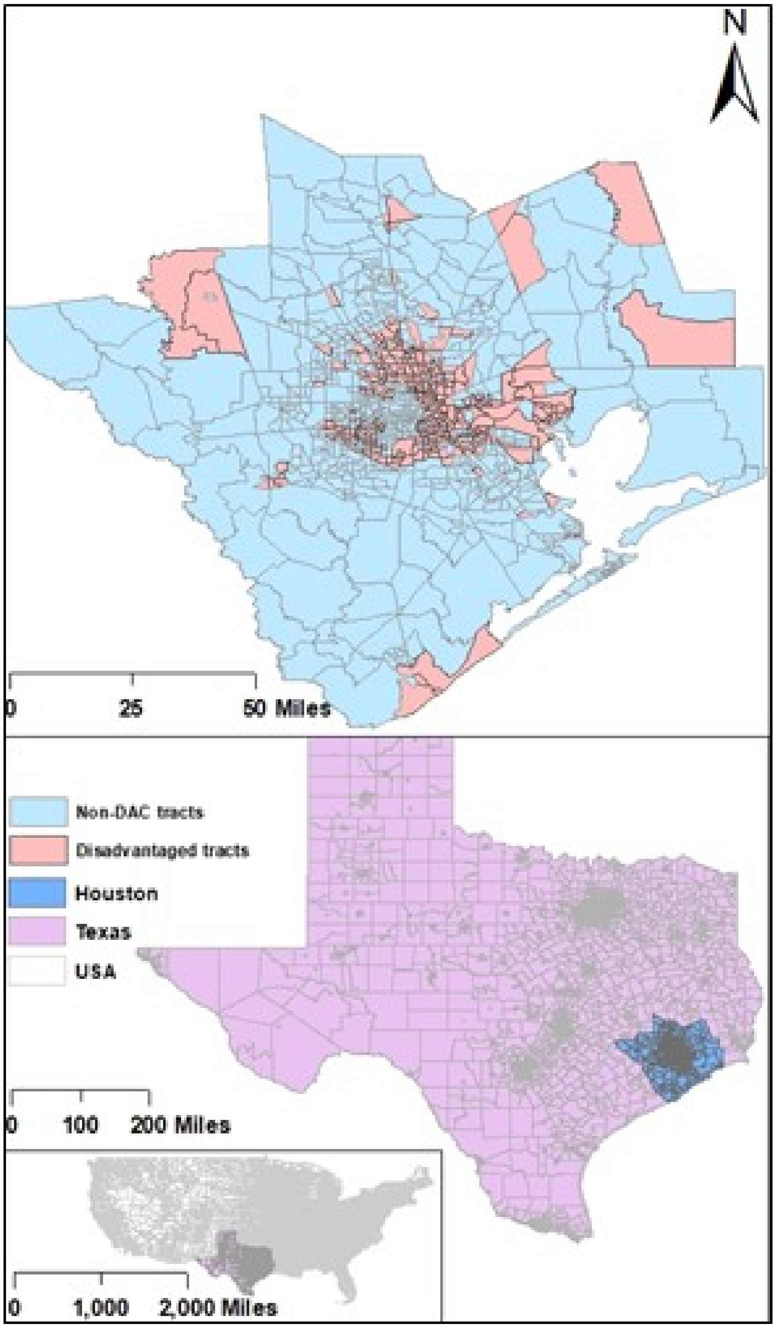

Figure 3-3 Disadvantaged tracts in the Houston MSA.

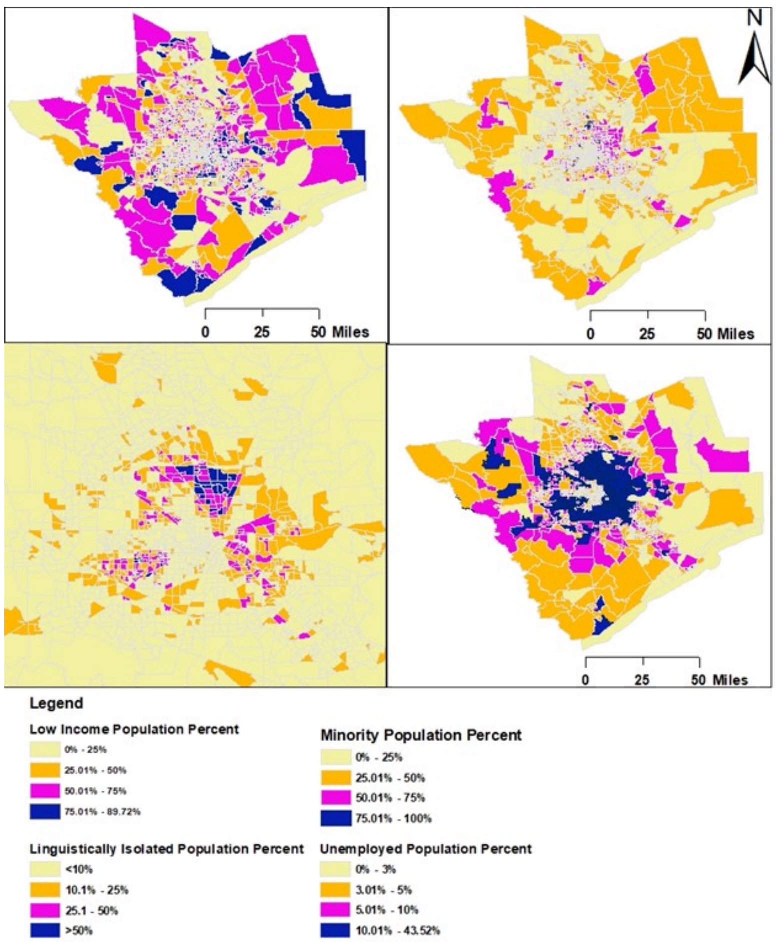

Figure 3-4 Top left shows concentration of unemployed population across the tracts of Houston, top right low income population, bottom left linguistically isolated population and bottom right panel the minority population

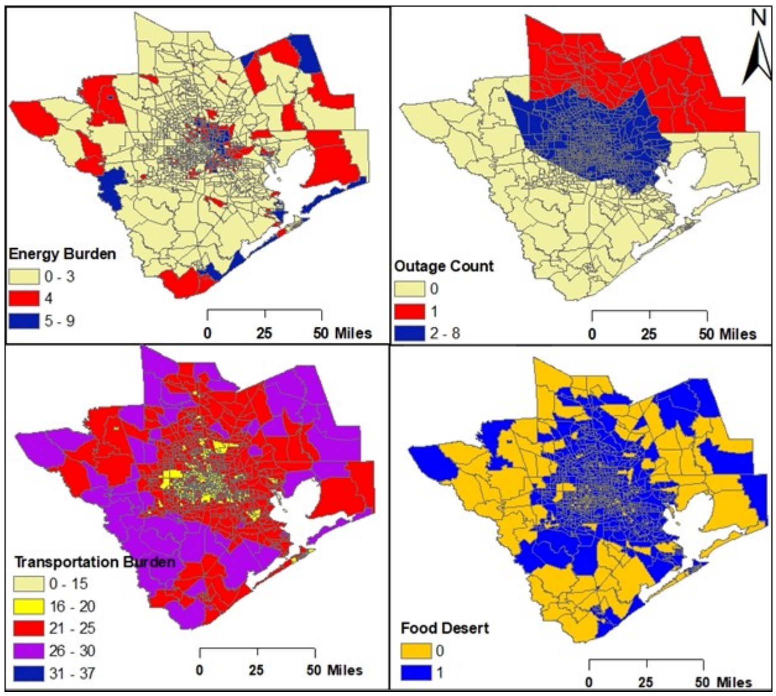

Figure 3-5 Transportation Burden: Transportation Costs as percent of income for the Regional Typical Household Center for Neighborhood Technology (CNT) Housing and Transportation Affordability Index (H+T® Index), 2016. Energy Burden: Annual average energy burden based on average annual housing energy costs divided by the average annual household income Low-Income Energy Affordability Data - LEAD Tool. Food desert: Share of neighborhood without access to affordable or good-quality fresh food (Percentage who live within 1/2 mile (urban) or 10 miles (rural) of supermarket.

respectively, although it wasn't clear whether these numbers included passengers transferring via Houston airports.

We were unable to access publicly available datasets describing daily passenger counts on flights by airport. However, via the Bureau of Transportation Statistics (BTS) we were able to access details, including the tail number, on domestic flights arriving and departing the busiest US airports each day [8]. Using the tail number, we were able to access the seating capacity for each plane via published data from the Federal Aviation Administration [9].

We began by comparing on a monthly scale for the time period of interest. Comparing IAH and HOU airports' passenger counts to the BTS flight data for those same airports, to compensate for the passengers on the international flights, we assumed that all recorded flights were at 100% capacity. We also assumed that roughly 50% of passengers were transferring flights at these airports; that is, the Houston metropolitan area was not the final destination of roughly 50% of arriving passengers, and that they were departing on some other flight. That is,

$$\text{Total passenger count} = (0.5 \cdot \text{Seats in incoming flights}) + \text{Seats in outgoing flights}$$

Aggregating seat counts for each plane that flew domestically into or out of either IAH or HOU airports, and using the above two assumptions, we estimated monthly passenger counts at IAH and HOU, combined, to be 2.18, 2.16, and 1.75 million passengers in December 2020, January 2021, and February 2021 respectively. Our estimates' error compared to the ground truth was 8%, 6%, and 2% respectively.

We then used the estimation method described above on a day-by-day schedule to estimate daily enplanements (the number of passengers boarding flights). The resulting values are treated as 'ground truth' but are actually estimates, and day-to-day estimates may be less accurate than more-aggregated monthly estimates. For example, passenger counts may vary by day of the week in a way that monthly aggregation averages out.

3.4.4. Hospitals

While we were unable to track the direct number of in-patients, out-patients, and visitors to hospitals in Houston area, as a proxy we were able to access the daily number of beds filled for a subset of Houston area hospitals. This dataset was provided courtesy of the SouthEast Texas Regional Advisory Council, and covered daily beds occupied for 34 hospitals and medical centers from the Houston Metropolitan area. While this data does not include out-patients or hospital vistors, we assume that the data is representative of overall temporal trends in the number of trips to hospitals taken per day.

[8] https://www.transtats.bts.gov/Fields.asp?gnoyr_VQ=FGJ

[9] https://www.faa.gov/licenses_certificates/aircraft_certification/aircraft_registry/releasable_aircraft_download

3.4.5. Grocery Stores

As grocery store chains do not share data on the number of purchases made or in-store visitors, we do not have a ground truth dataset showing exactly how many trips were made to grocery stores during the climate event. Instead, we examined two sampled datasets roughly capture trip data using different data sources. We used these two datasets as a comparison source against the mobility data to at least see if there were common patterns in food purchases, particularly over the course of the climate event. It should also be noted that the both of the comparison datasets capture grocery sales in terms of dollar amounts. Total sales islikely correlated with, but does not directly capture the number of grocery store trips. Increases in total amount spent on groceries can either be due to an increase in customer trips to grocery stores, or may be due to the same subset of customers increasing their total spending during periods of food stockpiling, such as around holidays and prior to a climate event.

The first dataset is available through the USDA [10], and provides total retails in a variety of separate food subcategories including dairy, fruits, grains, meats. The dataset was collected by a company called Circana, and relied on scanner data provided by a sample of food retail establishments. The available data was aggregated at the state level, and at the weekly level. For the grocery store trip analysis in this paper, we examined trends in Texas retail sales after aggregating purchases across all of the provided food subcategories.

The second dataset provides a sample of credit and debit card transactions at grocery stores across the Houston area. The data was compiled by a company called Facteus, which sells datasets of sampled, anonymized credit and debit card transactions from financial institutions with details on the vendor name and type of business. We accessed an aggregates form of this data which had been purchased and made publicly available by Purdue University's Center for Food Demand Analysis & Sustainability at the College of Agriculture [11]. The Purdue website provides weekly total retails at individual grocery stores, as well as aggregates at the state level. The data can be accessed through an interactive website, and needed to be manually copied into spreadsheets for analysis. We examined the weekly state level aggregates. We also aggregated weekly total retails across Houston for three chains that we selected based on their popularity as well as potentially providing insights on behavior across income levels: Aldi, H-E-B, and Whole Foods. For each chain, we added weekly sampled retails across all stores with Houston area zip codes.

3.4.6. Sports Games

Sports games, while not providing a critical infrastructure service, do provide an opportunity to analyze the percentage of attendees at a large gathering that were captured in the Veraset data. We analyzed trips to the NRG stadium, which hosts the Houston NFL football team, the Texans, and trips to Toyota Center, which hosts the NBA basketball team, the Houston Rockets.

[10] https://www.ers.usda.gov/data-products/weekly-retail-food-sales/
[11] https://ag.purdue.edu/cfdas/resource-library/trends-in-grocery-sales/

The NRG stadium published the audience attendance attendance at each NFL game [12]. Due to COVID restrictions, the stadium had limited seating capacity, the average audience attendance was 12,400 per game over the 2020 season while the stadium capacity was over 70,000. In addition to football games, the NRG Stadium hosted additional large events during the dataset period such as monster truck and motorcycle competitions [13]. We were unable to find any documentation or news reports indicating that the stadium was used as a warming shelter during the power outage. After the outage, the stadium parking lot had been used as a distribution point at various times by the Houston Food Bank [14], and also hosted a visit and speech by President Biden [15]. The attendance for these events is unknown, and it is unclear whether Veraset's algorithm would have geolocated users in the parking lot as being at NRG stadium.

The Toyota Center also provided precise audience attendance for each of its games [16]. There was also a water distribution event on February 23 shortly after the power outage, that was attended by the mayor and the Houston Rockets team.

[12] https://www.espn.com/nfl/team/schedule/_/name/hou/season/2020
[13] https://www.nrgpark.com/event-calendar/
[14] https://www.ctinsider.com/texas-sports-nation/texans/article/Texans-Cal-McNair-Hannah-Houston-Food-Bank-HISD-15967685.php
[15] https://www.npr.org/2021/02/26/971778961/biden-arrives-in-houston-to-check-on-recovery-from-deadly-winter-storms
[16] https://www.espn.com/nba/team/schedule/_/name/hou/season/2021

4. RESULTS

4.1. Trips to High-Attendance Events

A significant limitation of mobility data in general is that it does not provide regular, periodic tracking of individuals. As previously noted, location data is provided via certain mobile apps when users are actively using the app. We will provide some examples in this section to demonstrate why this may lead to non-uniform coverage of trip data. We suspect that the variations in coverage are due to differences in user behaviors at different locations - for example, locations with significant queuing lines may motivate users to browse their phones while idle, or there may be apps that users tend to use while at particular locations, e.g. a ride share app or an app to pick up a restaurant order.

We first examined coverage of Veraset users at major sporting events where we were able to obtain audience attendance numbers for many major events. Figure 4-1 and Table 4-1 detail the attendance at NRG stadium over the dataset period. Figure 4-2 and Table 4-2 provides similar data for the Toyota Center.

For both the NRG Stadium and Toyota Center, the Veraset sample size is approximately 1% of the audience size. For both sports stadiums, and in general across the Veraset data, we notice an unusual decrease in mobile data between January 1 and January 15 of 2021. This is notable with the Toyota Center data, where the audience attendance remains consistent over the dataset period, but the percentage of audience members included in the Veraset data decreases over time.

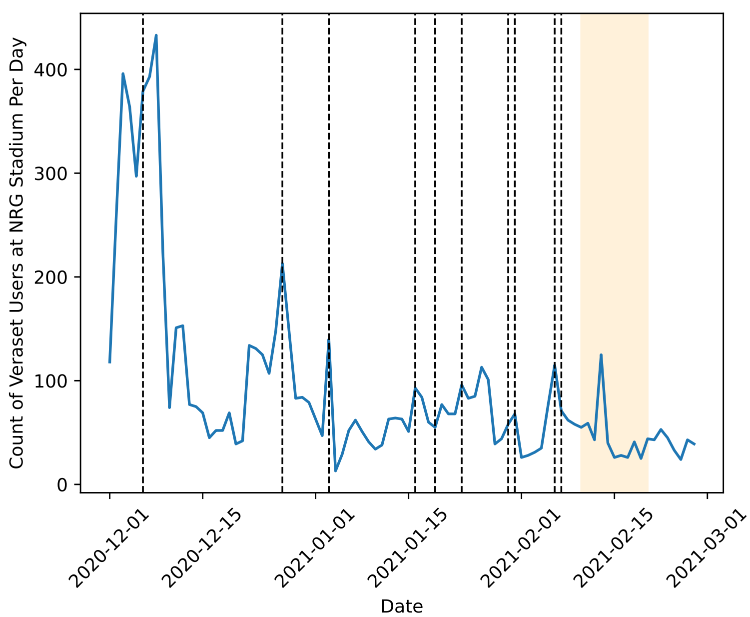

Figure 4-1 The number of unique Veraset users making trips to the NRG stadium per day *(blue)*, with the dates of known sports events indicated *(dashed black)*.

