BTS Daily Travel Metrics, Trips by Distance: Methodology and Validation

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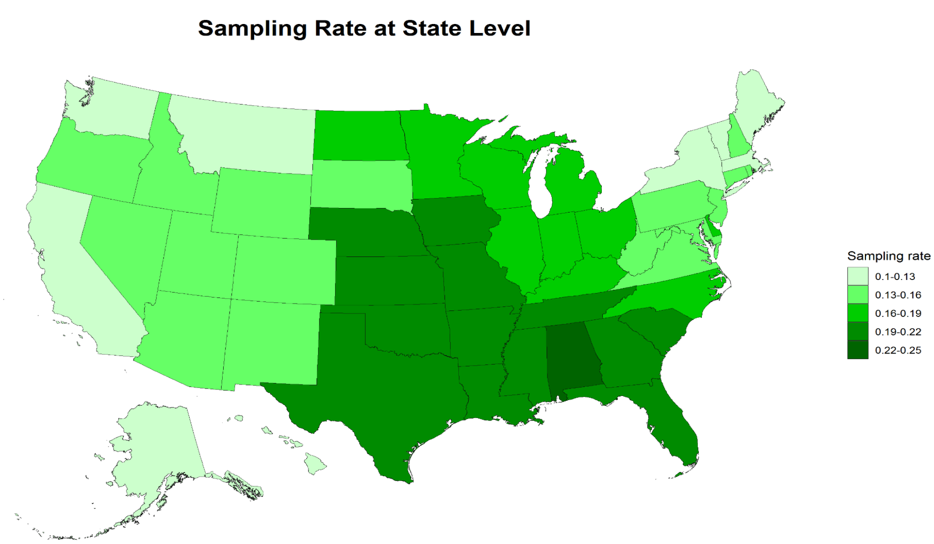
Summary

This report assesses the quality of the University of Maryland daily mobility data submitted to the Bureau of Transportation Statistics (BTS). The team first assesses the penetration rate across the nation and different socio-demographic groups. Twenty-four specific data quality metrics are developed to comprehensively summarize the quality of the data. Then, methods used for producing the daily mobility data are documented in detail. For the key parameters employed in identifying trips, sensitivity analyses have been conducted to assess the ranges of estimated number of trips as well as its long-distance portion. The results are found most sensitive to the time threshold for defining trip ends/stops. In addition, the sensitivity analyses are extended from unweighted to weighted results and have found that long-distance trip ratio decreases after the weighting procedure. Finally, the suitability of using the data for absolute estimates and for estimates of change over time is evaluated via comparisons with three external datasets. Based on these results, the team recommends making improvements on 1) device-level weights based on imputed socio-demographic groups; 2) trip-level adjustment factors based on imputed travel modes, time-of-day information and/or purposes. Based on these additional information, detailed data cross-tabulation and calibration/validation can be performed to ensure and enhance data quality.

1. Data Quality Assessment Review

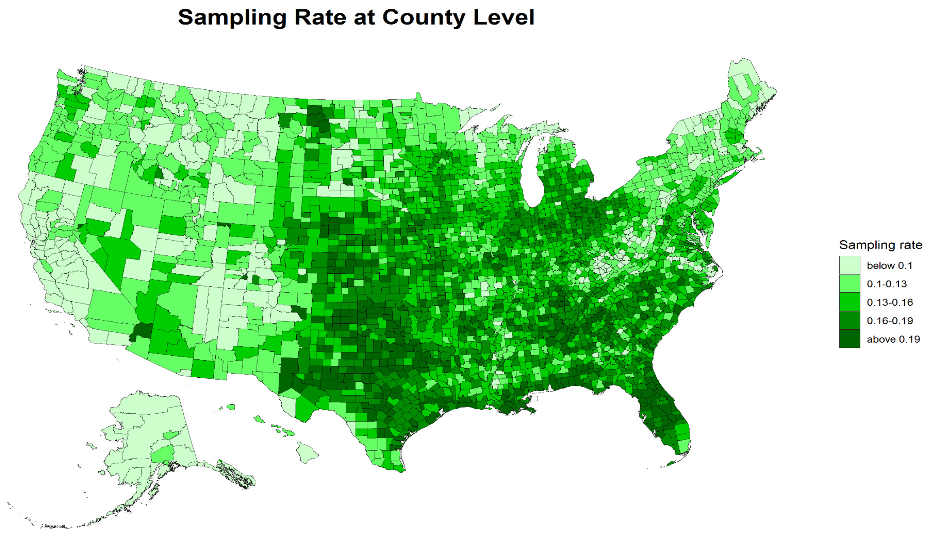
Passively collected mobile device location data generated from various positioning technologies such as cellphone, Global Positioning System (GPS), and location-based services (LBS), have become increasingly available for transportation planning and operations. A location sighting is generated when a mobile application updates the device's location with the most accurate sources based on existing location sensors such as Wi-Fi, Bluetooth, cellular tower, or GPS (Chen et al., 2016; Wang and Chen, 2018). The location sighting can reflect the exact location of mobile devices and thus provide location information describing individual-level mobility patterns. Typically, one location sighting records an anonymized device identifier (ID), latitude and longitude coordinates, time stamps, positioning accuracy, etc. Such location data will be referred to as sighting or sighting data in the remaining document.

The team ingested raw location sightings from multiple industry-leading data vendors. The number of data providers continues to change as the team is constantly investigating and integrating new data sources. The raw sighting data panel consisted of more than 261,000,000 Monthly Active Users (MAU[1]) and represented movements across the nation. After ingesting data from multiple data vendors, the team checks the quality of the sighting data and constructs the national effective data pool after identifying the home location of each device and merging sightings from duplicated devices. The deduplication algorithm considers the most frequent locations visited by each device including the identified home location to detect duplicate devices in our sample. The details of the home location identification algorithm are provided in the methodology section. Figure 1 demonstrates the coverage of the national effective data pool at the county and state levels. The national penetration rate[2] of the final effective LBS data pool used to produce the mobility data estimates is 14.6%.



[1] Monthly Active Users (MAU): devices with at least one sighting for a specific month. More details can be found in Page 6.
[2] Penetration rate: percentage of the mobile devices from the national effective data pool over population.

(a)



(b)

Figure 1. Sampling rate in absolute value of the national effective data pool employed in this project (a) at the state level, (b) at the county level for 2020 data product

Examining known biases in passively collected data:

To investigate the potential biases in our raw LBS data, we assessed the variation of penetration rate across counties considering their socio-demographic characteristics such as income and race. In total, 3142 counties from the continental United States (including Alaska) plus Hawaii are evaluated.

Penetration rate by household income:

One of the well-known potential biases in LBS data is the unequal device penetration rate with regard to the income level. The following figure depicts the variation of sample penetration rate for each household income category. The bar labels show the number of counties that fall into each income bin. The height of each bar represents the penetration rate, and the horizontal line denotes the average penetration rate across the nation.

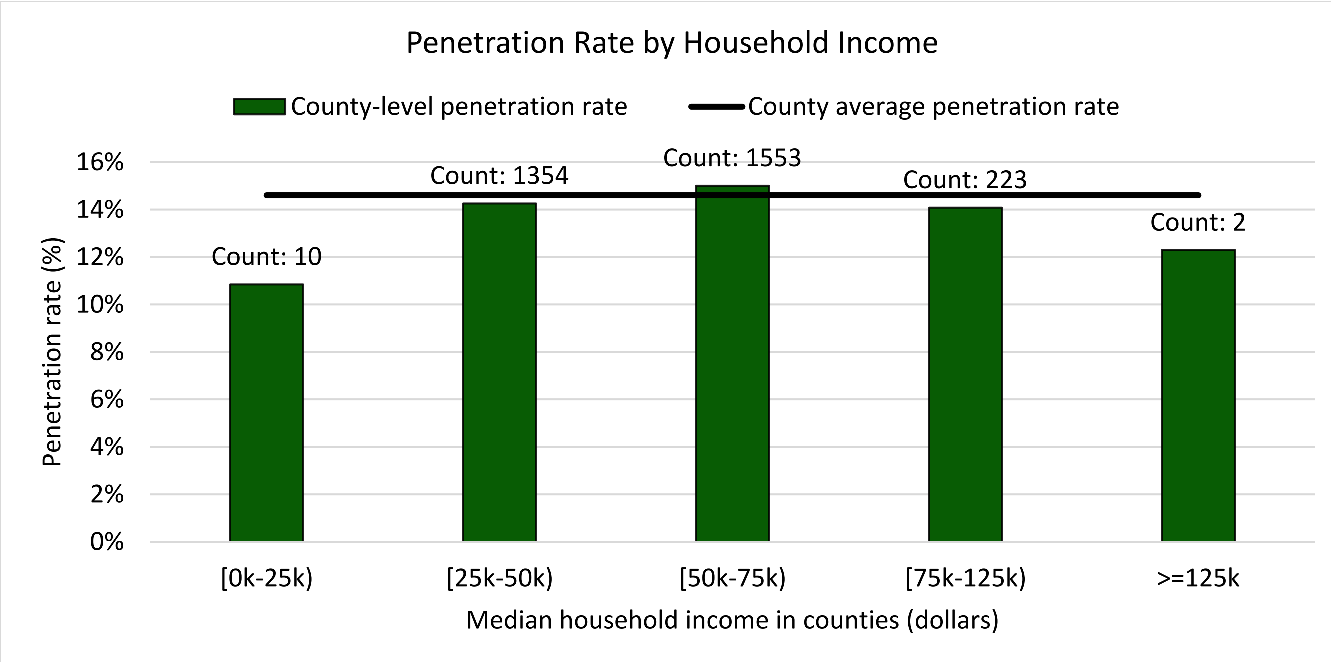
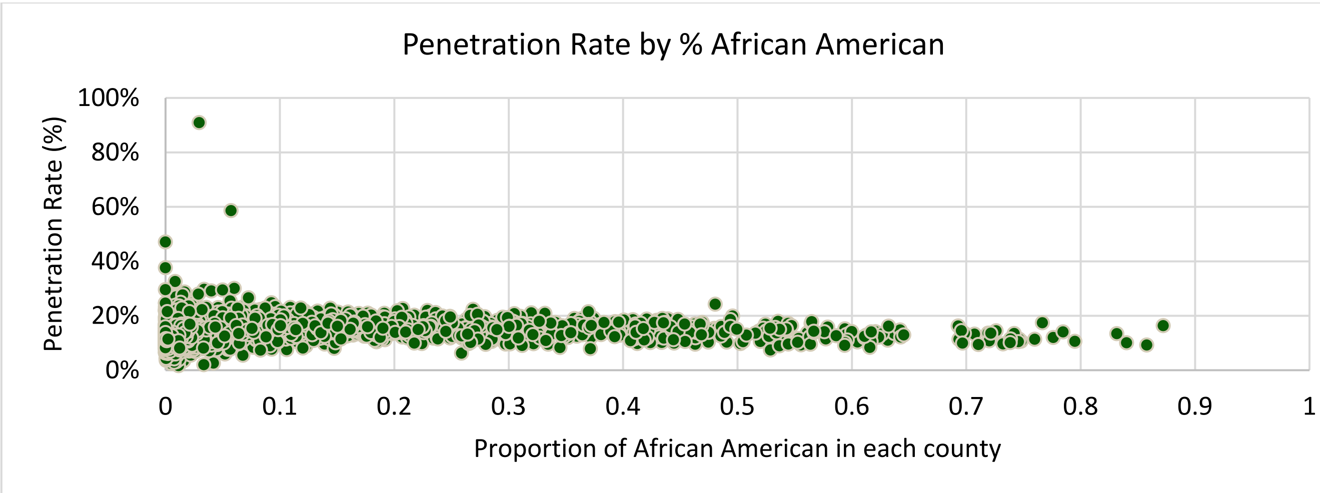