To provide an example of potential bias in which users are captured in the mobility dataset, we note an unusual trend in behavior for a particular restaurant in the Houston area. As shown in 4-3,

Date	Event	Attendance	Veraset Sample Size
2020-12-06	NFL (vs Indianapolis)	12316.0	379 (3.1%)
2020-12-27	NFL (Texans vs Cincinnati)	12344.0	213 (1.7%)
2021-01-03	NFL (vs Tennessee)	12504.0	140 (1.1%)
2021-01-23	Monster Energy AMA Supercross	9115.0	96 (1.1%)
2021-01-16	Monster Energy AMA Supercross	10830.0	93 (0.9%)

Table 4-1 Comparison of NRG stadium reported audience attendance at major events against the number of Veraset users (the Veraset sample size) with trips at NRG stadium during the event. The Veraset sample size is also listed as a percentage of the actual audience attendance.

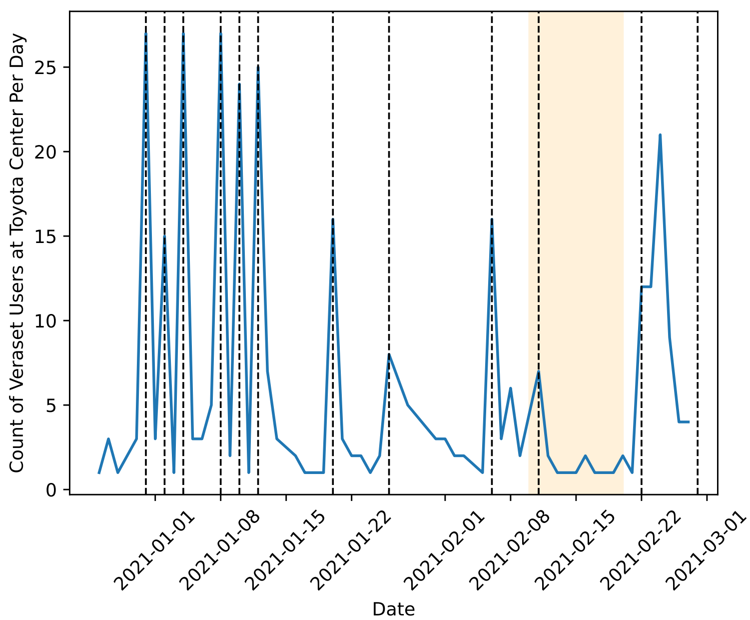

Figure 4-2 The number of unique Veraset users making trips to the Toyota Center per day *(blue)*, with the dates of known sports events indicated *(dashed black)*.

Date	Event	Attendance	Veraset Sample Size
2020-12-31	NBA (vs Sacramento)	3247	27 (0.8%)
2021-01-02	NBA (vs Sacramento)	3065	15 (0.5%)
2021-01-04	NBA (vs Dallas)	3070	27 (0.9%)
2021-01-08	NBA (vs Orlando)	3039	27 (0.9%)
2021-01-10	NBA (vs Los Angeles)	3327	24 (0.7%)
2021-01-12	NBA (vs Los Angeles)	3221	25 (0.8%)
2021-01-20	NBA (vs Phoenix)	3022	16 (0.5%)
2021-01-26	NBA (vs Washington)	2996	8 (0.3%)
2021-02-06	NBA (vs San Antonio)	3313	16 (0.5%)
2021-02-11	NBA (vs Miami)	3251	7 (0.2%)
2021-02-22	NBA (vs Chicago)	3025	12 (0.4%)

Table 4-2 Comparison of Toyota Center stadium reported audience attendance at major NBA basketball events against the number of Veraset users (the Veraset sample size) with trips at NRG stadium during the event. The Veraset sample size is also listed as a percentage of the actual audience attendance.

we observed a significant spike in attendance over a one week period for this particular restaurant. The number of Veraset users present in a single day at the restaurant was close to 800. As a point of contrast, the maximum number of Veraset users present at an NBA basketball game over the same period was 27, where we know that the true audience attendance was over 3,000 people. This type of behavior is difficult to explain based on the data alone. It is unlikely business for this restaurant spiked by over 400% over this one week period; we suspect that the unusual increase may be due to a particular event in which a particular tracking app was in frequent usage by attendees.

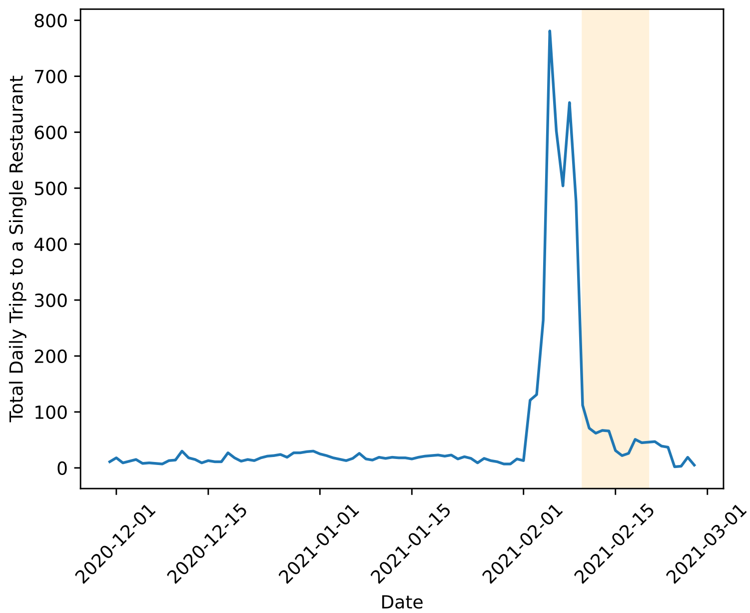

Figure 4-3 The total number of trips taken per day to a single restaurant in the Houston area. We note an unusual spike in visits immediately prior to the poower outage. The highlighted section indicates the power outage time period.

4.2. Population and Demographics

In this section we analyze the mobility data for its representativeness of the overall Houston population over various demographic categories. We find that the mobility data captures overall trends in the Houston population, and that there was not significant difference in Veraset sample sizes between DOE-identified disadvantaged CBGs versus non-disadvantaged CBGs. One point of concern is that the data may have poorer representation of lower income populations, as we detail in the analysis below.

We first analyze the distribution of Veraset users over the Houston Metropolitan Area using the 2020 US Census data. We analyze all Veraset users who have taken at least one trip over the dataset timeline, and we link each user to the CBG of their identified residential home. The *Veraset sample size* per CBG refers to the number of users with a residential home located in a given CBG. In total, we recorded data from 595,370 Veraset users, which is 8.5% of the estimated Houston Metropolitan Area population. For this analysis, we excluded the 4CBGs with zero population according to the 2020 Census, and the 19CBGs where the Veraset sample size was larger than the population.

As detailed in Section 3.3.2, although we estimate the population counts across demographic categories based on the 2020 Census data, due to limitations of the Veraset data, we aggregate and categorize Veraset data across CBGs based on the 2010 Census map. Per the 2010 Census, there are 3,017 census block groups in the Houston Metropolitan Area. Figure 4-4 shows the distribution of Veraset sample sizes as percentages of the CBG population after excluding CBGs with inflated Veraset sample sizes. The median Veraset sample size is 6.6% amongst CBGs with Veraset data. There are 2,181 CBGs where the Veraset sample size is more than 5% of the CBG population, and 836 CBGs where the Veraset sample size is less than 5% of the CBG population. In Figure 4-5, we show the same data as a scatter plot. The Pearsons correlation coefficient between the Veraset sample size and CBG population was 0.74.

We found that that residents of CBGs that were labeled as disadvantaged were well represented in the mobility data. In total, the DOE identified 368 tracts in Houston as disadvantaged, which spans 1,171CBGs. We compared the Veraset sample size between disadvantaged and non-disadvantaged CBGs, and found no significant difference according to an independent t-test ($p = 0.23$). A box plot comparing the Veraset sample size is shown in Figure 4-6, and also confirms the similar distributions between the two groups. For both the plot and the t-test, we compare the CBGs using the Veraset sample size as a percentage of the overall CBG population, to account for the possibility that there may be population size differences between the two groups.

We also analyze the mobility data for potential bias in terms of demographics. Given that we do not have access to demographic information on Veraset users, as a proxy we consider the CBG that is tagged as the residential home for each user and the demographic population of that CBG according to Census data. By comparing the number of Veraset users in a given CBG to the estimated population within the CBG along different demographcs, we can roughly estimate how well represented certain demographics are within the dataset. There are limitations to this approach; In addition to the fact that we cannot verify the true demographics of the Veraset users, it is difficult to measure the representativess of demographic groups which are a smaller percentage of the population and are not concentrated in any CBG. For example, there are no CBGs in Houston with a majority of disabled residents. The underlying demographics of Veraset users from a CBG with a large Veraset sample size may not necessarily include any disabled residents, even if the CBG itself contains a relatively higher proportion of disabled residents.

With these limitations in mind, we have attempted to evaluate the representativeness of the Veraset data. The demographic factors we examine, which are all tracked in the Census, include:

- White population
- Black population
- Asian population
- Population with income above $100K
- Population enrolled in SNAP

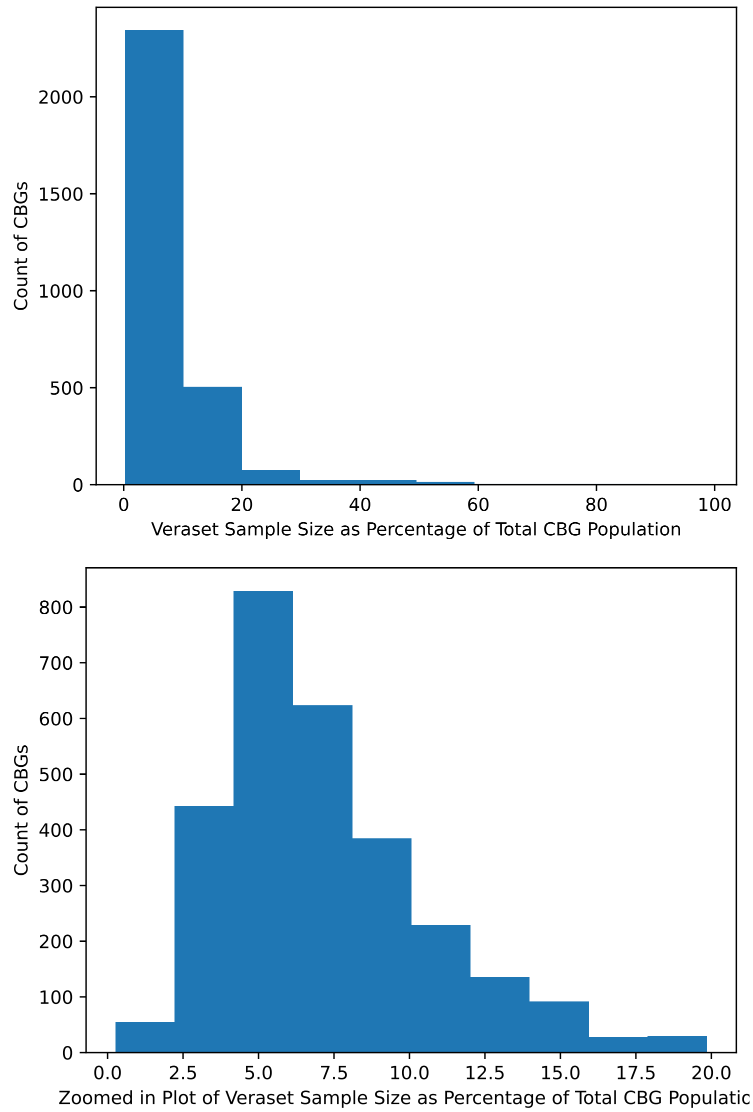

Figure 4-4 (*Top*) Distribution of number of users per CBG (sample size) as a percentage of the CBG population. (*Bottom*) Zoomed in version of top plot after to show distribution of Veraset sample sizes that are less than 20% . CBGs with sample size zero were removed from this plot.

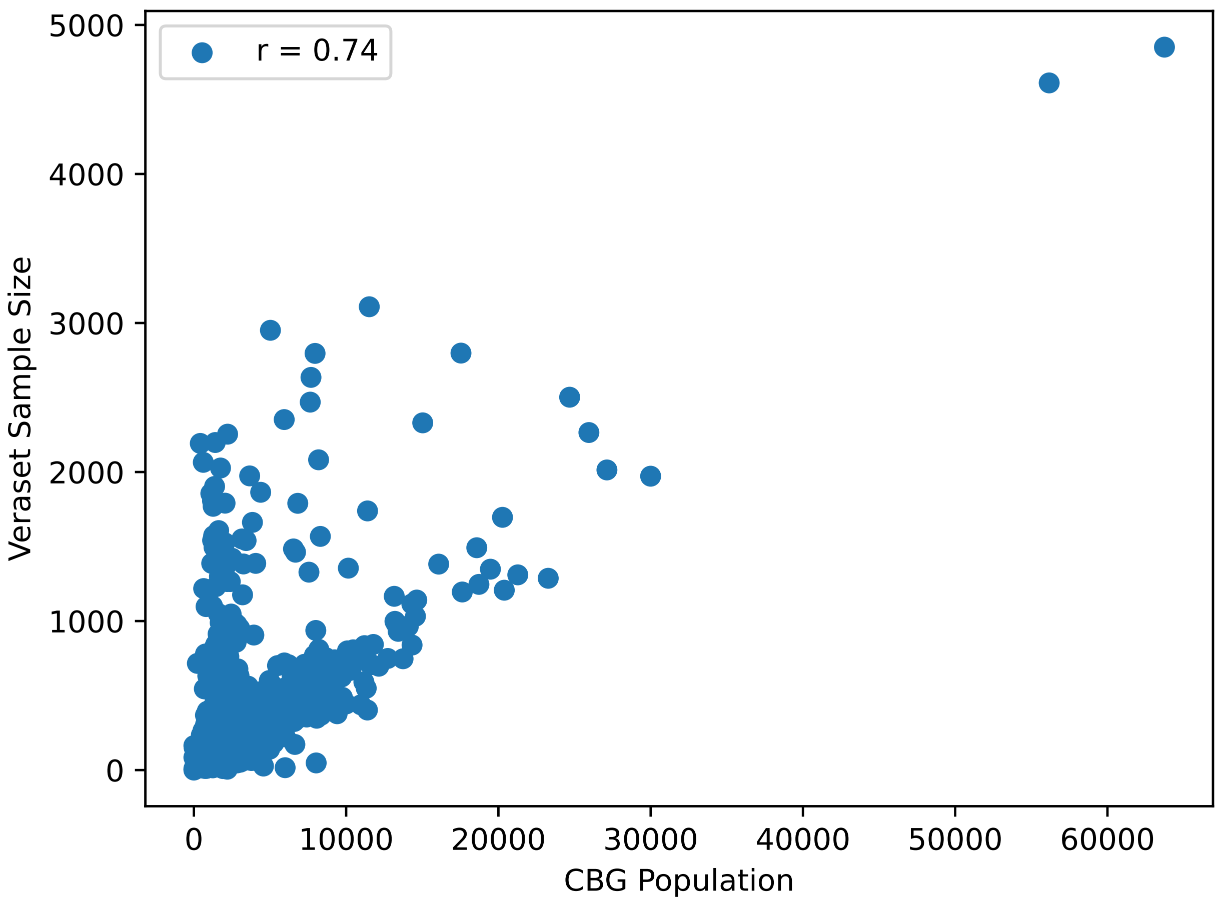

Figure 4-5 Distribution of each Houston CBG Census population count versus the CBG's Veraset sample size as a percentage of the total population. The Pearson correlation between the Veraset sample size and estimated CBG population, r, is noted. Note that the Census populations shown are the estimated population counts as detailed in Section 3.3.2

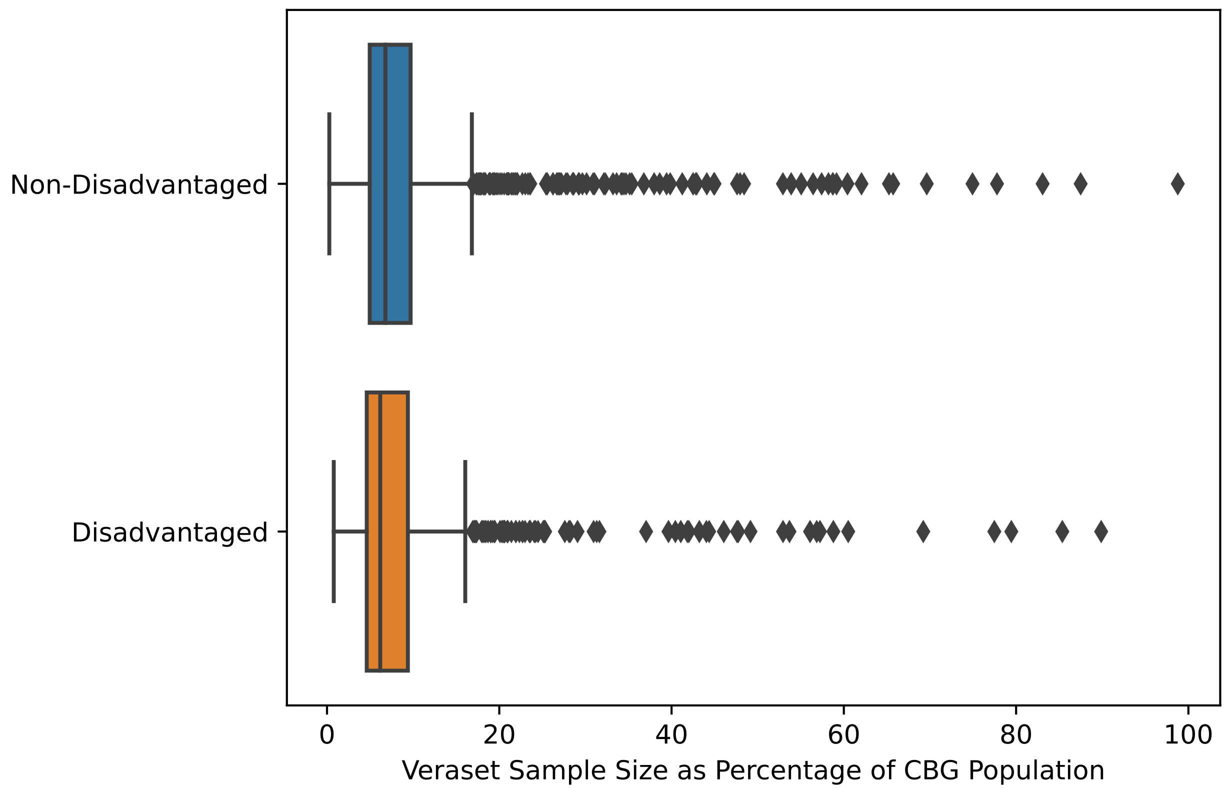

Figure 4-6 Box plot comparison of the Veraset sample size between disadvantaged and non-disadvantaged CBGs.

- Population with income below poverty level
- Senior (age 65 +) population
- Households a Disabled occupant
- Veteran status

Figure 4-7 depicts the relationship between each CBG population size for a particular demographic against the Veraset sample size. The Pearsons correlation is also indicated for each subplot. We note that it is particularly of interested that there is lower correlation between the Veraset sample size and the population living below poverty than there is between the Veraset sample size and the population with household income greater than $ 100K. We recommend further analysis to confirm that the Veraset data truly has poorer representation of lower income populations.

4.3. Grocery Stores

In this section we analyzed the trips to grocery stores in the Veraset mobility data, and compared it to other data sources to determine whether the mobility data is capturing temporal changes in grocery shopping behavior prior to and during the power outage. We find that while the data suggests there is preparation activity immediately prior to the power outage, and a potential spike indicating that some residents were able to revisit groceries in the middle of the power outage when power was partially restored to some sections of the city, these swings in behavior was much smaller in magnitude compared to a drop in mobility data that occurred between January 1st and January 15th, 2021 that we are unable to explain. We also found poor correlation between the Veraset data and datasets tracking spending patterns.

We filtered the mobility data to trips to grocery stores by only including entries marked with the 2017 NAICS codes for supermarkets. In addition we included trips to a few popular chains such as Walmart and Costco which are marked by the NAICS code for warehouse, which were searched for using the 'location name' field.

The distribution of grocery stores across the Houston area, as well as the number of trips to grocery stores taken by each device's home CBGs are highlighted in Figures 4-8 and 4-9. Based on the number of trips recorded, we do see higher representation in the suburbs than the city core for this type of service visitation.

In total, we located 450,840 trips to grocery stores over the data period, which is roughly 2% of all trips in the mobility dataset. These trips were taken by 116,966 Veraset users. The distribution of total grocery store visits across the dataset time period for individual Veraset users is shown in Figure 4-10, with the majority of users captured in the dataset after only taking a single trip.

The maximum number of trips taken by a single user was 246 trips. We suspect that this user was most likely a grocery store employee given that they were being tracked as being at the grocery store on a daily basis at multiple times. In Figure 4-11, we show the times of the day that four most frequent grocery store were tracked as being at the grocery store - we suspect all four are most likely employees. While it is difficult to definitively separate grocery store customers from

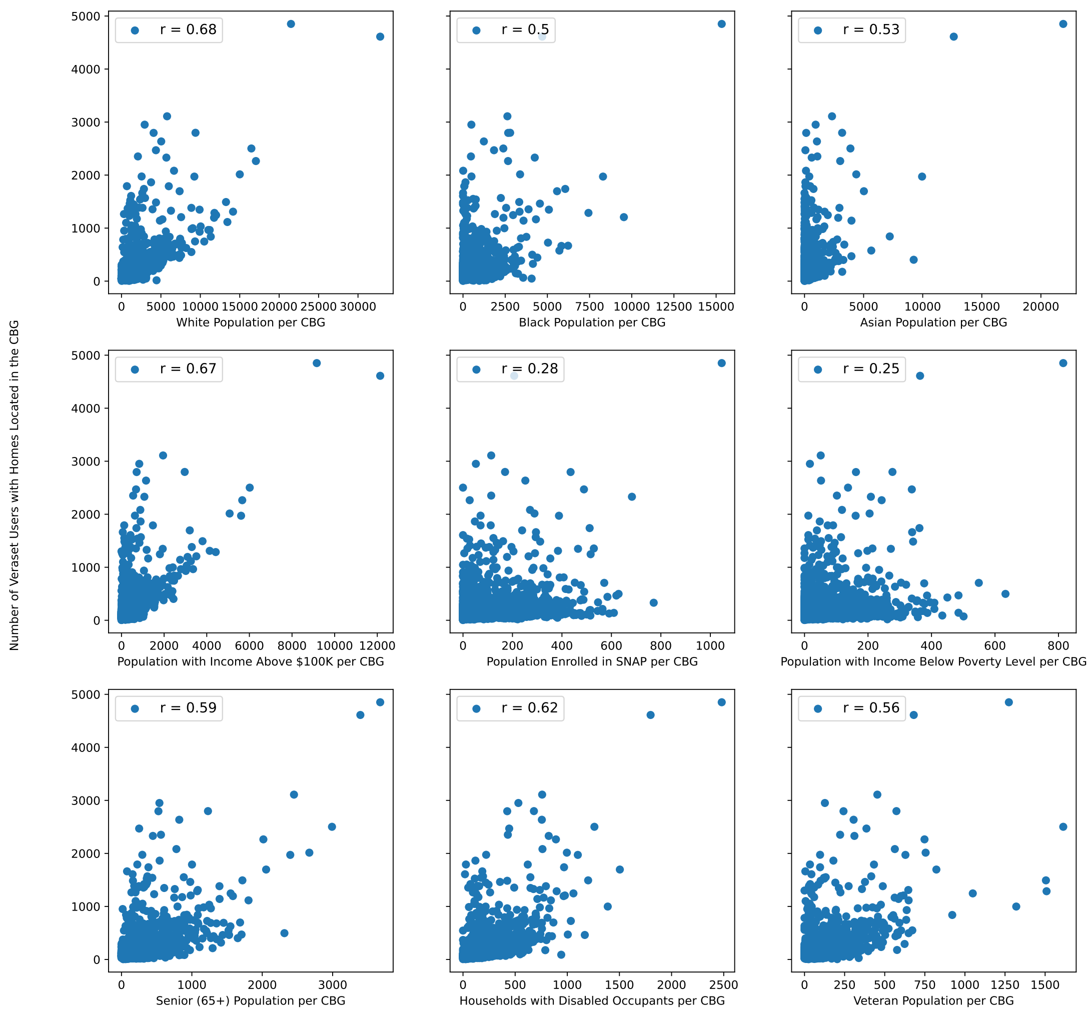

Figure 4-7 Distribution of multiple demographic populations per CBG versus the Veraset sample size from that CBG, expressed as a percentage of the CBG population. CBGs with zero population counts for a particular demographic are not included for visual simplicity. For each demographic category, we note r, the Pearson correlation between the Veraset sample size and estimated demographic population.

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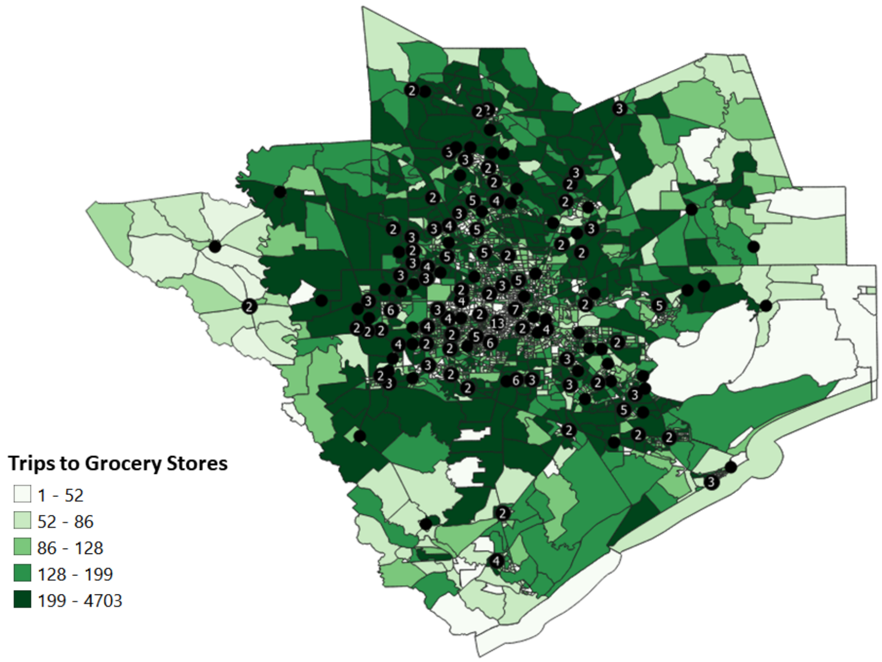


Figure 4-8 Number of trips to grocery store by device's home CBGs.

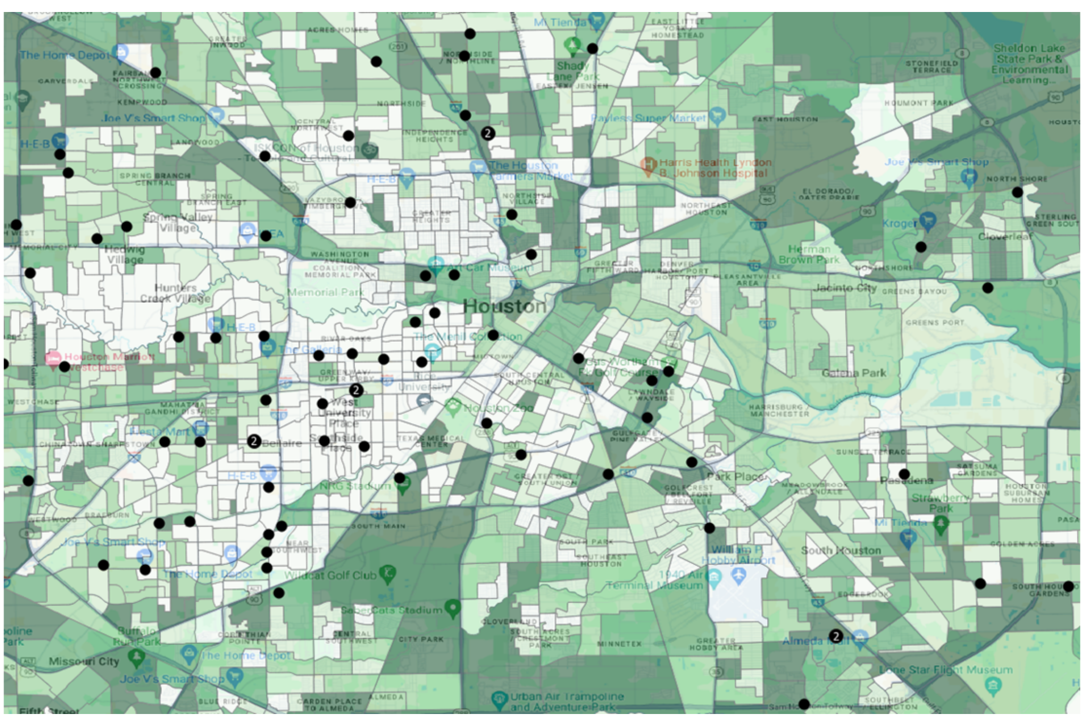


Figure 4-9 Number of trips to grocery store by device's home CBGs, zoomed in on city center.

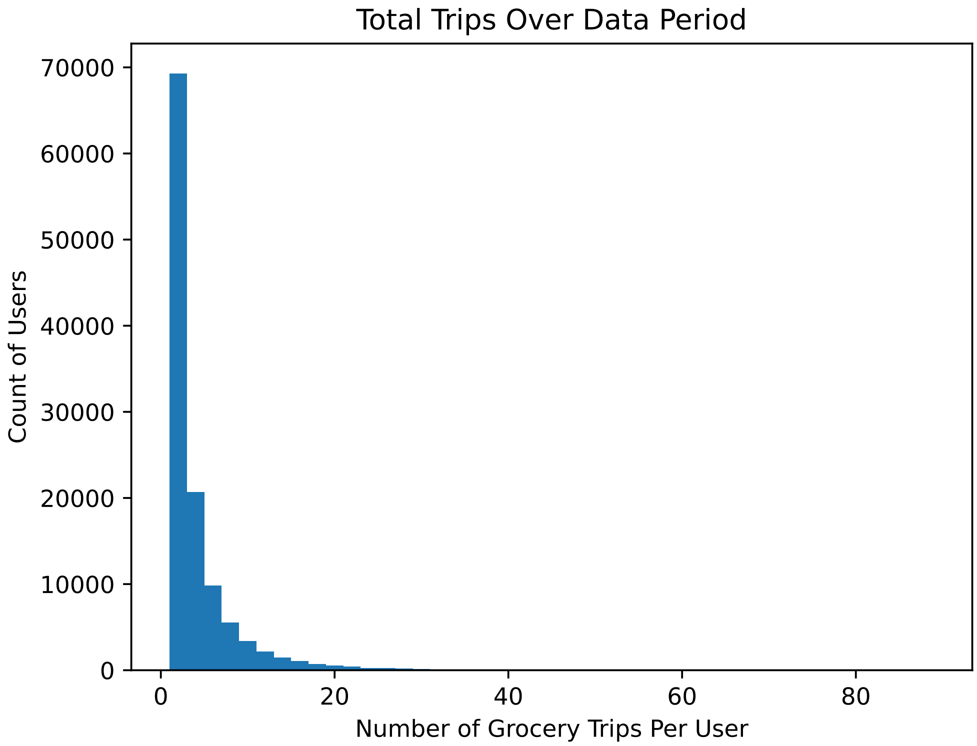


Figure 4-10 Histogram of the total number of trips taken by individual Veraset users over the full dataset time period.

employees, a reasonable assumption is that grocery store customers visit a grocery store at most once per day. We therefore filtered out all Veraset users with more than 89 grocery visits, which is the number of days over the full dataset period.