Figure 2. Device penetration rate by median household income at the county level

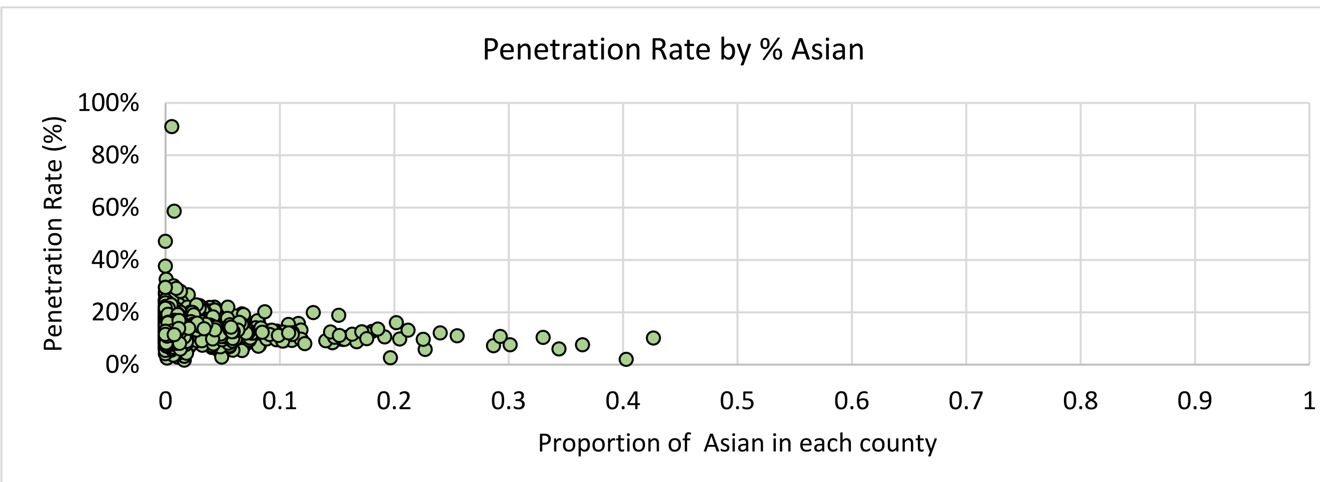
As Figure 2 suggests, there is no clear trend in sample penetration rate variation against the median household income of the county. The majority of the counties fall into the range of 25k-125k in which the penetration rate varies from 14.1% to 15% which is close to the average value of 14.6%.

Penetration rate by race:

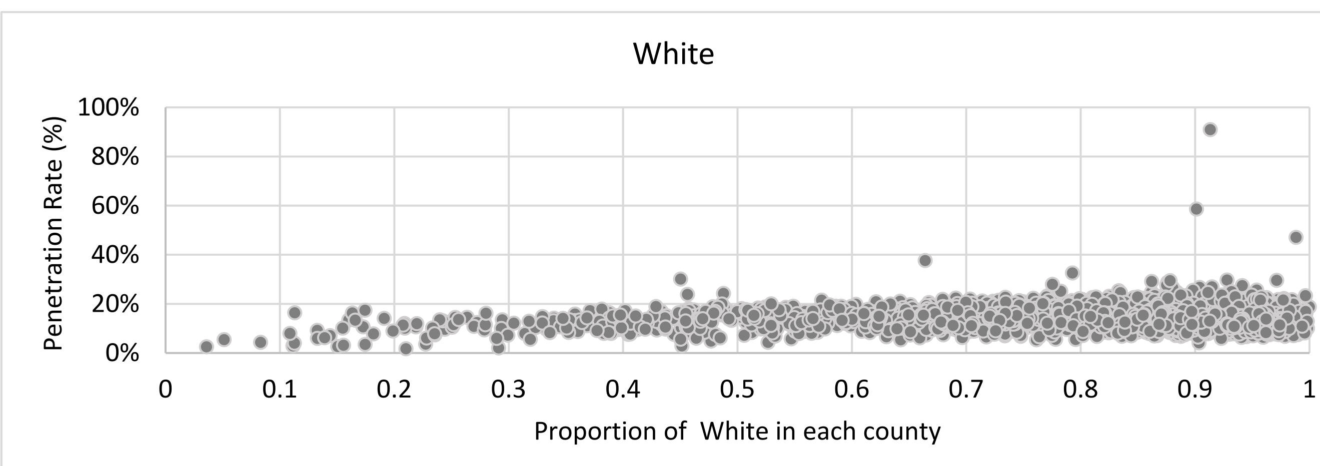
In addition to investigating the relationship between the device penetration rate and household income level characteristics, the team analyzed the variation of device penetration rate across counties considering different racial formations. We have conducted the analysis for several race categories including African American, Asian, and White. Figure 3. illustrates the penetration rate for each category.


Penetration Rate by % African American
Penetration Rate (%)
100%
80%
60%
40%
20%
0%
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Proportion of African American in each county

(a)


Penetration Rate by % Asian
Penetration Rate (%)
100%
80%
60%
40%
20%
0%
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Proportion of Asian in each county

(b)


White
Penetration Rate (%)
100%
80%
60%
40%
20%
0%
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Proportion of White in each county

(c)

Figure 3. Device penetration rate by race categories at the county level; (a) African American, (b) Asian, and (c) White

Based on the above charts, the variation across different bins in the African American category does not follow any specific pattern while for the other two categories, a clearer pattern can be observed. For the Asian category, we can observe that as the proportion of Asian population increases, the penetration rate decreases. The pattern for the White population is in the opposite direction. The increase in the percentage of White population leads to an increase in the device penetration rate. The range of average penetration rate changes for the Asian population category is from 15.3% to 9.2% while the range of device penetration rate for the white population is from 8.3% to 15.2%. Although the range of variation is within the range to be normalized, the team is currently working on two different solutions to mitigate any potential concerns. The first solution is the continuous effort to evaluate any additional data supplier to reduce data sampling biases as well as increase the overall device penetration rate. The second solution is to employ the socio-demographic imputation algorithm recently developed by the team to label the devices and implement the device-level weighting by different socio-demographic groups. The pros of the latter solution are briefly discussed in Section 2.

To further ensure the quality, the following data preprocessing steps are executed for data from each data provider and then integrated together.

- **Step 1**: remove raw sightings with invalid data entries, e.g., negative values for latitudes.
- **Step 2**: remove duplicate sightings considering all data attributes.
- **Step 3**: clean multiple sightings with the same timestamp for the same device. Based on the ranking of location accuracy, the sighting with the smallest location uncertainty is reserved.
- **Step 4**: remove raw sightings with location accuracy greater than 492 feet (150 meters), a threshold selected based on a sensitivity analysis evaluating the trade-off between location uncertainty and percentage of sightings removed.
- **Step 5:** identify and remove data oscillations.
- **Step 6:** for each device, sort the sightings by timestamps.

The most critical step of preprocessing is the removal of oscillations. Data oscillations are abnormal movements with unreasonable distance and time combinations between sightings. They exist in the raw sighting data due to known and unknown technical errors that occur during the data collection process. To simplify the extraction of moving patterns of devices and increase the computation efficiency, device trajectories are denoted by a sequence of level-7 geohash zones instead of latitudes and longitudes. Geohash is a public domain geocode system that encodes a geographic location into a short string of letters and digits. There are twelve levels of geohash zones, which differ in zone size, length of the zone name, etc. Specifically, the level-6 geohash zones (i.e., a grid of about 4000 × 2000 feet) and level-7 geohash zones (i.e., a grid of about 500 × 500 feet) are utilized in the current and following data processing steps. The simplified trajectories are utilized for detecting oscillations. If a device is observed within a specific location range (smaller than 0.5 mile), referred to as a "community," frequently enough (with more than 5 sightings) or long enough (for more than 5 minutes), the corresponding sightings are treated as true visits and form a "stable community." Based on the identified true visits, other locations are investigated to check oscillations. All level-7 geohash zones involved in a stable community are determined to be stable level-7 geohash zones. Then two heuristic rules are designed and employed to remove oscillations at the geohash zone level and the community level considering the moving speed and distance of the sightings.

Various dimensions of assessing data quality, such as consistency, accuracy, completeness, and timeliness, have been discussed in the literature (e.g., Cappiello et al., 2003; Batini et al., 2006; Wang and Chen, 2018) and in the team's previous work (Zhang et al., 2020). We employed a set of quality metrics to assess the preprocessed sighting data from each data provider. The high quality of sighting data contributes to a better representation of the entire population and a better coverage of each device's movements. The essential metrics employed in this project include sample consistency and population coverage (i.e., monthly active users, daily active users, and regularly active users), temporal consistency and coverage (i.e., temporal consistency, data frequency, device representativeness, active local hours, hourly coverage, and daily coverage), spatial consistency and coverage (i.e., geographical representativeness), and spatial uncertainty (i.e., location accuracy). The definition of each metric is described as follows.

- Sample consistency and population coverage
  - **Monthly active users (MAU):** the number of devices with at least one sighting for a specific month.
  - **Daily active users (DAU):** the number of devices with at least one sighting on a specific day for a specific month.
  - **Regularly active users (RAU):** the number of devices with at least ten days of more than ten daily sightings for a specific month.
- Temporal consistency and coverage
  - **Temporal consistency**: the average number of observed days for RAUs in a specific month.
  - **Data frequency:** mean, 25th, 50th, and 75th percentile of the average daily number of sightings by RAU devices.
  - **Device representativeness:** variance in the average daily number of sightings among RAU devices, measured by a Gini coefficient between 0 and 1, with 0 indicating equal sighting frequency and 1 indicating distinct sighting frequency for all RAUs.
  - **Active local hours:** mean, 25th, 50th, and 75th percentile of the average daily number of local hours observed for RAUs.

- **Hourly coverage**: variance in the average sighting volume by the hour of day for all RAUs, measured by a Gini coefficient between 0 and 1, with 0 indicating equal average number of sightings from the 24 hours and 1 indicating all sightings are from one hour.
- **Daily coverage**: variance in the total sighting volume by day of month for all RAUs, measured by a Gini coefficient between 0 and 1, with 0 indicating equal total number of sightings from each day in one month and 1 indicating all sightings are from one day.

o Spatial consistency and coverage

- **Geographical representativeness (by devices):** variance of population coverage among different counties, measured by a Gini coefficient[3] between 0 and 1, with 0 indicating equal sampling rate in all counties and 1 indicating that all RAUs are from a single county.
- **Geographical representativeness (by sighting):** variance of sighting volume divided by county-level population, measured by a Gini coefficient between 0 and 1, with 0 indicating equal sighting volume per person in all counties and 1 indicating that all sightings are from a single county.

o Spatial uncertainty

- **Location accuracy:** mean, 25^{th}, 50^{th}, and 75^{th} percentile of the positioning accuracy of RAU devices. Positioning accuracy is defined as the maximum distance between a device's recorded location and its actual location at 95% confidence level.

The quality metrics statistics from one-month raw sighting data panel in 2020 are computed and summarized below. The following numbers are provided to help data users compare the data quality of this raw sighting data panel with that of other similar data sources.

o Sample consistency and population coverage

- **Monthly active users (MAU):** 261,627,285 devices, implying a sampling rate of about 79% on a monthly basis.
- **Daily active users (DAU):** 101,467,511 devices on average during the month, implying an average sampling rate of about 30% on a daily basis.
- **Regularly active users (RAU):** 57,900,535 devices, indicating a sampling rate of about 17% regarding temporally consistent devices.

o Temporal consistency and coverage

[3] Gini coefficient (Gini, 1912) is a statistical measure of the equality of a given data. It can be calculated by the ratio of the area above the Lorenz curve to the summation of the area above and the area below the Lorenz curve. The Lorenz curve is a graph showing the distribution of the given data.

- **Temporal consistency**: 23.3 days (the highest possible number of which is 31 days), indicating the level of temporal consistency and coverage of the RAUs.
- **Data frequency:** mean, 25th, 50th, and 75th percentiles are 172.6, 26.4, 63.8, and 222.6 sightings per day, respectively, indicating the sighting frequency of RAUs.
- **Device representativeness:** 0.63, indicating a notable uneven distribution of average daily sighting volume for each RAU, which may be a result of distinct smartphone use behaviors and travel behaviors of different device owners. The team developed a weighting framework to address the uneven distribution.
- **Active local hours:** mean, 25th, 50th, and 75th percentiles are 5.31, 1.67, 4, and 6.67 hours respectively, indicating the temporal consistency and coverage of the RAUs.
- **Hourly coverage**: 0.19, indicating an even distribution of average daily number of sightings among the 24 hours for RAUs.
- **Daily coverage**: 0.1, indicating an even distribution of daily total number of sightings across all days in the month for RAUs.

- Spatial consistency and coverage

  - **Geographical representativeness (by device):** 0.4, indicating an even geographical distribution of RAUs per population.
  - **Geographical representativeness (by sighting):** 0.2, indicating an even geographical distribution of sightings per population.

- Spatial uncertainty

  - **Location accuracy:** mean, 25th, 50th, and 75th percentiles are 46.5, 13.1, 29.5, and 63.4 in feet, respectively, indicating the reliability of location sightings of RAUs.

2. Methodology

This section describes the methodology for producing the trip and population staying at home metrics, including the definition, assumptions, and estimation methods used to identify trips and population staying at home and the multi-level weighting and data expansion framework. The available accuracy measures and bias factors are also discussed.

2.1. Trip Identification

Trips are the unit of analysis for almost all transportation applications. Sightings from mobile device location data do not directly include trip information. Therefore, trip identification algorithms follow the sighting data preprocessing (as described in Section 1) and extract trip information from the cleaned sightings. The trip end identification algorithm for high-frequency mobile device location data, such as GPS data, has been well-studied and used in practical applications. To obtain trip ends, the rule-based methods are widely used with spatio-temporal parameters defined and selected according to domain knowledge and practical experiments, such as dwell time, speed, and distance (Wolf et al., 2001; Axhausen et al., 2004; Stopher et al., 2005; Tsui and Shalaby, 2006; Du and Aultman-Hall, 2007; McGowen and McNally, 2007; Bothe and Maat, 2009; Stopher et al. 2008; Schuessler and Axhausen 2009; Gong et al. 2012; Gong et al., 2014; Safi et al. 2015; Patterson et al. 2016). The detailed trip identification algorithm is described as follows with hyper-parameters selected based on previous studies and domain knowledge.

The algorithm starts with each device's identified home location (see Section 2.2). Long-distance tours are defined as tours in which a device is observed equal to or more than 50 miles away from its home location and the rest are defined as short-distance tours. The short-distance tours generally contribute to the daily local trips and the long-distance tours can include regular trips from super commuters (who usually work more than 50 miles away from home) and occasional trips for business and leisure travels. The algorithm considers short- and long-distance tours separately due to the differences in their nature.

In short-distance tours, the cleaned sightings can be categorized as stationary or moving sightings. Stationary sightings do not belong to any trips and moving sightings construct the trips. A recursive algorithm based on the rule-based model is utilized to identify if the sighting is stationary or moving and which trip the sighting belongs to. The rule-based model considers six attributes, i.e., the great circle distance, time interval, and speed between the current sighting and the previous and next sightings. The rule-based model has three hyper-parameters: a distance threshold of 984 ft (i.e., 300 meters), a time threshold of 5 minutes, and speed threshold of 3 miles per hour (3 mph or 1.4 m/s). The speed threshold is used to identify if a sighting is recorded on the move, and the distance and time thresholds are used to identify trip ends. The speed threshold is set as the walking speed (3 mph) as the walking speed is considered as the minimum moving speed of a regular trip. The thesis reviews the state-of-the-art methods and adopts 984 feet (300 meters) as the distance threshold and 5 minutes as the time threshold (Zheng et al., 2010; Axhausen et al. 2004). The 984-ft distance threshold and the 5-min time threshold can capture short-distance trips in urban environments with a small probability of identifying unintentional stops as trip ends, such as the stops at a traffic signal or in a traffic congestion.

The recursive algorithm checks every sighting to identify if they start a new trip or belong to the same trip as the previous sighting (Figure 4). If the previous sighting is not on a trip (i.e., a stationary sighting), the current sighting starts a trip if it has a speed faster than 3 mph to the next sighting. If the previous sighting is on a trip, the following rules are checked to identify if the current sighting belongs to the same trip, stops the trip, or starts a new trip:

- If a sighting has a speed faster than 3 mph from the previous sighting, the sighting belongs to the same trip as its previous sighting.

- If a sighting has a speed slower than 3 mph from the previous sighting and is more than 984 ft away from the previous sighting, the sighting does not belong to the same trip as its previous sighting. If the speed to the next sighting is also slower than 3 mph, the current sighting simply terminates the trip; otherwise, it becomes the start of a new trip.
- If a sighting has a speed slower than 3 mph from the previous sighting and is within 984 ft from the previous sighting, the cumulative dwell time for all the consecutive sightings meeting such criteria is computed and checked: 1) if the cumulative dwell time is less than five minutes, the current sighting belongs to the same trip, 2) otherwise, it terminates the trip if the speed to the next sighting is less than 3 mph or starts a new trip if the speed to the next sighting is more than 3 mph.

The algorithm may identify a local movement as a trip if the device moves within a stay location. To filter out such trips, all trips that are shorter than 984 ft are removed.

In long-distance tours, all the trip ends are first identified and named as “secondary stops.” Primary stops are then identified from the secondary stops as places where the device stays for a significant amount of time and/or from which the device makes local trips. A subtour is considered a segment of a long-distance tour that falls between two primary stops. Therefore, all sightings between two primary stops are considered to be on the same subtour. Furthermore, the primary destination of a tour is defined as the farthest stop that is located at least 50 miles away from the home location of the device. As shown in Figure 5, similar recursive algorithm for the short-distance trip identification (Figure 4) is applied after the secondary stops, primary stops, and primary destination are identified.

In summary, trips are defined and identified based on three spatio-temporal hyper-parameters, the potential influences of which are discussed in Table 1. Since the trip identification is highly correlated to the hyper-parameters, a sensitivity analysis follows in the next section.

Table 1. Definitions and Potential Bias Factors for Trip Identification Parameters

Hyper-Parameter	Functions	Potential Bias Factors
Speed threshold	Identifies the stationary or moving status of the device	The speed is calculated by dividing the great circle distance by the time interval between two consecutive sightings. Due to the spatial and temporal accuracy of the raw sightings, the error in the speed may lead to an early or late start or termination of a trip, which may slightly influence the trip distance estimation.
Distance threshold	Identifies the maximum distance range of a trip end	The distance threshold may identify local trips within a stay location. Although a post-processing filter is applied, it may still keep trips within a large stay location, e.g., shopping centers and national parks.

Time threshold	Identifies the minimum dwell time of a trip end	Trip ends with dwell time shorter than the time threshold may be ignored, e.g., pick-up and drop-off trips. In the meantime, a severe traffic congestion or an emergency stop on the roadside may also be identified as a trip end.