We next examine the number of daily trips to grocery stores over time. This is shown in Fig 4-12, which totals the number of trips logged at grocery stores by users from CBGs identified as disadvantaged versus non-disadvantaged CBGs. Overall we found similar trends between the disadvantaged and non-disadvantaged CBGs. The data indicates that trips to grocery stores were more frequent in December and early January compared to February, particularly during the power outage event. There is a sharp decrease as expected in trips on Christmas, and a spike after New Years, possibly due to residents restocking on food supplies after the holidays. Immediately prior to the climate event, there is an increase in grocery trips, followed by a sharp decrease at the start of the power outage, Feb 10, 2021. There is a spike again during the middle of the power outage, possibly due to residents restocking on food supplies after power was restored to a subset of neighborhoods, and when road conditions may have improved.

We also compare the temporal trends in mobility grocery store visits against our two additional data sources, a sampling of credit card transactions at grocery stores, and a sampling of grocery store sales using barcode scanner data. As shown in Figure 4-13, neither the credit/debit card transaction data reflects similar temporal patterns as the Veraset data. This may be due to a few reasons. Neither dataset can really be a considered a ‘ground truth’ data source, since they are also a sampled data sources. In addition, the credit card and sales transactions obviously do not

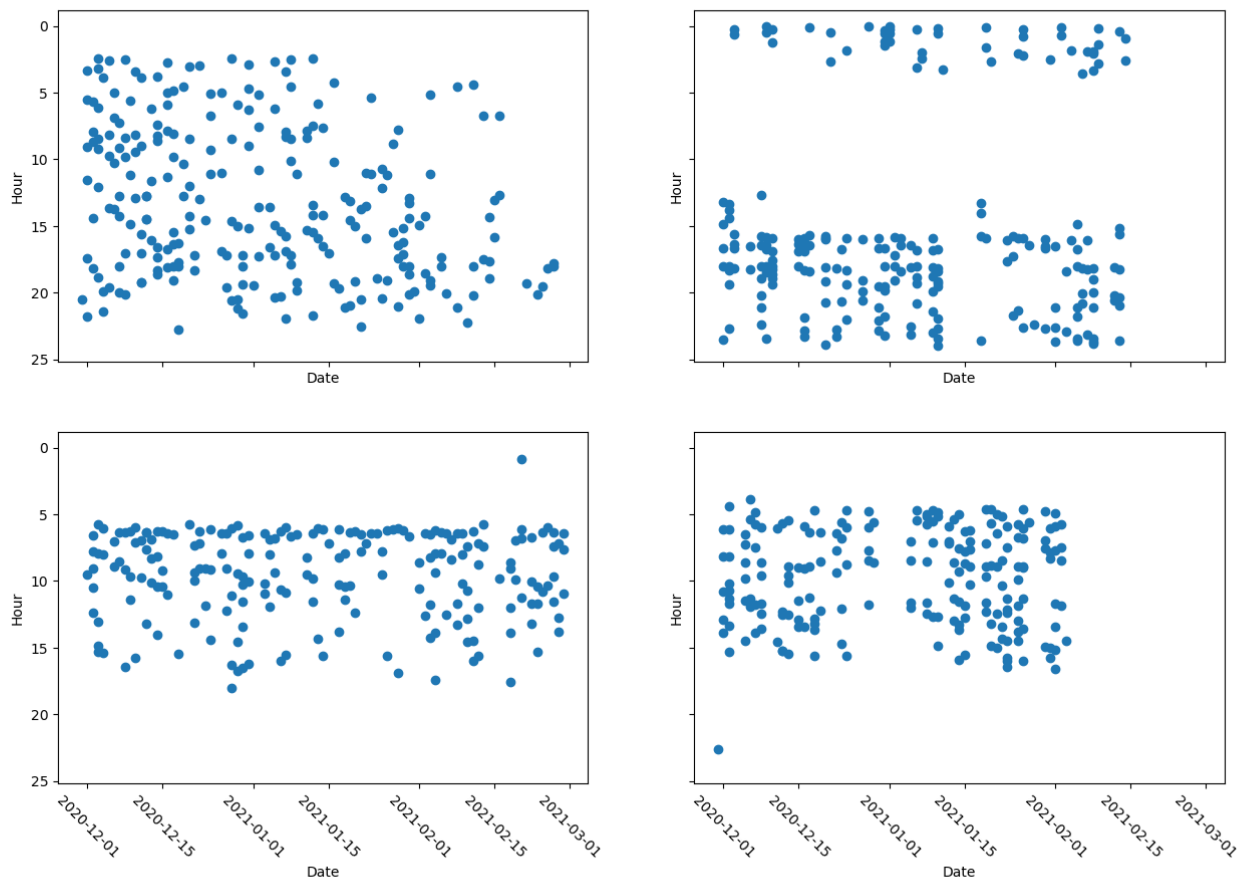


Figure 4-11 Daily visits to grocery stores by the top four Veraset users. We suspect that all four are grocery store employees. The y-axis indicates the time of day that a trip was recorded.

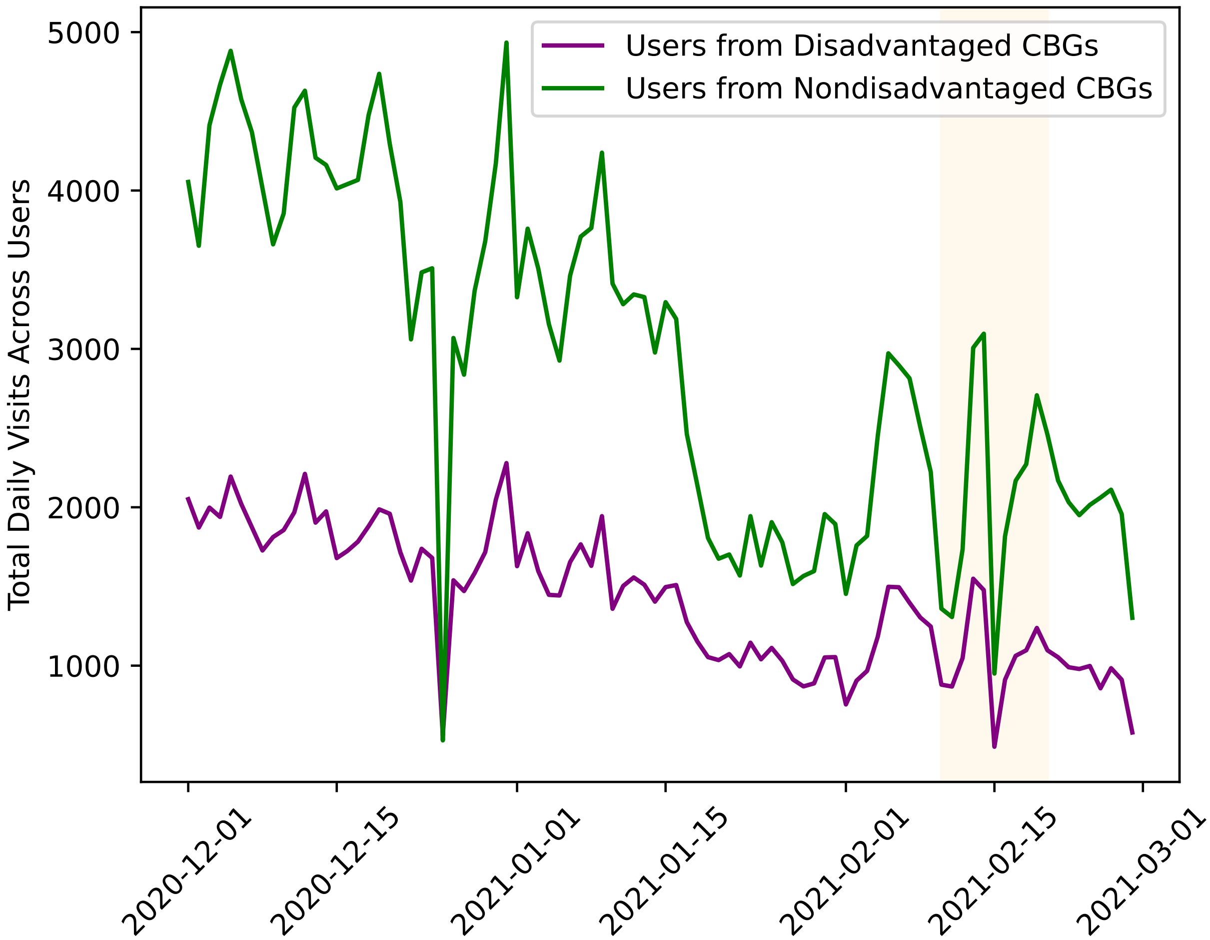


Figure 4-12 Total visits to grocery stores logged by users from disadvantaged *(purple)* versus nondisadvantaged *(green)* CBGs. The dates for the power outage are highlighted.

directly capture trip data - it is likely that right before the power outage event that residents were stocking up on food supplies, so retail sales may have increased even as the total number of trips remained the same, or even lowered. Furthermore, the transaction and sales data were aggregated per week, so some of the sharp spikes in behavior may been smoothed over from the aggregation. This analysis emphasizes that without a proper ground truth data, which most grocery chains are unwilling to share publicly, it is difficult to determine whether the mobility data is accurately capturing changes in mobility patterns over time.

We were also interested in understanding how well trip data to individual grocery chains were captured in the mobility data, which is shown in Figure 4-14. We found that in general, the temporal trends to the more popular chains (e.g. HEB and Kroger), also reflect the larger trends found the overall grocery data. Which less well captured grocery stores (e.g. Whole Foods), there was simply not enough trip data to capture any trends in mobility behavior.

To further analyze data for individual grocery stores, we compare mobility data to three of the grocery store chains, Kroger, Aldi, and Wholefoods, against credit card transaction data for these individual stores. The results are shown in Figure 4-15. We see that even with credit card transaction data, the Whole Foods data in particularly is quite noisy, it may simply be difficult to accurately capture transaction information without aggregating over a large number of store locations.

4.4. Hospitals

We analyzed the temporal trends in visits to medical facilities in the Veraset data. The Veraset data does appear overall to track well with our ground truth dataset, and we also note that similar behavior trends are observed from Veraset users from disadvantaged CBGs versus non-disadvantaged CBGs.

To filter the Veraset data to only hospitals and medical facilities, we searched for NAICs codes related to medical services, particularly focusing on those related to emergency care that residents would be more likely to access during the power outage. Specifically, we used the follwing 2017 NAICS code values (listed by NAICS category description):

- Physicians Office: 621111
- HMO Medical Center: 621491
- Kidney Dialysis Center: 621492
- Ambulatory and Medical Services: 621493
- Outpatient Centers: 621498
- Ambulance Service: 621910
- Blood Bank: 621991
- General Medical or Surgical Hospital: 622110
- Disaster Emergency Service: 624230

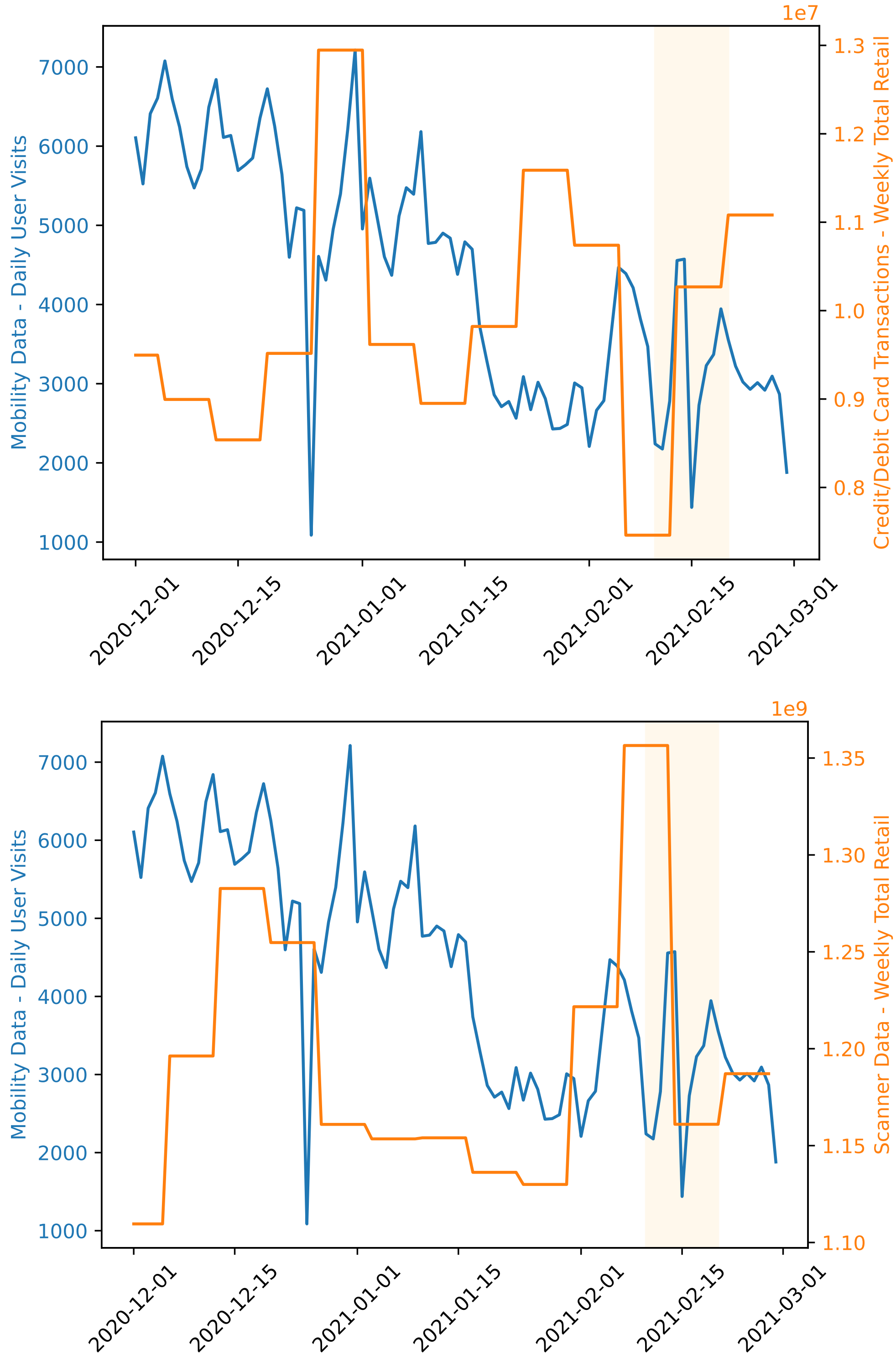


Figure 4-13 Total trips to grocery stores in the mobility data (*blue*), compared a sampling of total credit/debit card transactions (*top, orange*), and a sampling of retail sales (*bottom, orange*). The dates for the power outage event are highlighted. Note that the credit/debit card and retail sales data were aggregated per week.

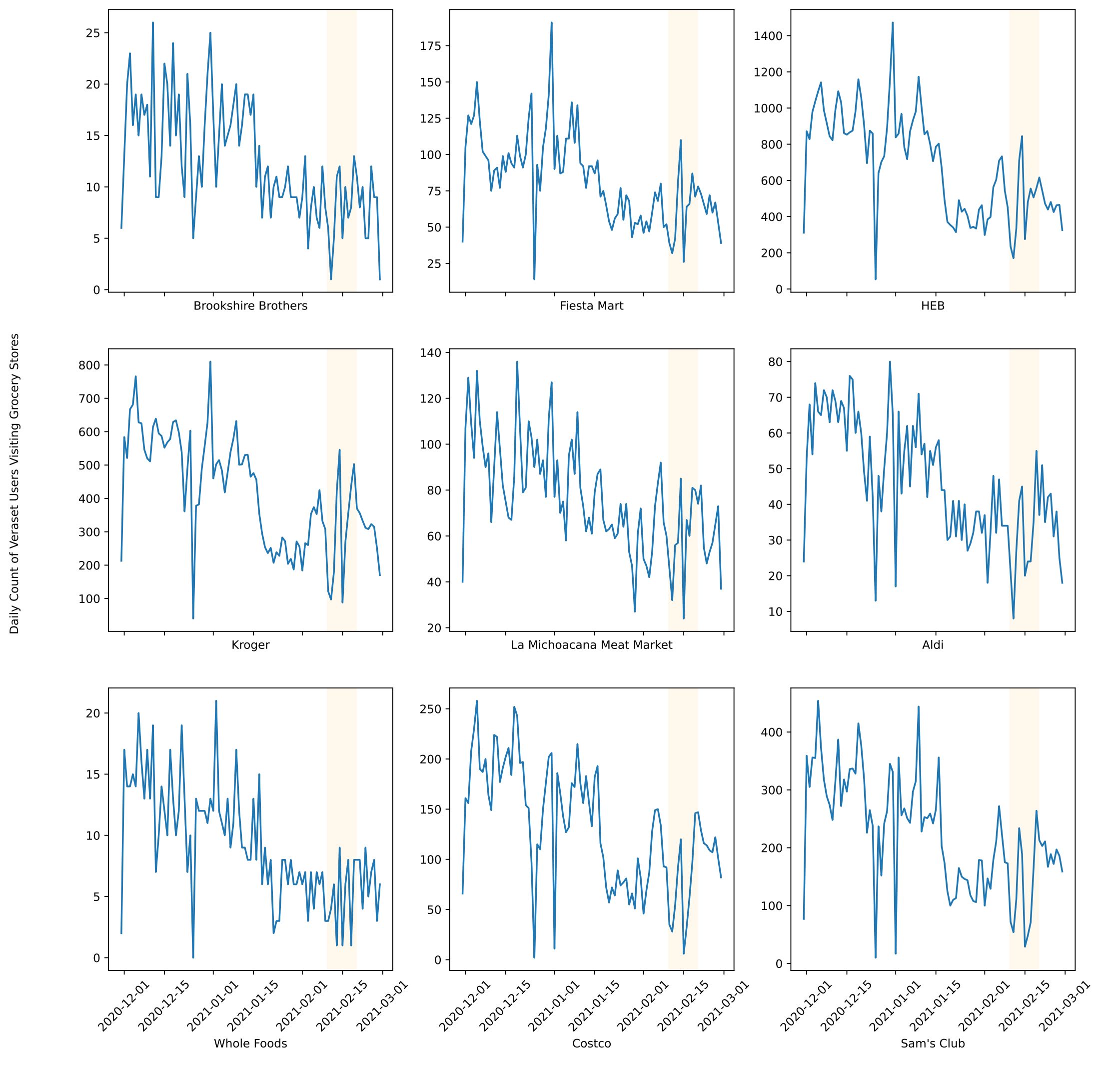


Figure 4-14 Comparison of total number of unique users vising different grocery chains per day. The dates for the power outage are highlighted.

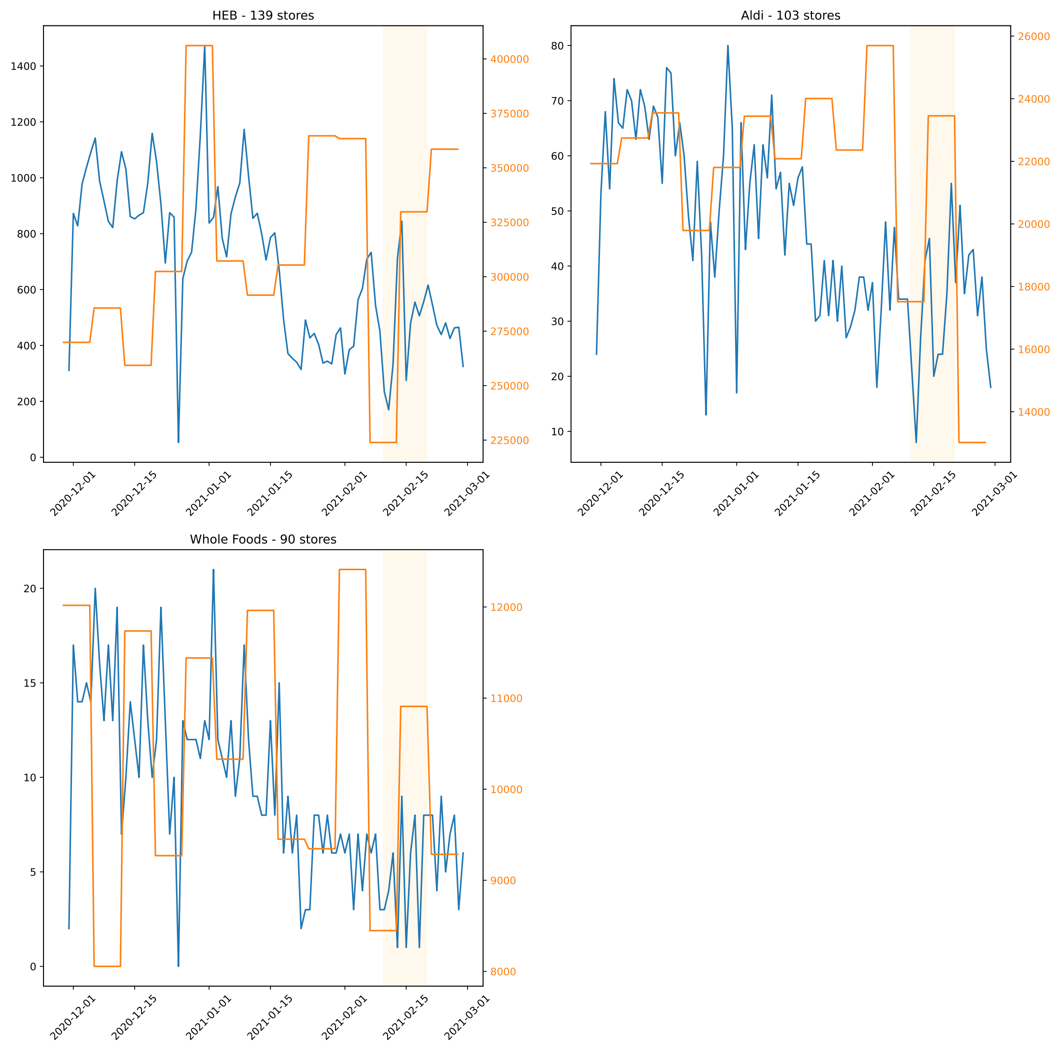


Figure 4-15 Comparison of trips in the Veraset data to individual grocery store chains (*blue*), compared a sampling of total credit/debit card transactions at these same chains(*top, orange*). The total number of stores at each chain is indicated in the figure title. The dates for the power outage event are also highlighted. Note that total credit/debit card transaction data were aggregated per week.

- Miscellaneous Ambulatory Health Care Service: 621999
- Speciality Hospital (not including psychiatry), e.g. cancer treatment: 622310
- Outpatient Care: 621498

In total, there were 181,951 trips to medical facilities during the data period that were taken by 25,065 . The hospital trips were roughly 0.6% of the total Veraset trips. The distribution of total medical trips by individual Veraset users is shown in Figure 4-16, where the maximum number of trips taken by a single user was 100 . Note that unlike some of the other infrastructure services analyzed in this report, airports and grocery stores, it is particularly difficult to separate healthcare workers from patients and visitors in this dataset, as the mobility patterns of long-term care patients is likely indistinguishable from the behavior of medical staff.

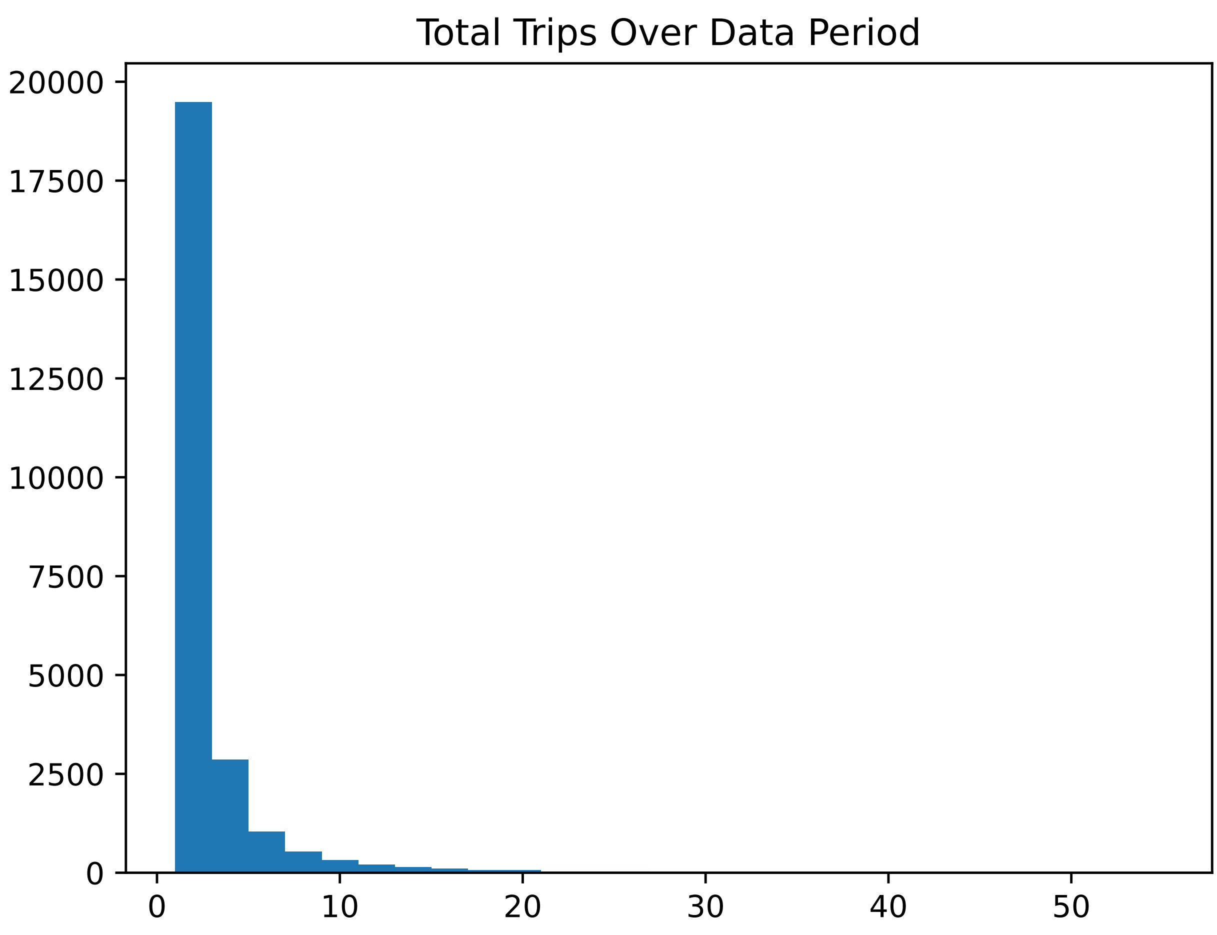


Figure 4-16 Histogram of total hospital trips by individual Veraset users.

We also show the distribution of medical facilities and trips from home CBGs for medical visits in the Houston area maps in Figures 4-17 and 4-18.

To verify the temporal trends in hospital visits, we compare total trips per day in the Veraset data against the total number of occupied patient beds in a subset of hospitals. We found that there was

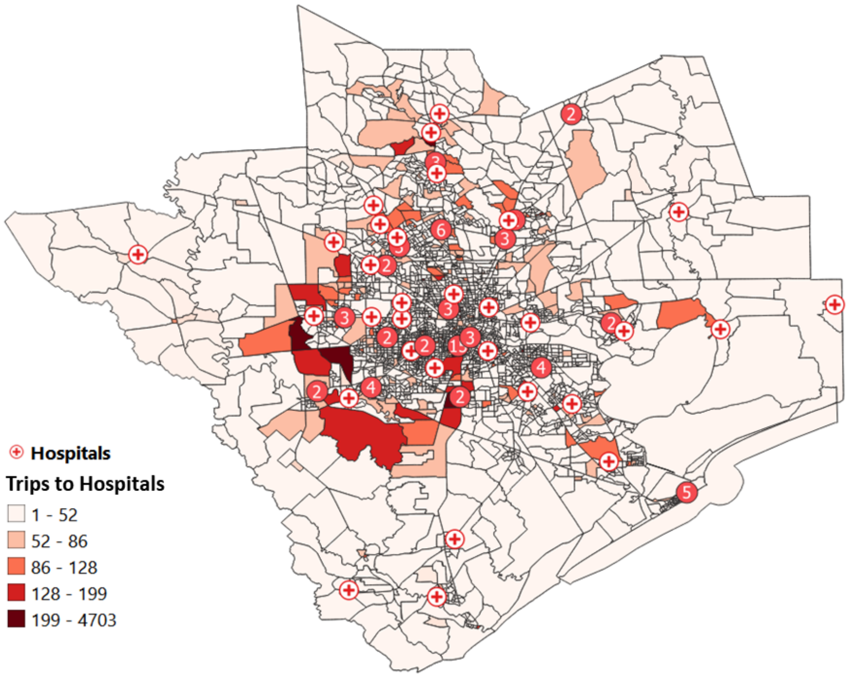


Figure 4-17 Count of number of trips to hospitals from the user's home CBG.

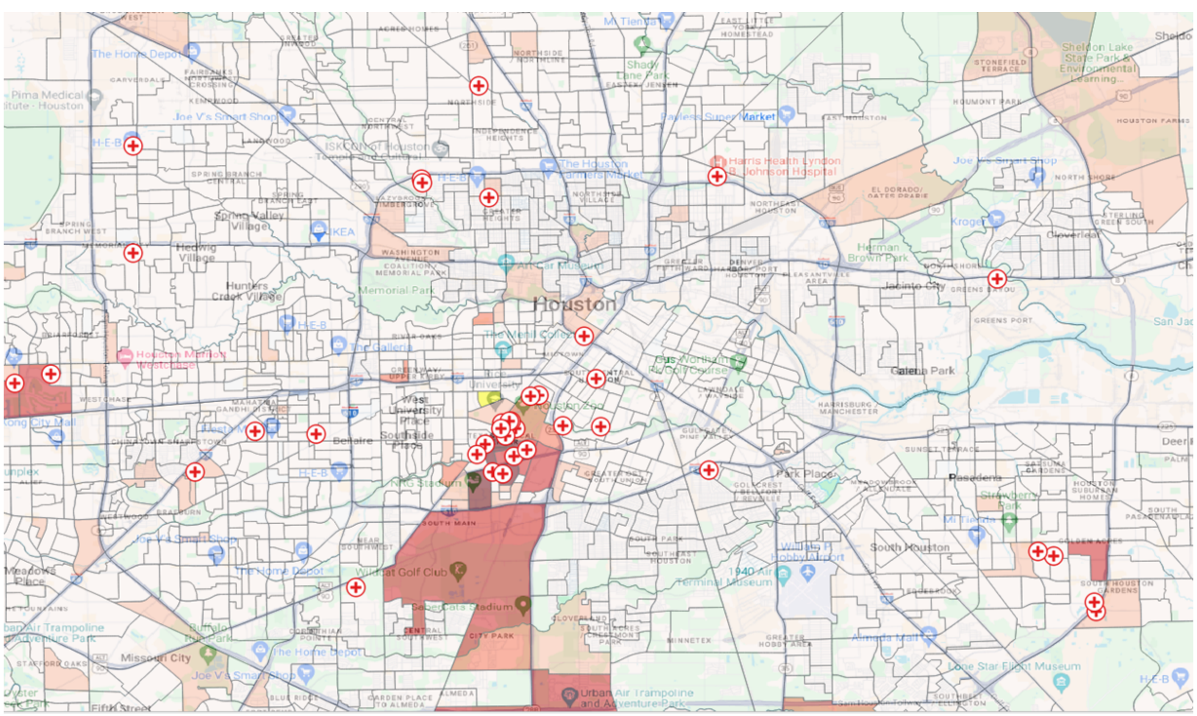


Figure 4-18 Count of number of trips to hospitals from the user's home CBG, centered on the city core.

not enough data to analyze temporal trends in individual hospitals, so instead we took a total aggregation of trips to hospitals in the Veraset data and total number of occupied beds in the ground truth data.We first show a comparison of average occupied beds per day versus average trips per day during the baseline period and during the power outage event in Table 4-3.