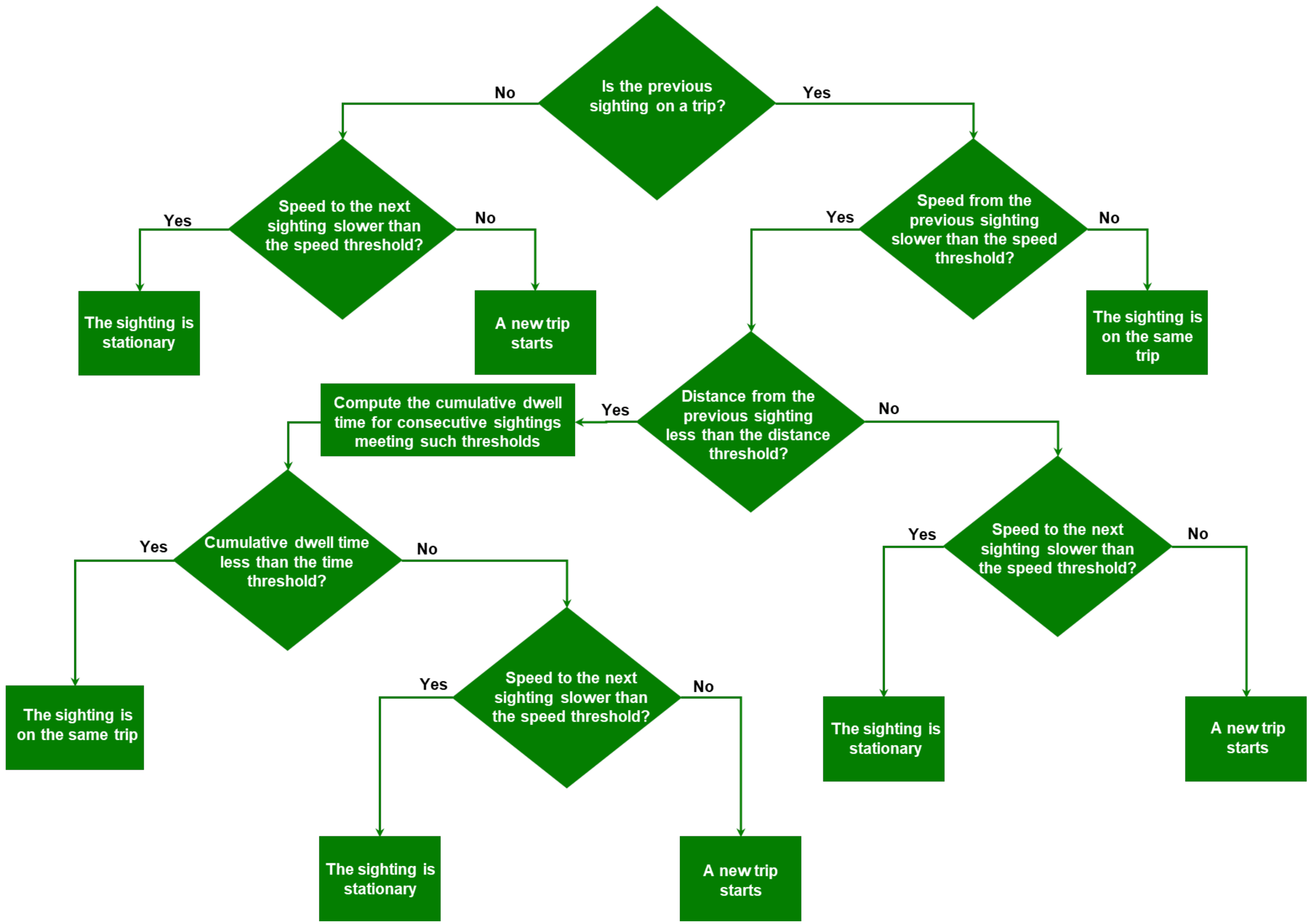


Figure 4. Recursive algorithm for short-distance tour and trip identification

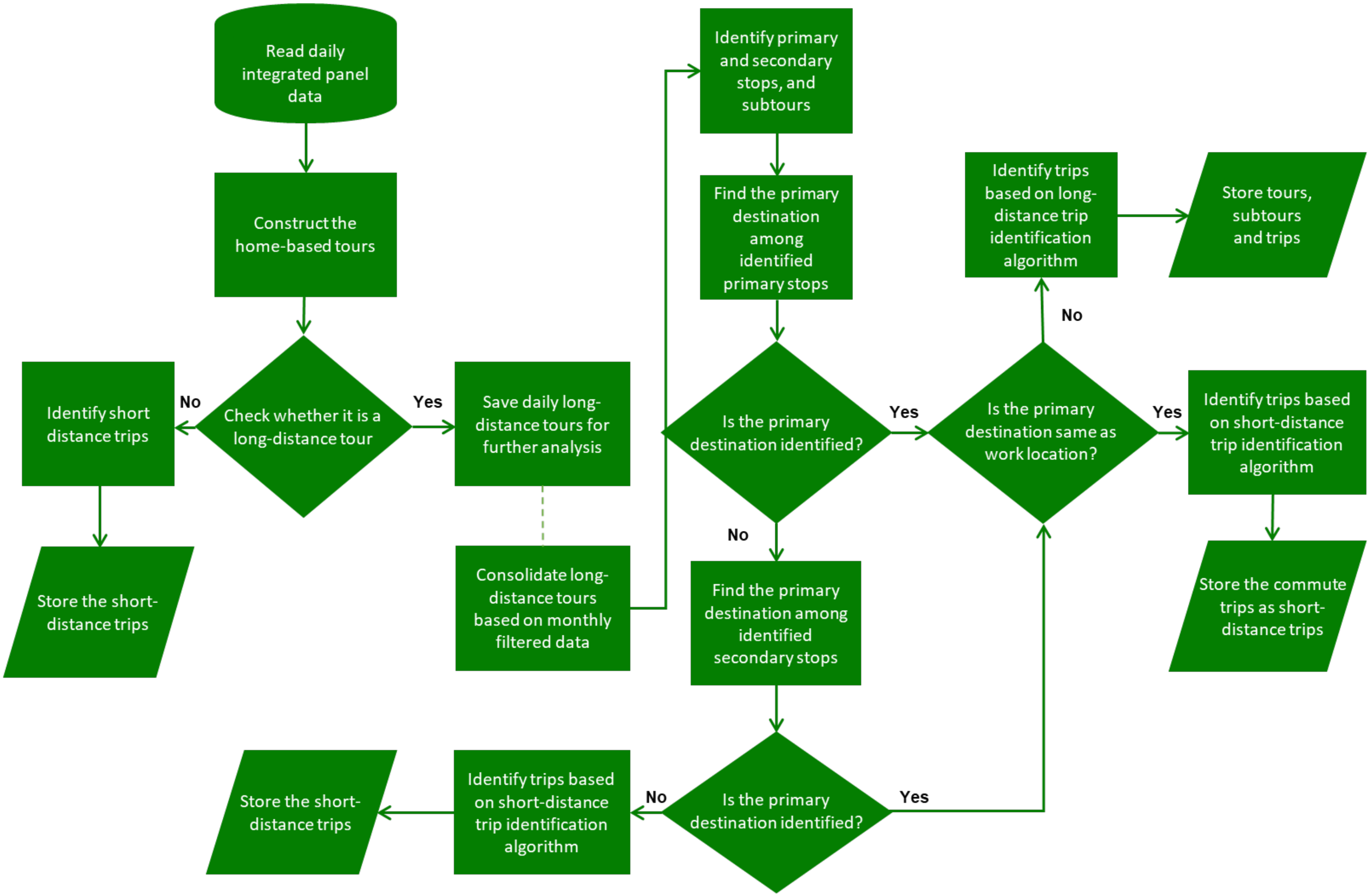

Read daily integrated panel data
Construct the home-based tours
Check whether it is a long-distance tour
No
Identify short distance trips
Store the short-distance trips
Yes
Save daily long-distance tours for further analysis
Consolidate long-distance tours based on monthly filtered data
Identify primary and secondary stops, and subtours
Find the primary destination among identified primary stops
Is the primary destination identified?
No
Find the primary destination among identified secondary stops
Is the primary destination identified?
No
Identify trips based on short-distance trip identification algorithm
Store the short-distance trips
Yes
Yes
Is the primary destination same as work location?
No
Identify trips based on long-distance trip identification algorithm
Store tours, subtours and trips
Yes
Identify trips based on short-distance trip identification algorithm
Store the commute trips as short-distance trips

Figure 5. Recursive algorithm for long-distance tour and trip identification

2.2. Population Staying at Home

Population staying at home is defined as the number of residents making no trips with a non-home trip end more than one mile away from home, i.e., making no movements more than one mile away from home. The metric is based on the imputed home location and the imputed trips.

To efficiently process the tremendous amount of mobile device location data, the algorithm utilizes geohash to aggregate the latitudes and longitudes into candidates for meaningful places. Considering the location uncertainty of sightings and the possible household activities conducted around the home, the algorithm first identifies the home location at a level-6 geohash zone (a grid of about 4000 × 2000 feet) and then selects the most frequently observed location at a level-7 geohash zone (a grid of about 500 × 500 feet) within the identified level-6 geohash zone as a more precise representation of home location. The actual home location will be identified as the centroid of the level-7 geohash zone.

People spend most of their time, especially nighttime, at home. The framework first identifies three frequently observed level-6 geohash zones as home location candidates based on the overall observed days in a month (at least three days or half of the total observed days for each device), the average observed hours in those observed days (at least two hours), and the average sightings in those observed hours. The method favors the home location candidate that is most frequently observed during nighttime and selects it as the home location at level-6 geohash zone level. The first two steps are then repeated at a smaller geospatial resolution (level-7 geohash zone) to find a more precise representation of home location. To properly identify nighttime period, we investigated 2017, 2018, and 2019 American Time Use Survey (ATUS) (USBLS, 2019) and defined nighttime as 9:00 p.m.–5:59 a.m., since more than 80% of full-time and part-time workers are observed to visit home at least once during that period.

The parameter for the minimum average number of observed hours, i.e., 2 hours, is calibrated based on the Pearson correlation test between the county-level number of imputed residents (i.e., sample devices with imputed home locations) and a population over 16 reported by the American Community Survey (ACS) for home location identification. The Pearson correlation value based on the selected parameter is higher than 0.95.

The major parameter influencing the stay-at-home population estimates is the one-mile radius from imputed homes. The one-mile radius is selected to avoid counting people's leisure movements around homes, such as jogging and walking a dog, when identifying if they stayed at home amid the COVID pandemic. However, the universal parameter may introduce some bias in estimating the population staying at home in different regions, e.g., urban versus rural areas. For example, people living in rural regions usually need to make longer trips than people in urban areas for essential errands. Therefore, people in urban areas are more likely to be identified as staying at home (Pan et al., 2020). The accuracy of population staying at home estimates could be further improved when considering the specific trip purpose of each trip.

2.3. Weighting and Data Expansion

Sighting data is a sample and does not cover the entire population of the U.S. Known biases associated with sighting data and the OD products derived from such data sources include but are not limited to the following:

- The owners of the devices in the sample do not represent the full population of the U.S. and are not equally representative of different socio-demographic groups.
- Data coverage may be different in urban and rural areas because of different mobile device penetration rates across the U.S.
- Not all movements of devices are necessarily observed. There is a higher probability of observing location records when the trip lasts longer, and the travel mode uses a transportation network with a more stable communication network.
- There are temporal biases in the location records of the observed devices due to different levels of mobile device usage during different hours of the day.

Weighting and data expansion are two important steps to generate population-representative statistics from a survey. For this project, a multi-level weighting and data expansion framework (Figure 6) is applied (device- and trip-level) to produce OD products that are representative of the entire U.S. population and its corresponding movements.

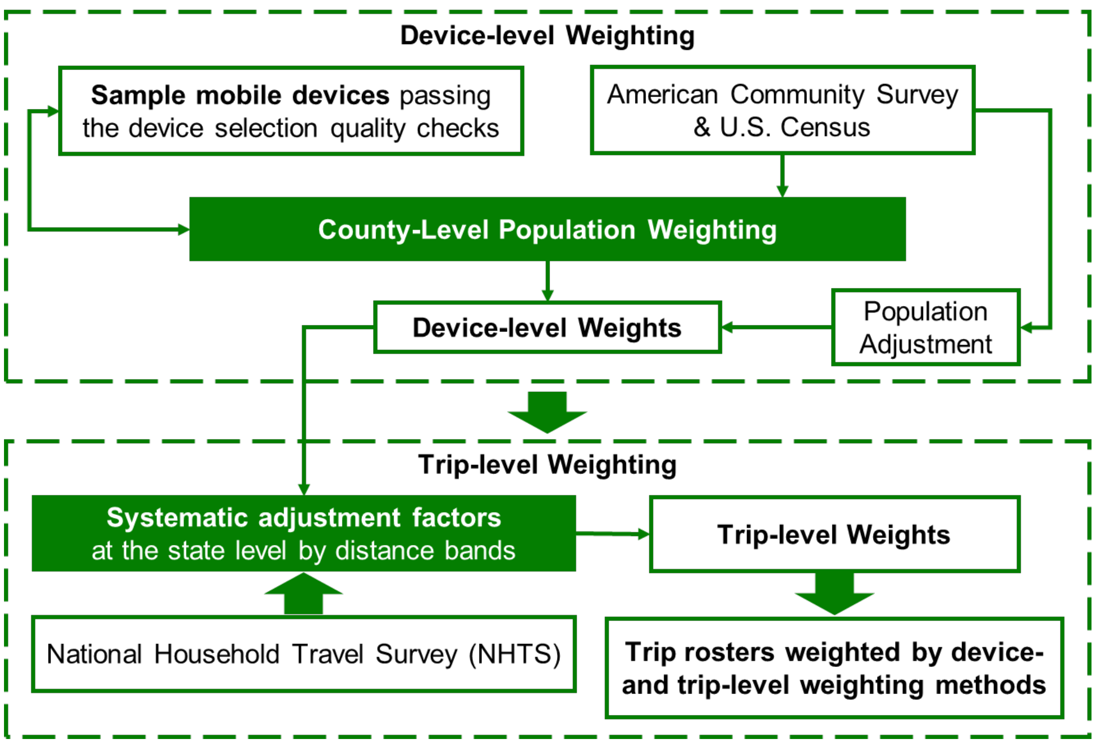


Figure 6. Flowchart of the multi-level weighting

The device-level data expansion is conducted at the county level to expand the sample devices to represent the county-level population. Next, the population-level trip estimates are further weighted in terms of trip distance. It is assumed that the identified trips from the mobile device location data set may have a systematic bias in different trip distance bands. Therefore, ten benchmark work days before the pandemic are selected and a set of adjustment factors by distance bands is developed between the identified trips from mobile devices and the estimated trips from the 2017 National Household Travel Survey (NHTS) (USDOT 2017). The systematic adjustment factors by distance bands are carried on during and after the pandemic breakout and are applied to the device-level weights to estimate the trip-level weights.

There remain some potential unaddressed biases, including: 1) the unequal representation of different socio-demographic groups; 2) the unequal representation of movements in different time periods of a day; 3) temporal changes in the quality and characteristics of mobile device location data. The accuracy of weighted trip estimates could be further improved by weighting the sample devices based on the imputed socio-demographic groups and including more dimensions in developing the trip-level systematic adjustment factors.

3. Sensitivity Analyses

As discussed in the methodology section, trip identification algorithms generally rely on several spatial and temporal characteristics such as time, distance, and speed between consecutive location points. All these criteria can significantly affect the result of trip identification. Therefore, within the scope of this analysis, the team has conducted a comprehensive round of sensitivity analysis on the predetermined thresholds to evaluate their impacts on tour and trip rates as well as the travel distance distribution. In the following subsections, the sensitivity analysis results on each of these three criteria have been investigated using the 4 weeks of Maryland residents' data in 2021 (from January 31st to February 27th).

3.1. Time Threshold

Time threshold is among the most influential factors in trip identification that helps to detect the trip end. A Longer time threshold would allow trips to have more significant trip intermediate stops and is expected to lead to a higher share of long-distance trips. In our algorithm, we set the time threshold to 5 minutes to avoid identifying short stops at the intersections as a significant stop and to detect all the significant trip ends with a dwell time longer than 5 minutes. For the purpose of sensitivity analysis, we have considered five different time thresholds to evaluate the impact of different criteria. The five selected time thresholds are 3, 5, 10, 15, and 30 minutes. Figure 7 summarizes the daily trip rates for each scenario.

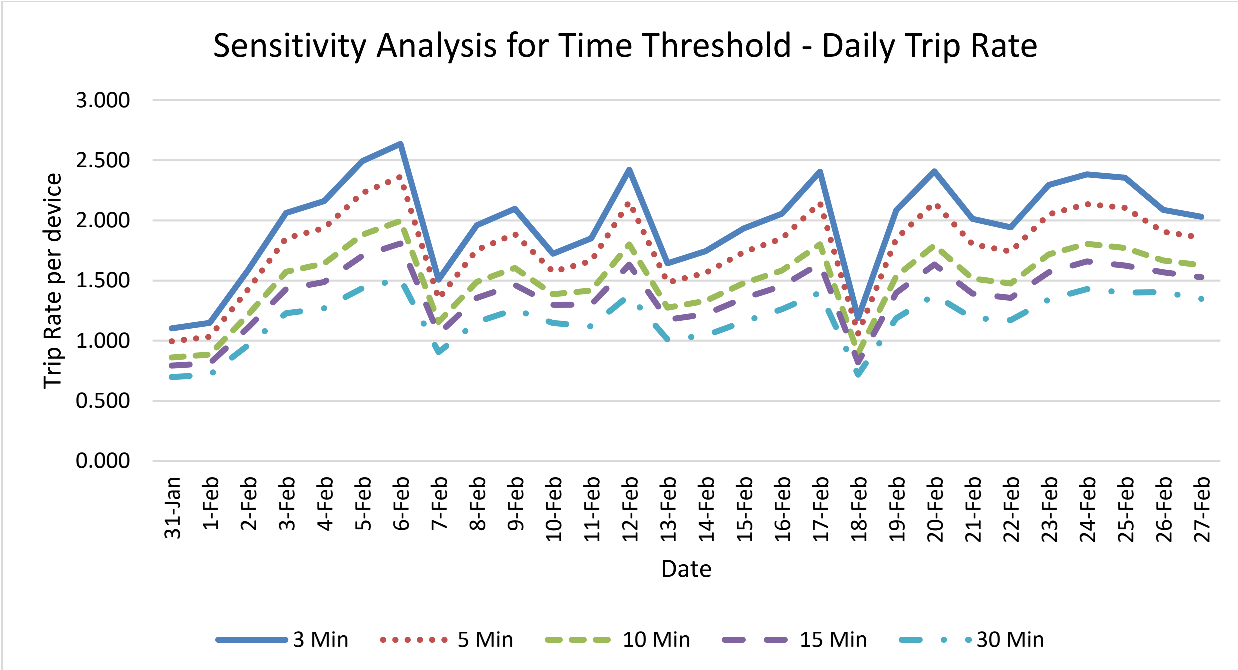


Figure 7. Daily trip rate sensitivity to time threshold

In addition to the trip rate, we also investigated the ratio of long-distance trips for each scenario. Figure 8 summarizes the ratio of trips longer than 50 miles. We also compared our estimates with the baseline ratios estimated by the 2017 NHTS and 2018-2019 MD Household Travel Survey.

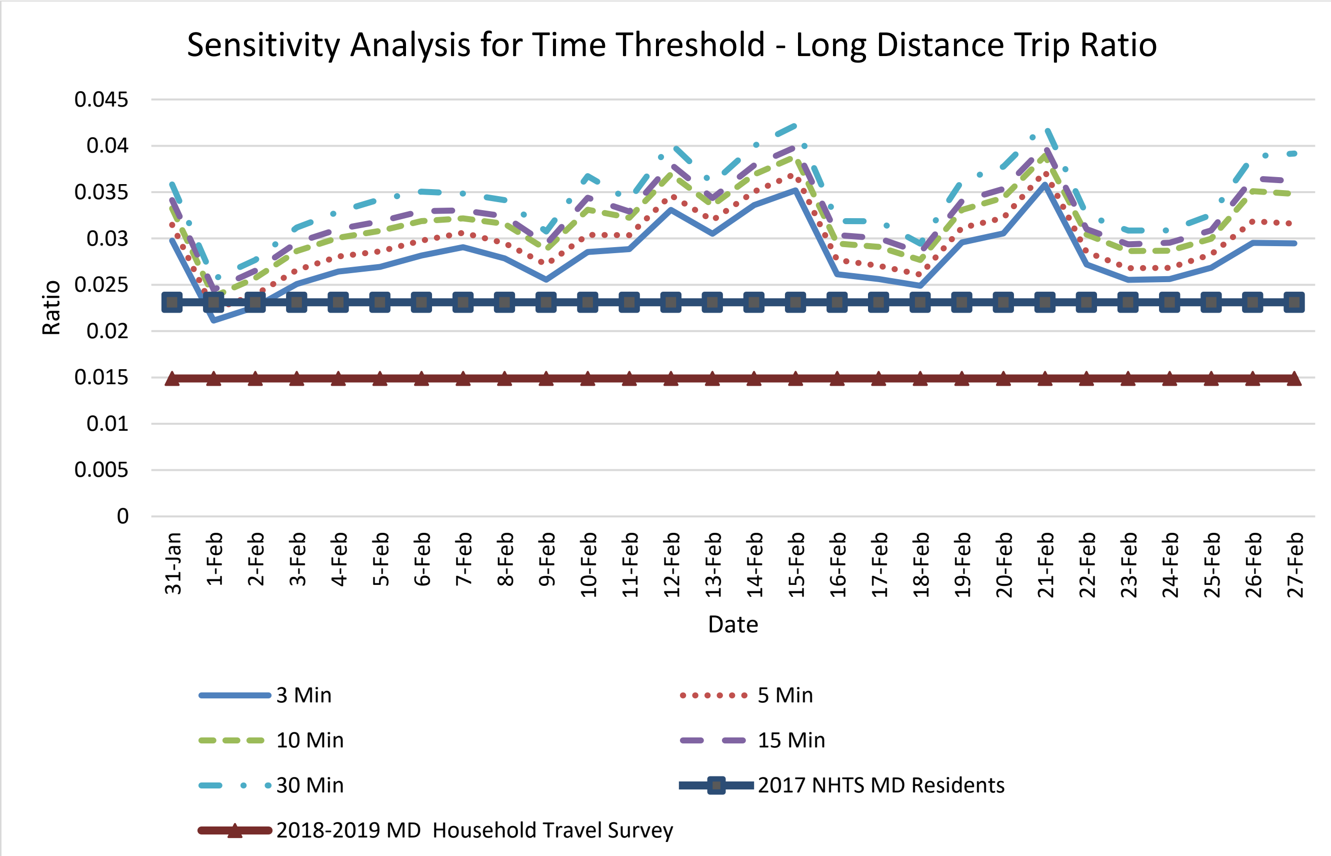


Figure 8. Long-distance trip ratio sensitivity to time threshold

As expected, an increase in travel time threshold lead to a lower number of trips in general while it increases the ratio of long-distance trips.