	Baseline Dates (2021-01-15 - 2021-02-09)	Event Dates (2021-02-10 - 2021-02-2020)	Percent Change from Event to Baseline
Ground Truth	7356	7096	-3.5
Veraset Data	1512	1061	-29.8

Table 4-3 Comparison of average occupied beds per day over the baseline period and the climate event according to the sample of ground truth reports in contrast to the average recorded number of unique Device IDs visiting hospital locations in the Houston area.

In Figure 4-19, we show the total daily hospital visits in the Veraset data against the number of occupied patient beds. Differences between the two datasets may be attributed to the fact that the two datasets are not necessarily capturing the exact same data - the mobility data will also include trips by staff and visitors in addition to patients. In comparison to other infrastructure analysis sections, the hospital visitation data appears to more closely track the beds occupied data. We observe similar cyclic dips in the data (we suspect this is due to reduced hours or closed medical offices on the weekends, and observe a drop in both datasets during the power outage.

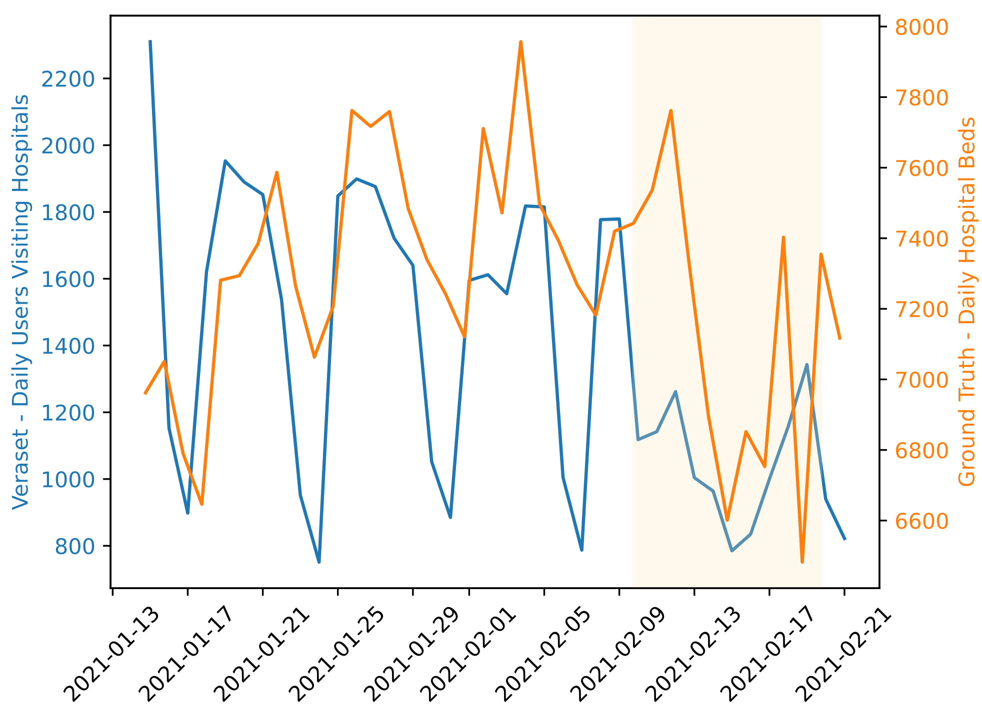


Figure 4-19 Comparison of total number of unique users vising hospitals each day in the Veraset data (*blue*) for all of Houston versus the total occupied beds across a sample of Houston hospitals (*orange*). The time period for the climate event is highlighted.

We also plot the timeline comparing daily total trips by users from disadvantaged versus advantaged CBGs in Figure 4-20. The overall trends did not vary significantly between disadvantaged and nondisadvantaged CBGs, with similar drops during weekends and a drop in visits during the power outage.

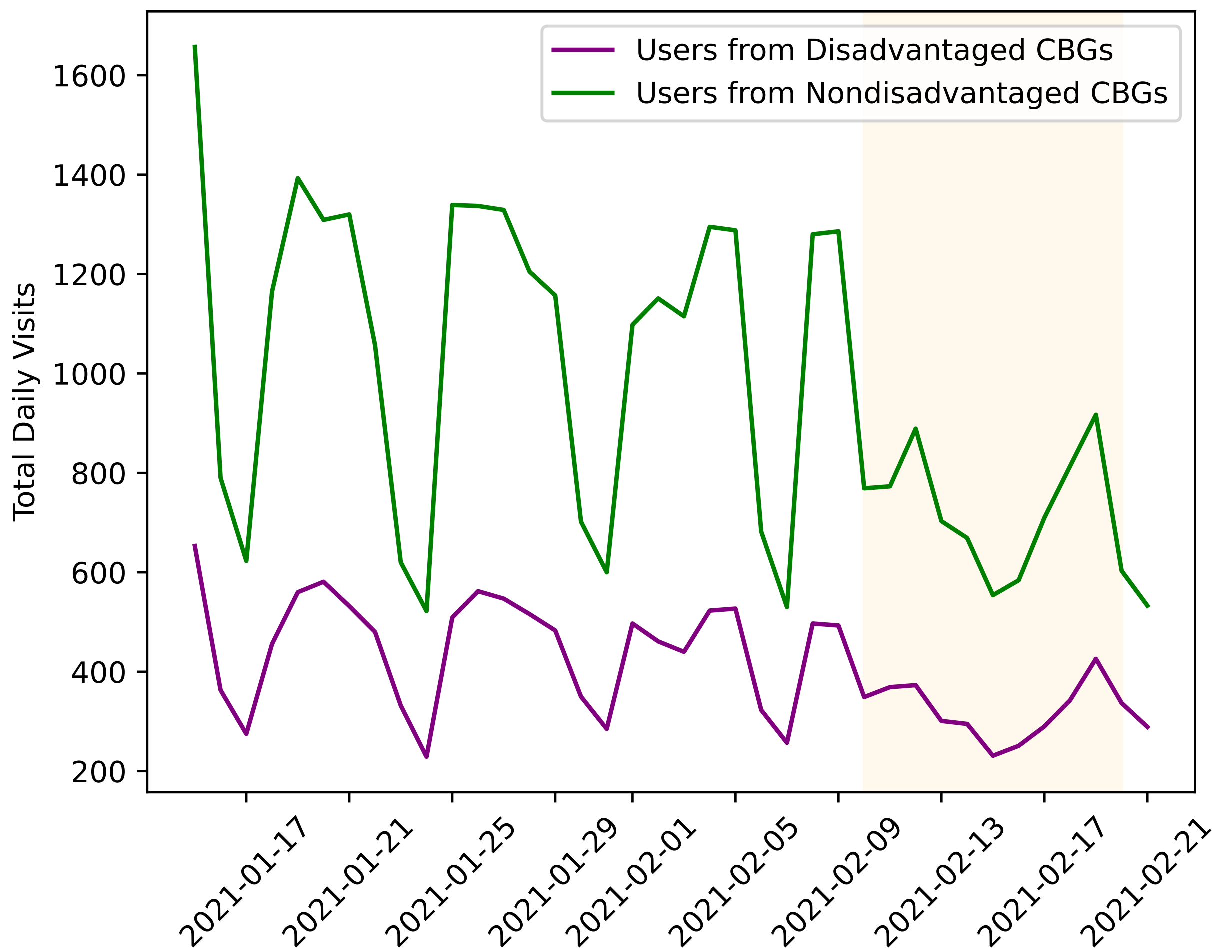


Figure 4-20 Total visits to hospitals logged by users from disadvantaged *(purple)* versus nondisadvantaged *(green)* CBGs. The dates for the power outage are highlighted.

We also want to highlight that this analysis showed that it is difficult to capture visits to individual hospitals. Figure 4-21 shows the trips logged for individual hospitals. The hospitals shown are a subset of the hospitals that had provided daily occupied bed information for our ground truth dataset, with the colors indicating trips by individual users to a given hospital. As is clear from the plot, the data for individual hospitals is fairly scarce, and many of the daily trips are by the same individuals, who are likely either staff or long term patients at the hospital for an extended stay.

4.5. Airports

For airports, we examined some visit patterns according to frequency and the geographic distribution of visits. Typically, we expect that passengers are low-frequency visitors, while

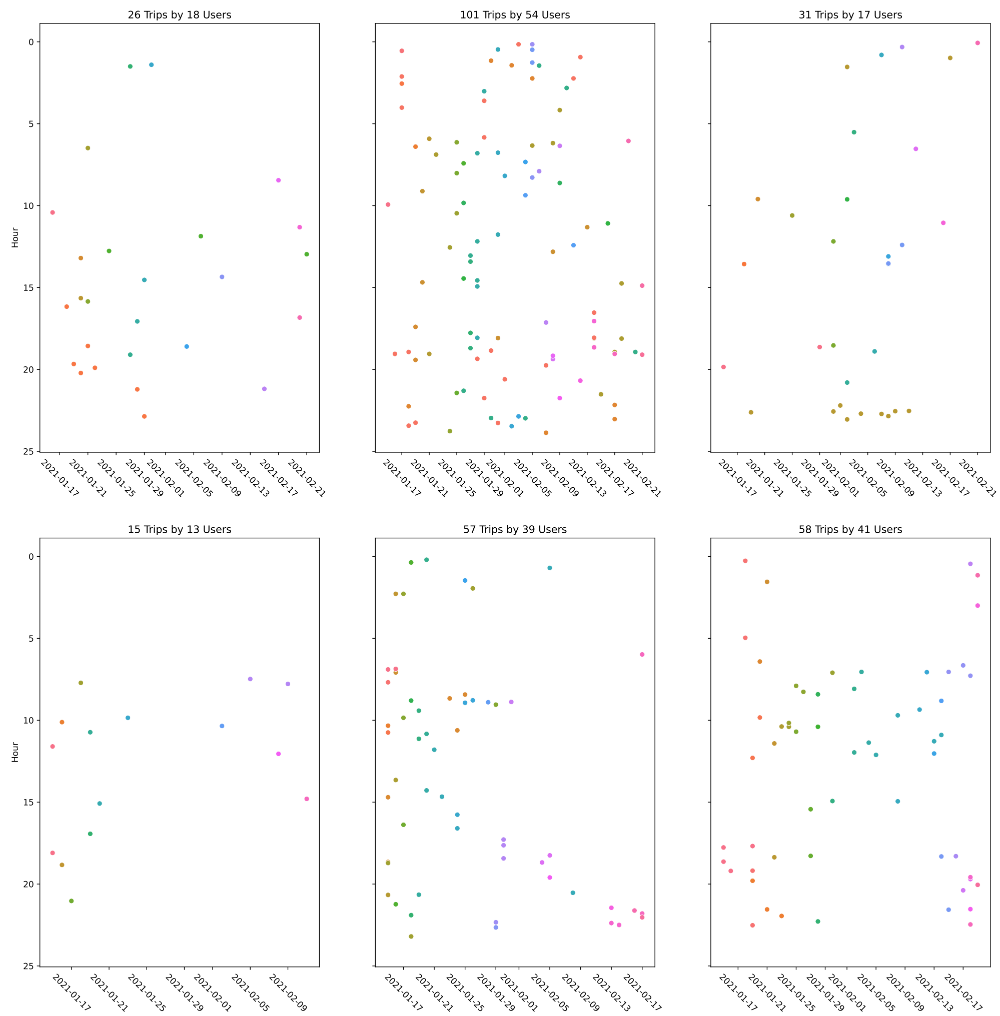


Figure 4-21 Trips logged at individual hospitals. Each graph shows the day and hour of visit for an individual hospital. The colors in each subplot indicate trips by a unique Veraset user to that particular hospital.

employees and ride-hail drivers may record visits more frequently. However, in practice, more-frequent visitors' reasons for being at airports are difficult to determine based on visit patterns. We did find that for low-frequency visitors to the major airports, home locations are widely distributed throughout the area, suggesting that the airport data may be capturing visitation behavior from residents throughout Houston, during a holiday period.

Visits to airports were determined according to the following steps:

1. Use a regular expression (regex) string to search for visits where 'airport,' case-insensitive, appears in the name of the location visited
2. Determine the set of CBGs and NAICS codes appearing in the resulting fields
3. Exclude any NAICS codes associated with businesses performing non-airport functions, such as taxi or limousine services.

The resulting visits all had the NAICS code 488119, 'other airport operations.'

The AOI encompasses two major airports, William P. Hobby Airport (HOU) and George Bush Intercontinental Airport (IAH). It also encompasses more than twenty smaller airports and airfields, including Ellington Airport (KEFD) and Scholes International at Galveston (KGLS). Of the airports in the AOI, about twenty appear in the Veraset visits dataset with the selected NAICS code.

Figure 4-22 shows the time series data for the Veraset counts of visits to any airport (left axis) compared to the estimated number of passengers either beginning or finishing their journey in Houston (right axis). A strong dip in number of passengers over the Christmas holidays is clearly visible in late December, as is the closure of the airports in mid-February due to the weather event. The two time series datasets appear to be similar in December, but diverge afterwards. It is not clear whether this is because the estimated total passenger counts are less accurate in January due to fewer seats being occupied, or whether the devices tracked in the visit data simply visit the airport less frequently in January relative to the number of passengers.

Figure 4-23 shows the distribution of visit counts to any airport by distinct devices, over the entire time period of the dataset. Roughly three-quarters of device IDs that visit an airport using NAICS code 488119 do so fewer than three times. Since the time period of the data includes Christmas and the New Year, the large spike at 1-2 visits is expected, as many people travel by air during that time, and they might be expected to use a Veraset-reporting app both when departing and when returning. However, we do not observe a large spike in devices that visit airports 40-60 times during the data time period, where there were roughly 60 weekdays during the time period of interest and we expected the data to include airport employees. Instead, while there is a small bump around 40-60 visits, the distribution is roughly negative exponential, with some devices visiting airports more than once per day.

Fig. 4-24 shows the time series, by day and hour (including minute), of the four devices that visit airports most frequently. All four devices record airport visits more than once per day on average. It is difficult to determine why these devices record so many airport visits. These devices may belong to airport employees or people who work at facilities located within the airport, who use cell phone apps reporting to Veraset sufficiently frequently to record many visits. Or the devices

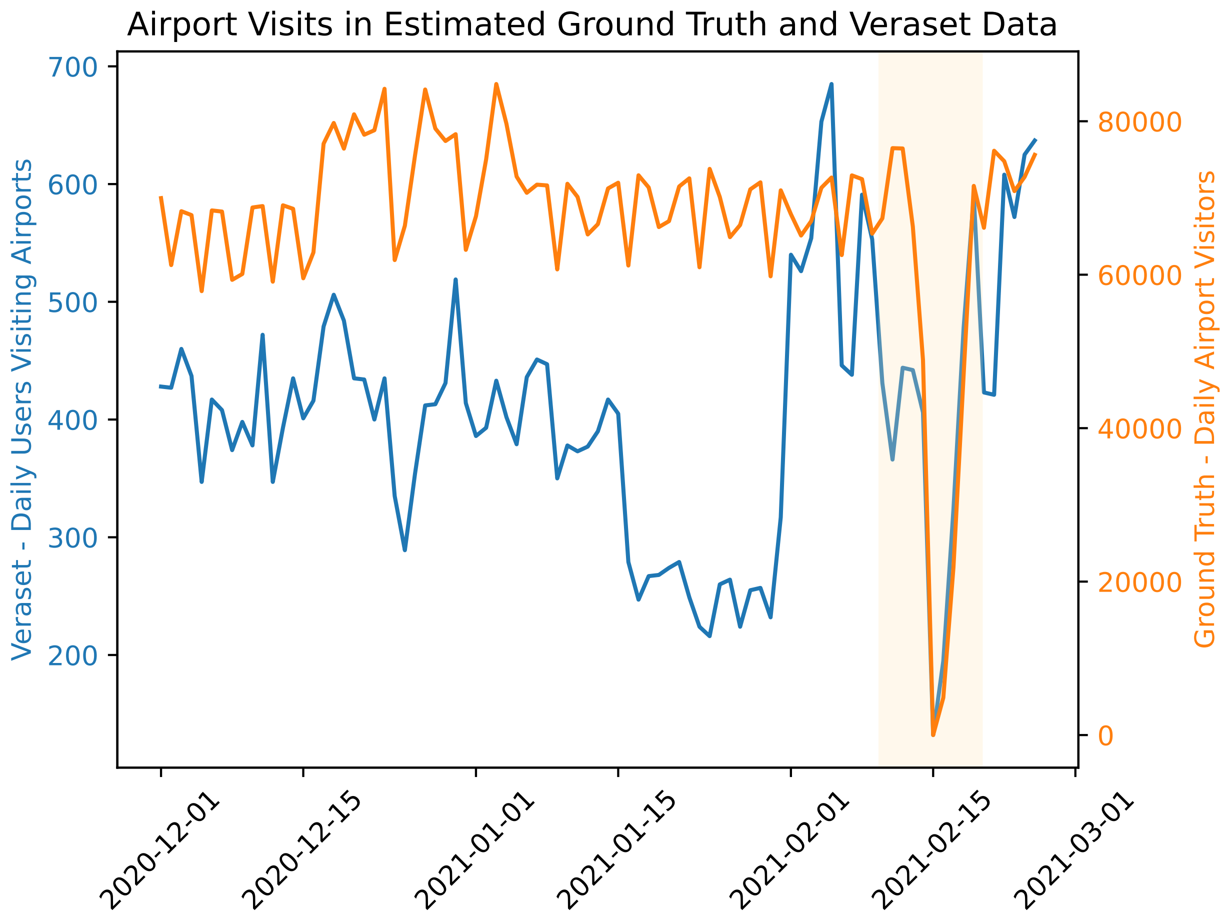


Figure 4-22 Visits to airports in the dataset compared to those estimated as ground truth. Although the correspondence appears to be fairly good in December and the rapid decrease in visits during the weather event also appears, January visits as compared to estimated passenger counts do not match well. It is not clear whether this is because the estimated passenger counts are less accurate in January due to fewer seats being occupied, or whether the Device IDs tracked in the visit data simply visit the airport less frequently in January relative to the number of passengers.

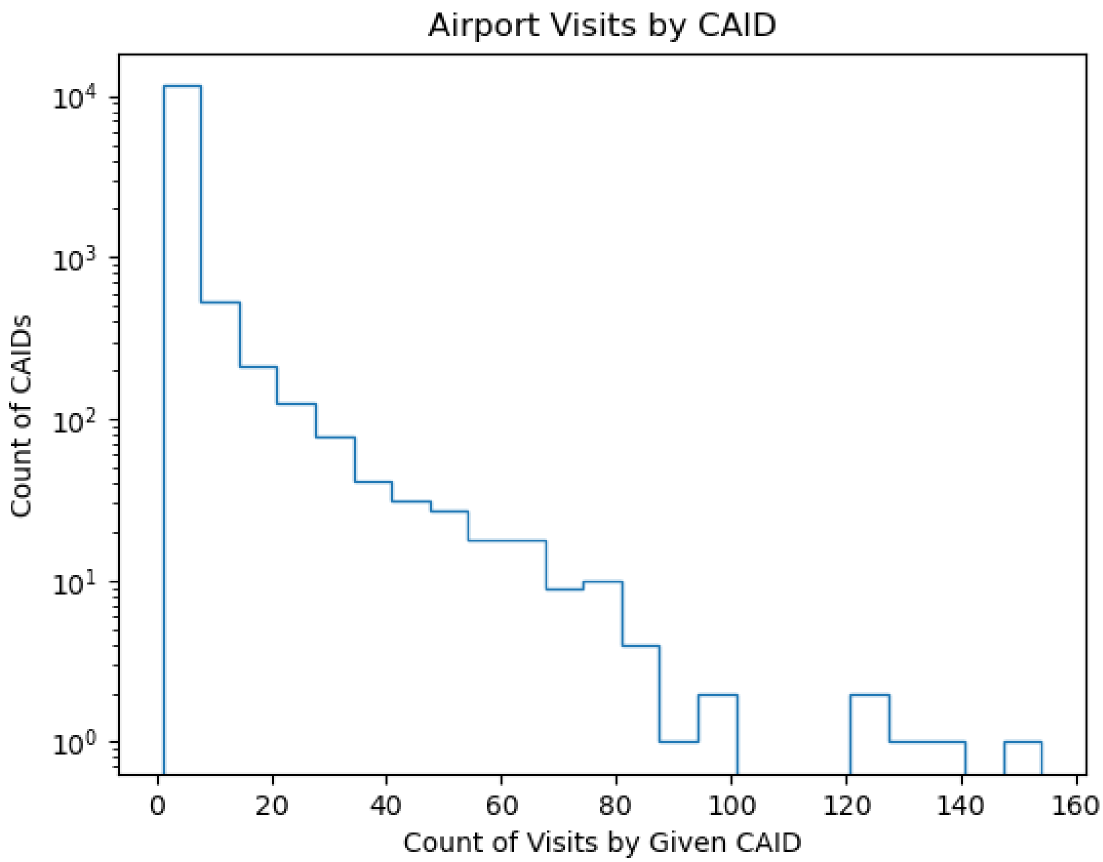


Figure 4-23 Semilog-scale histogram showing distribution of visit counts across device IDs (CAIDs) whose homes are in the AOI. Roughly three-quarters of device IDs that visit an airport using NAICS code 488119 do so fewer than three times. Despite expectations, there is not an obviously bimodal distribution around "holiday or irregular travelers" (fewer than five airport visits) and "employees" (around 40-90 airport visits); the distribution is roughly negative exponential.

may belong to taxi, ride-hail, or shuttle drivers, who may make multiple distinct visits to the airport during specific time periods. The device in the upper left appears to mostly visit during daytime in December, but has a few early-morning visits in both December and January: we believe this visit pattern corresponds to a ride-hail or taxi driver who primarily visited the airport during the holiday rush season, and otherwise picked up passengers on an ad-hoc basis. The other devices in this figure are more ambiguous, as they do not record airport visits outside of specific hours during the time period, and appear to briefly stop visiting the airport during the studied time period - possibly taking vacations outside of peak travel season. These devices may be ride-hail or taxi drivers, or they may be airport-based employees using apps while at work, either for business or for personal use.

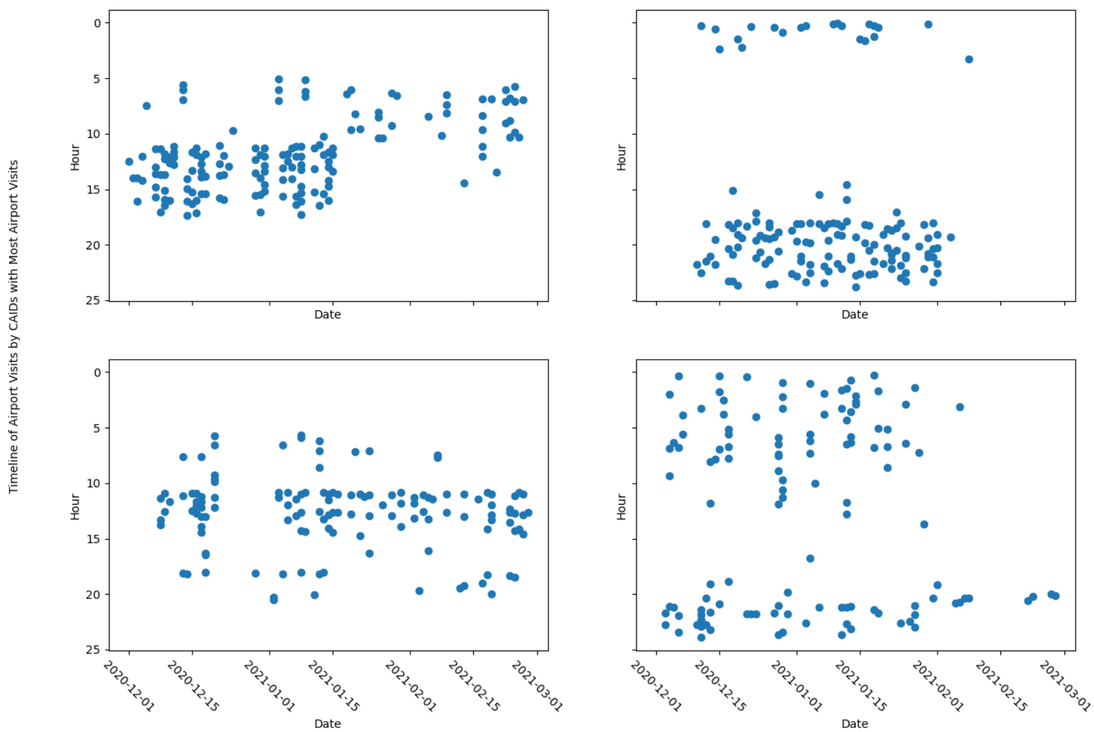


Figure 4-24 Visit patterns of the four Device IDs with the most airport visits, to any airport, among device IDs with homes in the AOI. High frequency in a specific month may indicate that these visits correspond to temporary or seasonal work, or seasonal demand for the work these devices' users perform. The device ID in the upper left appears to mostly visit the airport in December during daytime, but has a few early-morning trips in both December and January, possibly indicating ride-hail service during a peak holiday month, and more sporadic provision of ride-hail service after. The device ID in the lower left does not appear to visit the airport outside of preferred or scheduled hours, but may visit multiple times a day; it is difficult to tell whether this device is for a ride-hail driver, an employee using a specific app while at work, or some other pattern.

Figure 4-25 shows the visit patterns of the four device IDs with the most airport visits, among devices with fewer than 50 visits to any airport. The 50-visit threshold was chosen because there are roughly 60 weekdays in a 90-day period, and December-February includes holidays that might decrease the number of days worked by an employee (although this is not guaranteed in an airport). Like the most frequent airport visitors in Fig. 4-24, it is difficult to determine why these device IDs are making these visits. The device in the lower left may be an employee or shift worker at the airport, as they appear to record visits around 8 P.M. or around 3 A.M. The major airports in Houston appear to close many of their businesses (including security) around 12:30 A.M.; for this device, as an employee 8 P.M. or later visits, along with very early morning visits, support the possibility that the associated individual is an employee, possibly working overnight shifts, as security opens around 4 A.M.[17,18]. The device ID in the lower right may be a ride-hail driver, or may be a temporary employee.

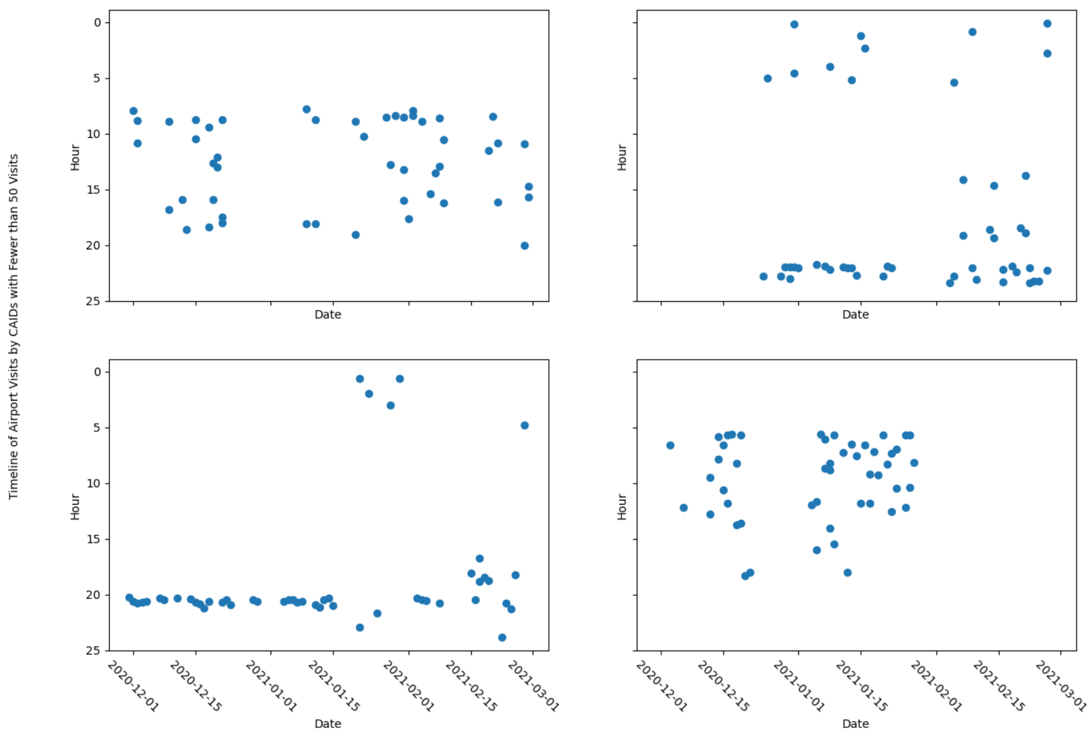


Figure 4-25 Visit patterns of four device IDs with the most airport visits, among device IDs with fewer than 50 visits to any airport, among device IDs with homes in the AOI. It is more difficult to determine why these device IDs are making these visits. The device ID in the lower left may be an employee or shift worker at the airport, as they appear to record visits either around 8 P.M. or around 3 A.M. The major airports in Houston appear to close many of their businesses (including security) around 12:30 A.M.; this device may belong to an employee working overnight shifts. The device ID in the lower right may be a ride-hail driver, or may be an employee.

Figure 4-26 shows CBGs that contain visits marked with NAICS code 488119, ‘other airport operations,’ and areas that are marked as aerodromes (airports) in OpenStreetMap (OSM). Not all airport facilities that appear in the Veraset data coincide with OSM aerodromes, particularly very small airports that may only provide services to private vehicles, or which provide cargo, emergency, or flight training. Some airports are not represented by visits with NAICS code

[17] https://www.fly2houston.com/hou/security
[18] https://www.fly2houston.com/iah/tsa-hours

488119, most notably Ellington Airport. While Ellington Airport does appear in the broader Veraset dataset, the visits are marked with other NAICS codes that were excluded.

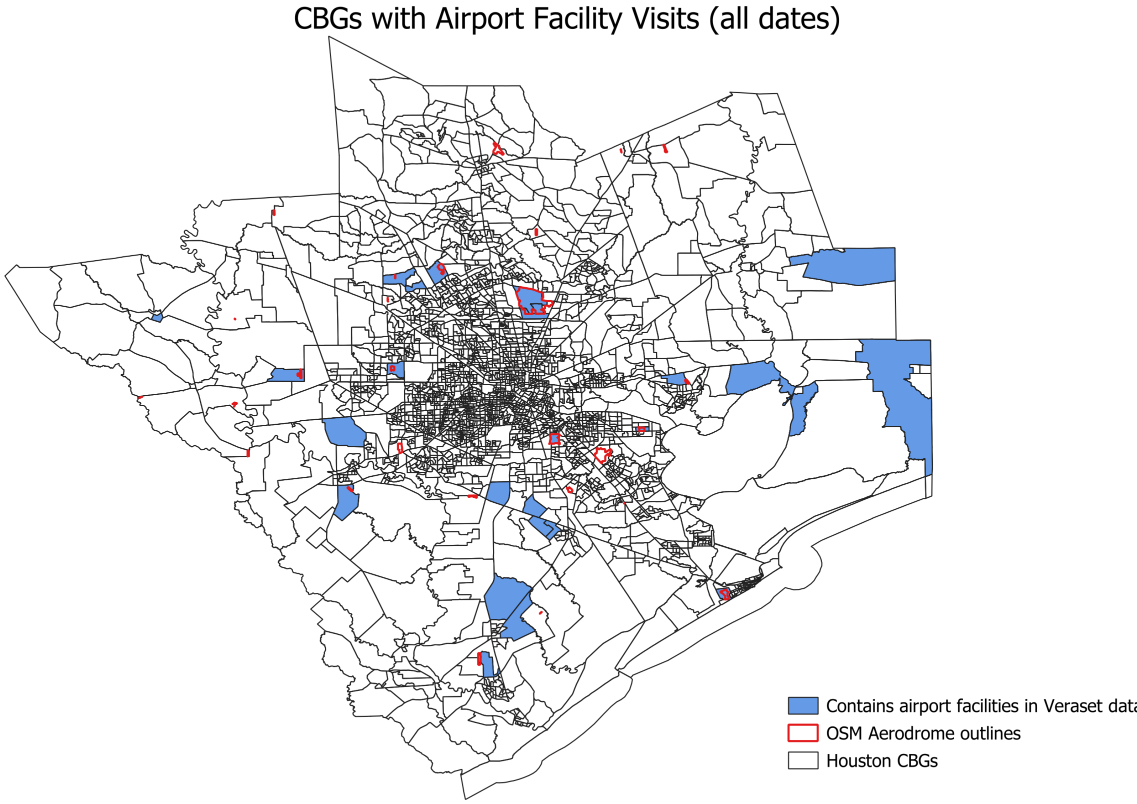


Figure 4-26 Census block groups that contain visits to facilities marked with NAICS code 488119, 'other airport operations'. Red outlines show boundaries of OpenStreetMap-designated 'aerodromes'. Some CBGs contain small or private airports that are not marked in OSM, while some airports do not have visits labeled with this NAICS code.