3.2. Speed Threshold

Speed threshold is another influential factor in the trip identification algorithm which affects the trip detection both in terms of initiating and terminating a trip. As shown in the trip identification framework, the speed between consecutive sightings for a device should be greater than the defined speed threshold for starting the trip. Once a trip starts, then the algorithm checks the speed of the device continuously to evaluate the status of the device. Once the speed of the device drops below the speed threshold, then the algorithm evaluates the traveled distance and the dwell time to terminate the trip. By increasing the speed threshold, the chance of detecting the trip decreases while the chance of terminating the trip increases. To analyze the impact of the speed threshold, we have tested five speed criteria in our algorithm, including 1, 2, 3, 4, and 5 miles per hour. Figure 9 shows the changes in trip rate trend for each defined speed threshold. We have not tested any speed faster than 5 mph as it would exceed the preferred walking speed and would lead to not detecting slow mode trips.

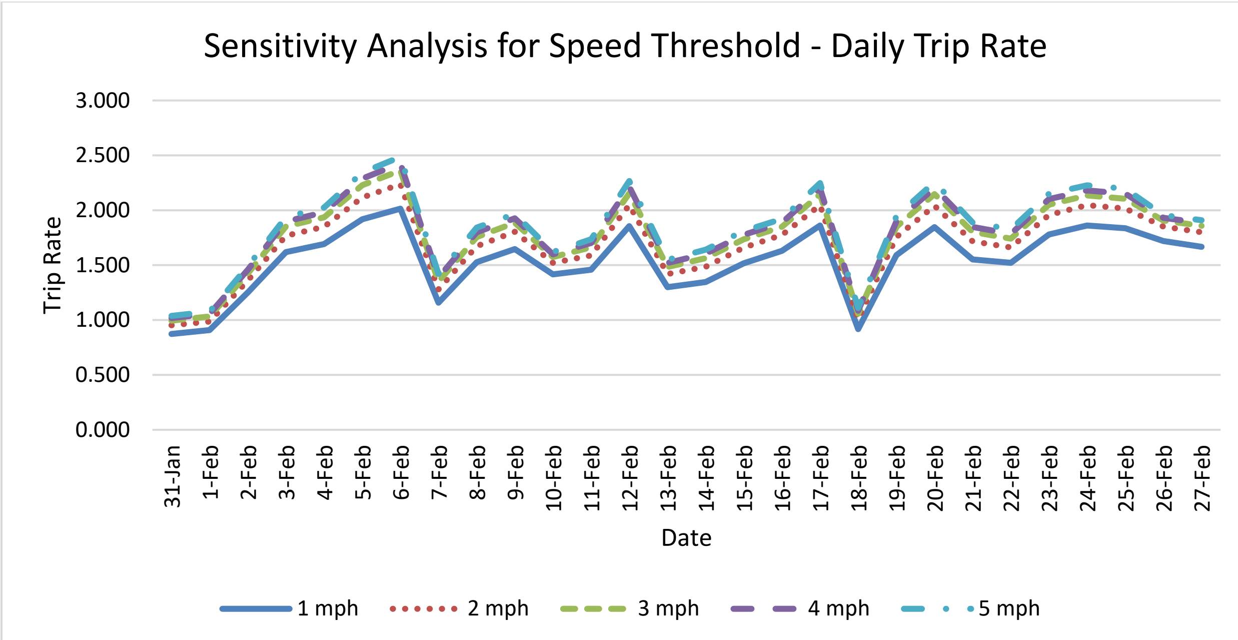


Figure 9. Daily trip rate sensitivity to speed threshold

As it can be seen in the above figure, increasing the speed threshold increases the number of identified trips. This observation suggests that the impact of ending the trip and the potential breakdown of a single trip to several trips is dominating the impact of neglecting some slow trips. To further investigate the impact of changing the speed threshold, we have also examined the changes in the ratio of long-distance trips (trips longer than 50 miles). Figure 10 illustrates the changes in long-distance trip ratio for each speed threshold scenario.

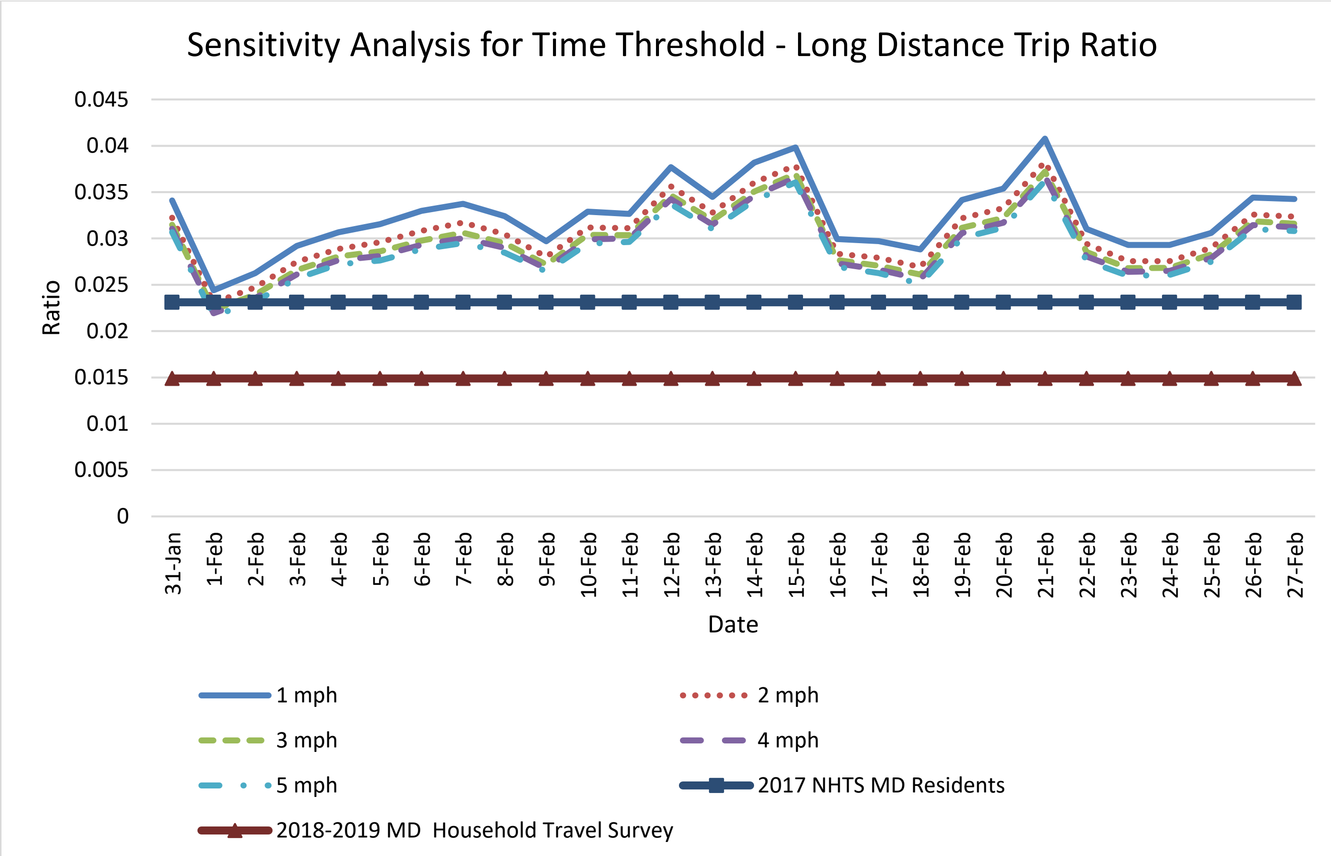


Figure 10. Long-distance trip ratio sensitivity to speed threshold

The results suggest that the higher speed threshold criteria lead to a lower rate of long distance trips. It is also a result of imposing the higher speed thresholds, which tend to break down longer trips into shorter trip segments.

3.3. Distance threshold

Distance threshold is another factor in the trip identification that plays an internal role in connecting the speed and time thresholds. As the purpose of distance threshold is to ensure the reasonableness of trip end identification, we did not expect a significant influence of this parameter in the number of trips. However, to ensure that we have controlled for the impact of this threshold, we have analyzed the outcome of the trip identification algorithm using five different distance thresholds. Figure 11 shows the summary of the sensitivity analysis for 500 ft, 1000 ft, 2000 ft, 3000 ft, and 1-mile distance thresholds on daily trip rates.

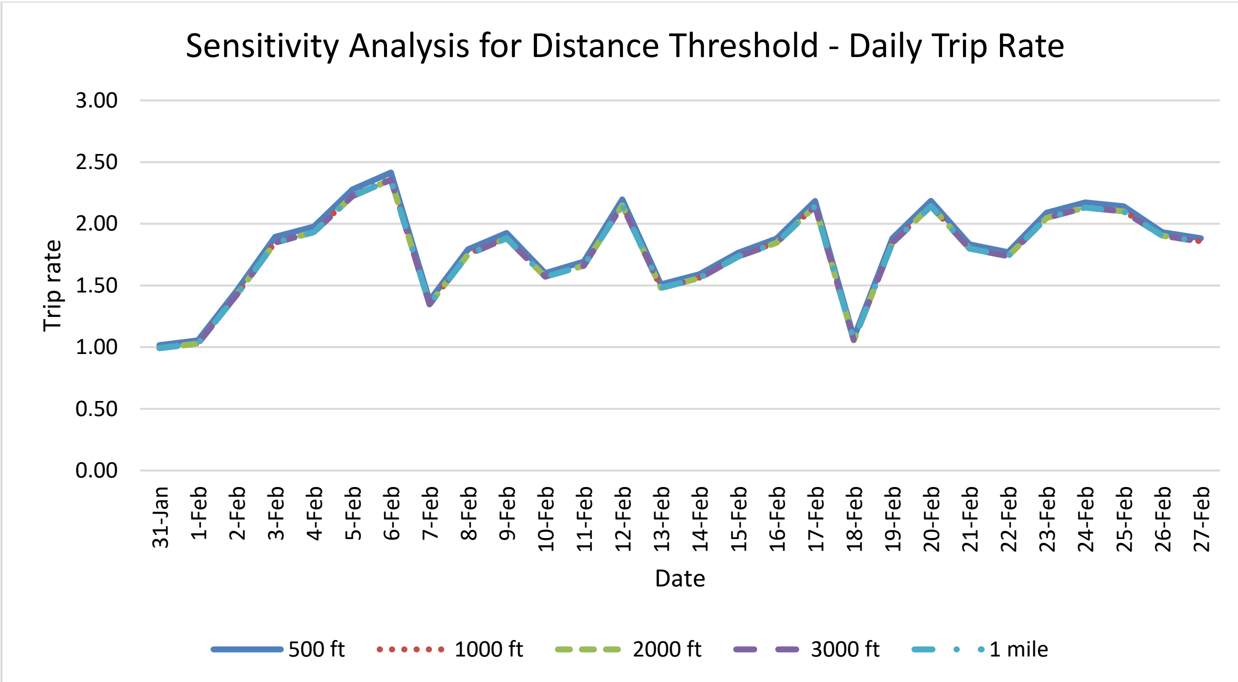


Figure 11. Daily trip rate sensitivity to distance threshold

As it can be seen in Figure 11 and as it was expected, the trip distance threshold did not show a significant impact on the daily trip rates. The long-distance trip ratio was also studied to ensure that no significant differences would be observed by changing the trip distance threshold (Figure 12).