Figure 4-27 shows counts of visits associated with NAICS code 488119, to the CBG where that visit occurred. Unsurprisingly, IAH and HOU show up more frequently than the other airports. Scholes International at Galveston also has a relatively high count of visits. Other, smaller airports have fewer visits, but do appear in the dataset. However, as previously noted, it is difficult to determine what these visits to other airports are for: these visits may be by people using these airports to travel, or as taxi or ride-hail service drivers, or for other services these airports may provide.

Fig. 4-28 shows a map of the home CBGs for low-frequency visitors (< 10 visits during the time period) to Houston Hobby and Bush Intercontinental airports. These CBGs are widely distributed throughout the Houston MSA, as would be expected for major airports in a large metropolitan area.

Fig 4-29 shows the home CBGs of high-frequency visitors to HOU, IAH, and Scholes Airport, respectively. For IAH and HOU, the home CBGs of these high-frequency visitors are much more

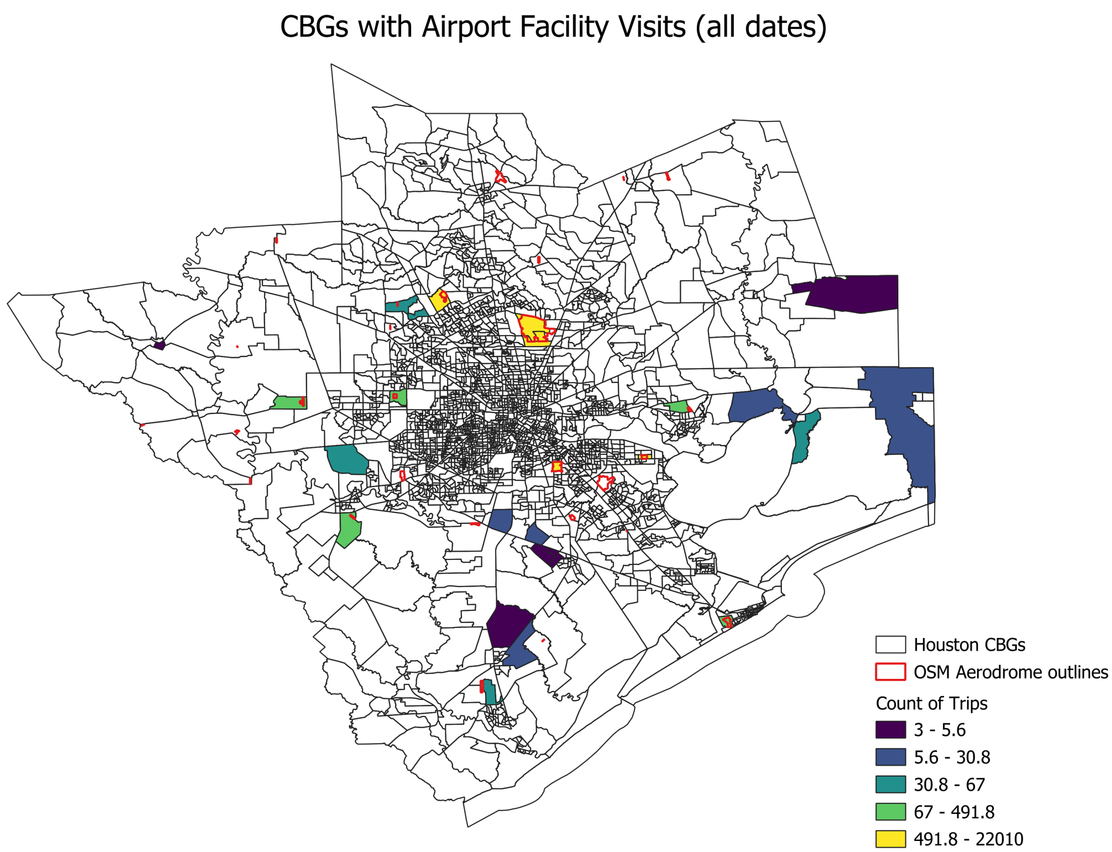
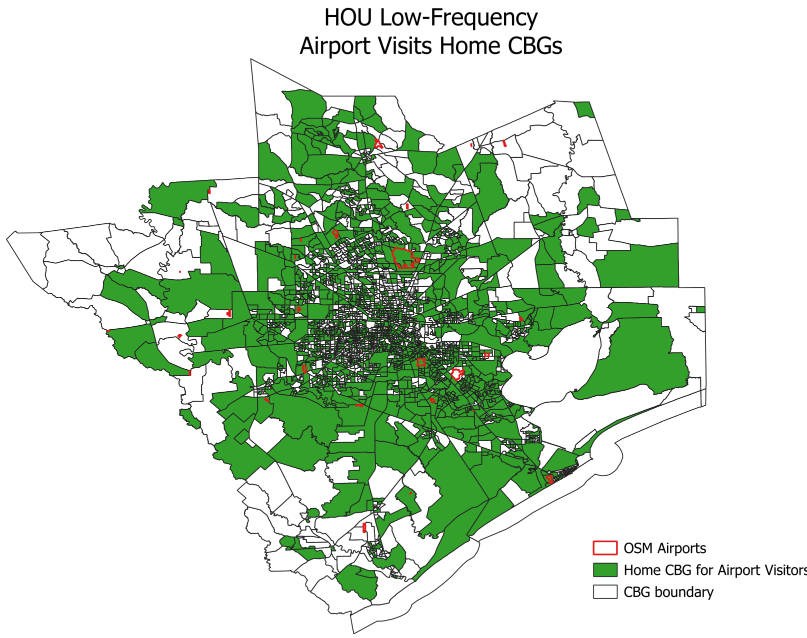


Figure 4-27 Comparison of counts of visits to airports, by CBG. Red outlines show boundaries of OpenStreetMap-designated 'aerodromes'. Some CBGs contain small or private airports that are not marked in OSM, while some airports do not have visits labeled with this NAICS code. The major airports, HOU and IAH, have very high visit counts compared to the smaller regional airports or airfields, but these smaller airports are visited.



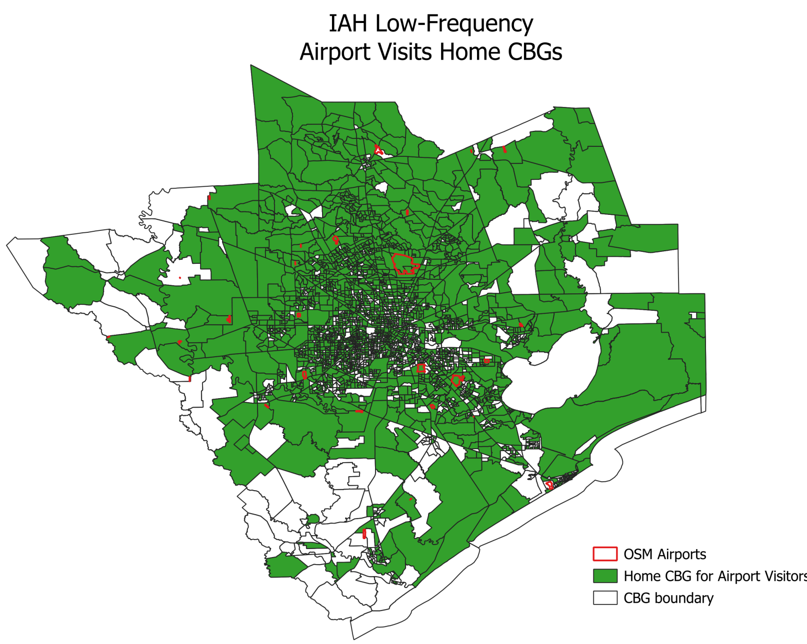


Figure 4-28 Map of home CBGs for low-frequency visitors ($<$ 10 visits) to William P. Hobby Airport (HOU) (*top*) and Bush Intercontinental Airport (IAH) (*bottom*). In both cases, these CBGs are widely distributed across the metropolitan area.

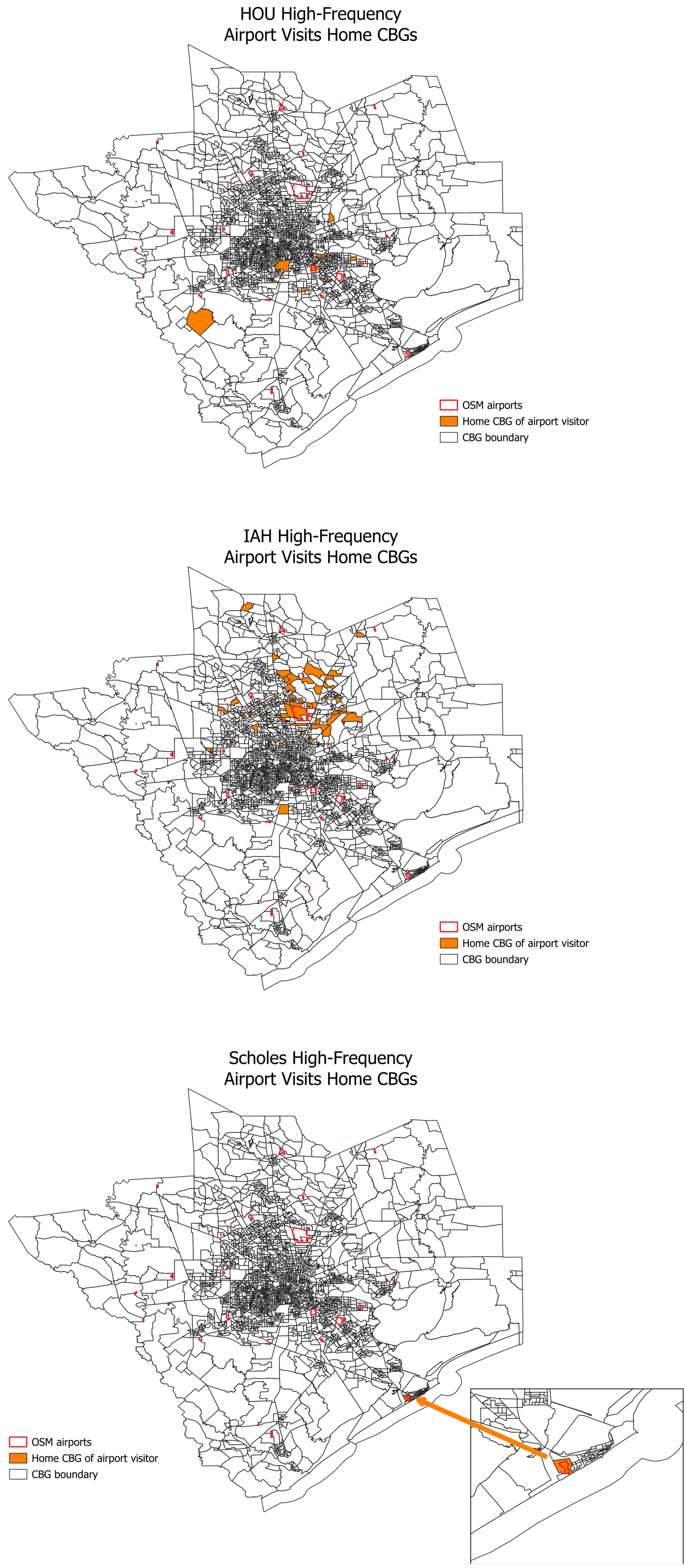


Figure 4-29 Map of home CBGs for high-frequency visitors (≥ 10 visits) to to William P. Hobby Airport (HOU) (*top*), Bush Intercontinental Airport (IAH) (*middle*), and Scholes International at Galveston (KGLS) (*bottom*). The number of high-frequency visitors is relatively small compared to less-frequent visitors, with only a single such device for Scholes (*inset*). Many of the CBGs from which the visitors to HOU and IAH originate are close to the airport but not exclusively so.

concentrated around the airports themselves, albeit with some exceptions. Scholes Airport in Galveston has only a single high-frequency visitor, whose identified home is in the same CBG where the airport is located.

5. CONCLUSION

Before using mobility data for analysis or prediction, it is crucial to evaluate the data for it's representativeness, both of the underlying geographically-distributed population demographics, as well as how well temporal trends within the data reflects real-world shifts in mobility patterns.

Inaccessibility or lack of true ground truth publicly available visitation data posed a major challenge for analyzing temporal trends in visits to specific infrastructure sectors. For hospitals we were able to access occupied beds, but were unable to access the total trips made by visitors and staff as well. Airports publish the monthly passenger departure and arrivals, but do not publish daily totals, and public logs on flight takeoffs and arrivals do not include the number of occupied seats. Grocery store chain likely track but are unwilling to share proprietary data on number of daily visitors. As a proxy we were able to access sampled transaction data via data aggregators, however grocery purchase totals does not necessarily correlate with number trips to grocery stores.

The lack of meta details within the mobility data also posed challenges for infrastructure analysis. The widespread geographic distribution of user homes (at the CBG level) across the Houston for each infrastructure service suggests visitation data is well captured in the Veraset data for the overall Houston Metropolitan area. This is particularly important for services with mostly low-frequency visitors such as airports. However, we do not have details on the underlying demographics of individual users, which makes it difficult to determine if alterations in visitation behavior (e.g. holiday travel patterns to airports) is equally distributed across different population groups.

An additional challenge across infrastructure sectors is distinguishing trips by visitors or customers from staff. This is important for visitation pattern analysis where we want to understand travel patterns based on basic needs, and distance travelled when people need to select, for example, a grocery store to shop from amidst all food options near their home. Based on the frequency of visits, we were able to make reasonable assumptions in the airport and grocery analysis to exclude mobility data from users who were most likely employees. However, for low mobility data users, it is difficult to verify the trip type. Also, for a sector such as hospitals where in-patients and staff may be at the hospital with equal frequency, visitation patterns may be indistinguishable.

Analysis on population and demographic trends suggests that the Veraset mobility data is well sampled across the overall Houston population area, as well as racial populations. When comparing the data against DOE-identified disadvantaged communities, we see that disadvantaged and non-disadvantaged communities are overall equally represented within the data. When comparing against Census data however, our analysis does suggest that the Veraset data may be undersampling lower income populations (which was also found in [24] which also examined the Houston population during a similar time frame), particularly with respect to populations living below poverty level and/or enrolled in SNAP (. However given the lack of demographic information for individual Veraset users, further data is required to verify that the data is actually biased towards higher income populations.

The primary concern raised about the Veraset data is its representativeness of temporal patterns in trip behavior. As noted in previous sections, we note a drop in total trips taken between January 1 and January 15, 2021 (which can be seen in Figure 3-2, which is unlikely to be entirely caused by holiday activity. When comparing the Veraset data trips at major sports games, we can see a decrease in Veraset trips taken while the actual audience attendance remained steady over the dataset period according to published stadium records. Variations in privacy settings and mobility data shared may contribute to shifts in the amount of mobility data collected and shared, however these details have not been shared by Veraset. We also observe significant deviations in trip patterns over time between mobility data and our reference 'ground truth' datasets, though we do not have sufficient information to determine whether this is due to the limitations of the reference datasets, or variations in mobility data availability over time.

In general the temporal sparsity of the mobility data also poses a challenge for any analysis purely relying on mobility data. For the purposes of looking at disaster impacts on disadvantaged communities, the Veraset cellphone mobility does cover the overall Houston area. However, we note that the majority of Veraset users took less than 50 trips in total over a 3 month period (see Figure 3-1), and visit patterns to individual facilities are also sparsely represented (e.g. see Figure 4-21 for an example of trip patterns to individual hospitals). To account for data sparsity, we recommend either (1) analyzing data at an aggregated level (e.g. comparing individual CBGs or disadvantaged versus non-disadvantaged CBGs) to account for trip sparsity at the individual user or facility level, or (2) supplementing this dataset with other providers and further calibrating with ground-truth datasets.

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