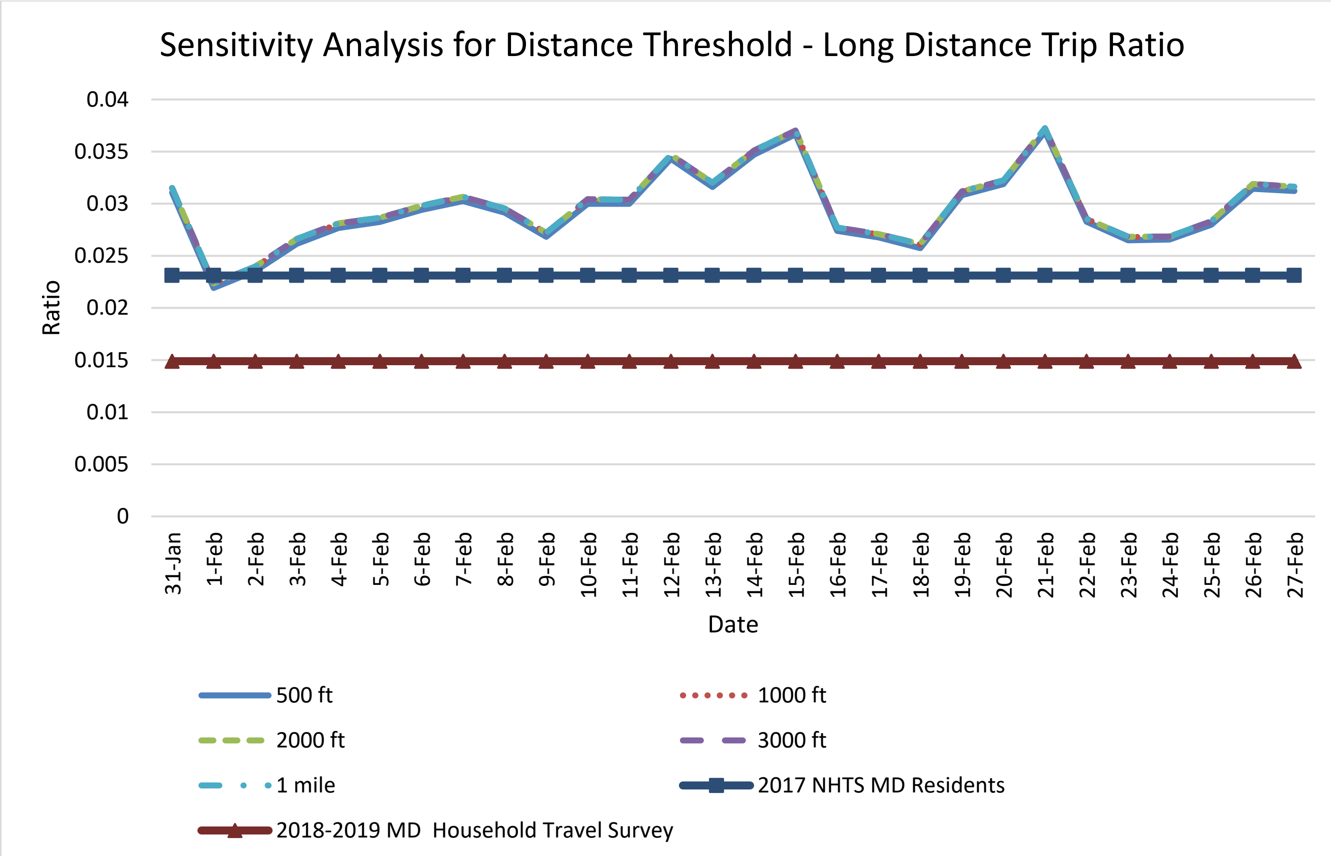


Figure 12. Long-distance trip ratio sensitivity to distance threshold

3.4. Sensitivity Analysis on Weighted Results

In addition to investigating the impact of each hyper-parameter in the trip identification on raw trip rates, the weighted results are also evaluated to analyze the impact of different parameters on the final data products (Figure 13). For this purpose, we have implemented our multi-level weighting and data expansion framework on all the scenarios. It can be observed that the changes in all three hyper-parameters have similar influences on unweighted and weighted trip totals, which implies that the weighting and data expansion framework does not distort the travel trends identified from the sighting data.

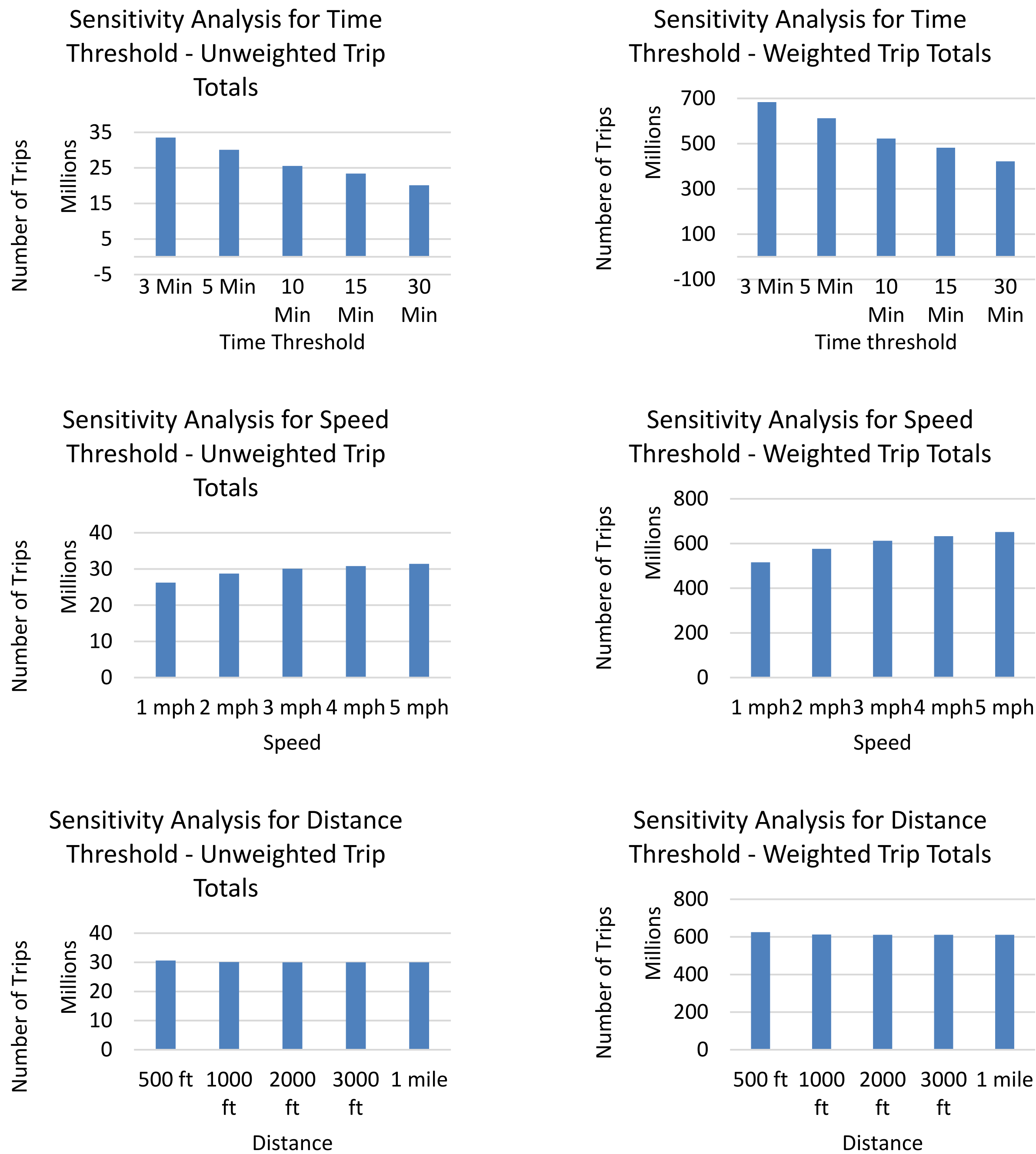


Figure 13. Unweighted and weighted result comparison for sensitivity analysis scenarios

In addition to the number of trips, the long-distance trip ratio along with the ratio of people staying at home have been calculated for all the scenarios (Figure 14). In general, the time threshold has the most significant influences on both ratios from the weighted results: the longer time threshold leads to a larger share of long-distance trips--similar to the observation in the unweighted results--and a slightly higher share of the population staying at home since fewer trips are identified. Meanwhile, the speed threshold has a significant impact on the long-distance trip ratio while barely changing the percentage of the population staying at home. Since a larger speed threshold would end a trip more easily, the longer trips are highly possible to be broken down into shorter segments, which leads to a smaller share of long-distance trips. Like the unweighted results, the distance threshold barely influences the estimates of the long-distance trip ratio and the percentage of population staying at home.

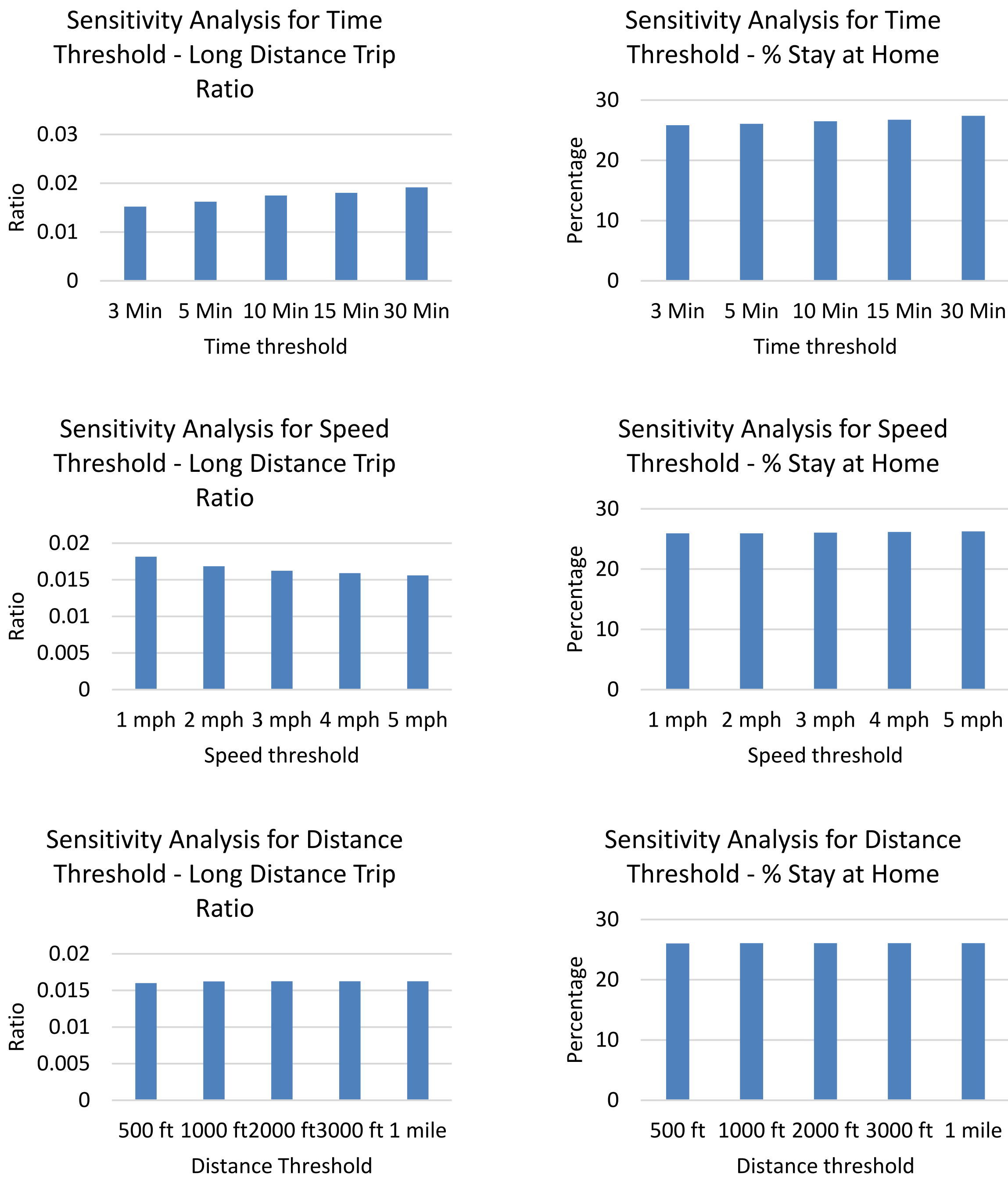


Figure 14. Sensitivity analysis on weighted results for long-distance trip ratio and percentage of people staying at home

3.5. Summary of Sensitivity Analyses

Sensitivity analyses have been conducted to assess the ranges of the estimated number of trips as well as its long-distance portion based on the key parameters employed in trip identification. The analyses find that the most influential parameter is the time threshold, representing the presumed minimum dwell time at trip ends. A smaller time threshold would lead to more trip ends being recognized. For instance, a commute trip with an intermediate stop at a coffee shop that has a dwell time longer than the time threshold would be split into two trips. Compared to time threshold, the influence of the speed and distance thresholds on daily trip rates and long-distance trip ratio is marginal.

The long-distance trip ratio estimated from mobile device location data (using Maryland data for February 2021) is higher than that from both national and regional household travel surveys (using the Maryland portion of 2017 NHTS data and 2018-2019 Maryland household travel survey). This is found reasonable since more long-distance trips are expected to be captured in mobile device location data due to its continuity in the data collection process. The impact of the pandemic on long-distance travel patterns might also play a role in tilting the long-distance trip ratio. More empirical evidence, such as a timely travel survey, is needed to assess such innate behavioral pattern change.

The analyses also point out that the long-distance trip ratio after the weighting process becomes smaller compared with that from the unweighted results and that from the 2017 NHTS estimates. Again, such decrease should be assessed against up-to-date travel survey data or other ground truth travel trends when such empirical data becomes readily available. It, however, does suggest a few research and development directions for improvement on methodology:

1) establishing device-level weights by imputed socio-demographic groups to address the unequal representation of different socio-demographic groups in the mobile device location data;

2) establishing trip-level adjustment factors by imputed travel mode and time of day information to address the unequal representation of travel movements by different travel modes and in different periods; and

3) further calibration and validation of weighted trip estimates by imputed travel modes according to external ground truth data sources, such as the National Transit Database (NTD), the Airline Origin and Destination Survey (DB1B) database, and the Air Carrier Statistics database (T-100 data bank).

4. Data Quality Summary

This section provides a summary of quality aspects regarding the travel statistics following the domains and dimensions defined in "A Framework for Data Quality" developed by the Federal Committee on Statistical Methodology (FCSM, 2020) (Table 2, Table 3, and Table 4).

Table 2. Data Quality Aspects in Terms of Data Utility

Domain	Dimension	Data Quality	Threats
Utility	Relevance	The travel statistics target at revealing the person mobility trends before, during, and after the breakout of the COVID pandemic. Person- and trip-level metrics, estimated on a daily basis at the county, state, and national levels for the entire U.S., enables the investigation of person mobility trends at a high level of granularity regarding both spatial and temporal aspects.	The travel statistics were not supplemented with a detailed user guide, which may lead to potential misuse by data users.
	Accessibility	All the travel statistics are published by BTS and accessible via https://data.bts.gov/Research-and-Statistics/Trips-by-Distance/w96p-f2qv.	The raw sighting data are not publicly accessible but our team will try to maximize the transparency of the raw data quality and the data processing methodology.
	Timeliness	The travel statistics have an 8-day lag due to the initial time lags of raw sighting data from different upstream data providers and the computation process. The current time lag is insufficient to support real-time research on travel trends but our team could coordinate more timely delivery with a reduced number of data providers that are able to provide raw sighting data in a timelier manner.	The upstream mobile device data policies related to data collection and privacy protection may cause significant fluctuations in data volumes, which may increase the time lag of raw data delivery and impact the timeliness of the final data products.
	Punctuality	Our team has made punctual data delivery for more than one year with occasional changes in the delivery timeline with advance notice.	Similar to the threats in timeliness, the upstream mobile device data policies related to data collection and privacy protection may cause significant fluctuations in data volumes, which may exacerbate the punctuality of the final data products.

Table 3. Data Quality Aspects in Terms of Data Objectivity

Domain	Dimension	Data Quality	Threats
Objectivity	Accuracy and reliability	The accuracy and reliability of the raw sighting data and computational algorithms have been discussed in detail in Section 1, 2, and 3.	The threats to accuracy and reliability of the raw sighting data and computational algorithms have been discussed in detail in Section 1, 2, and 3.
	Coherence	The population staying at home estimates and the number of trip estimates are straightforward and should be comparable with other relevant data. For validation, our team has compared the trip estimates with 2017 NHTS trip estimates.	The definitions of population staying at home and a trip are specific as described in Section 2, which might be different from definitions from other similar data sources.

Table 4. Data Quality Aspects in Terms of Data Integrity

Domain	Dimension	Data Quality	Threats
Integrity	Scientific integrity	The production of the deliverables adheres to scientific standards and use of scientific methods. All the data products are free from inappropriate political influence. Our team also keeps exploring the best available scientific and statistical methods.	None.
	Credibility	The University of Maryland team has a proven track record in utilizing mobile device location data to quantify person and vehicle movements. The major algorithms employed to impute the travel statistics have been previously validated. In addition, best practices in data management and data governance, already implemented at the UMD CATT Lab for two decades, have been applied to manage all data and metadata in this project to ensure data credibility.	As our team keeps exploring the best available computational algorithms in processing the sighting data and estimating the travel statistics, more biases and quality issues in previous data products may be discovered.
	Computer and physical security	The data storage, integration, and related computation are fulfilled through Amazon Web Services (AWS) with the cloud-service industrial-standard encryption and security. The access to all the raw data and intermediate outputs is strictly restricted. Best practices in data management and data governance, already implemented at the UMD CATT Lab for two decades, have also been applied to manage all data and metadata in this project to ensure data credibility.	Our team continues working on minimizing the human errors and insider threats to avoid unauthorized access to systems and data.
	Confidentiality	All raw data providers on the team are committed to privacy protection. Most data providers on our team are already in compliance with the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) regulations, and the rest are in the process of acquiring compliance. Our mobile device location data providers anonymized all the raw data and removed any personal identifiable information (PII) to ensure privacy protection before transferring the data. This means that we do not process, use, or distribute personally identifiable information in our products.	There are risks and misconceptions regarding the emerging area of market analytics using location-based information. These risks include the possibility that anonymized data could be linked together to subsequently re-identify an individual. We follow a proven approach to minimize the possibility that data could be linked together to re-identify an individual.

5. A Summary of Fitness for Using the Data for Absolute Estimates and for Estimates of Change over Time

In this section, the team makes an endeavor to assess the fitness for using the daily travel data for absolute estimates and for estimates of change over time. It is worth noting that limited ground truth data is available for such an assessment. The team has collected, explored and analyzed data from Maryland Statewide Travel Survey (Westat, 2020), Google Mobility Report (Google, 2020) and traffic loop detectors maintained by Maryland Department of Transportation (MDOT) and Regional Integrated Transportation Information System (RITIS) as comparable datasets.

The only data source that could be employed to assess the absolute values of trip rate statistics is the trip rates recorded by the Maryland Statewide Travel Survey (MTS). MTS was collected from 7,500 households residing in 18 out of 24 county-level jurisdictions within Maryland (Westat, 2020). Travel behavior during a one-day period was collected. The MTS study has found that the average trip rate per person in Maryland is 3.31 (weighted, Westat, 2020), which is visualized together with the UMD trip rate estimates in 2020 in Figure 15.

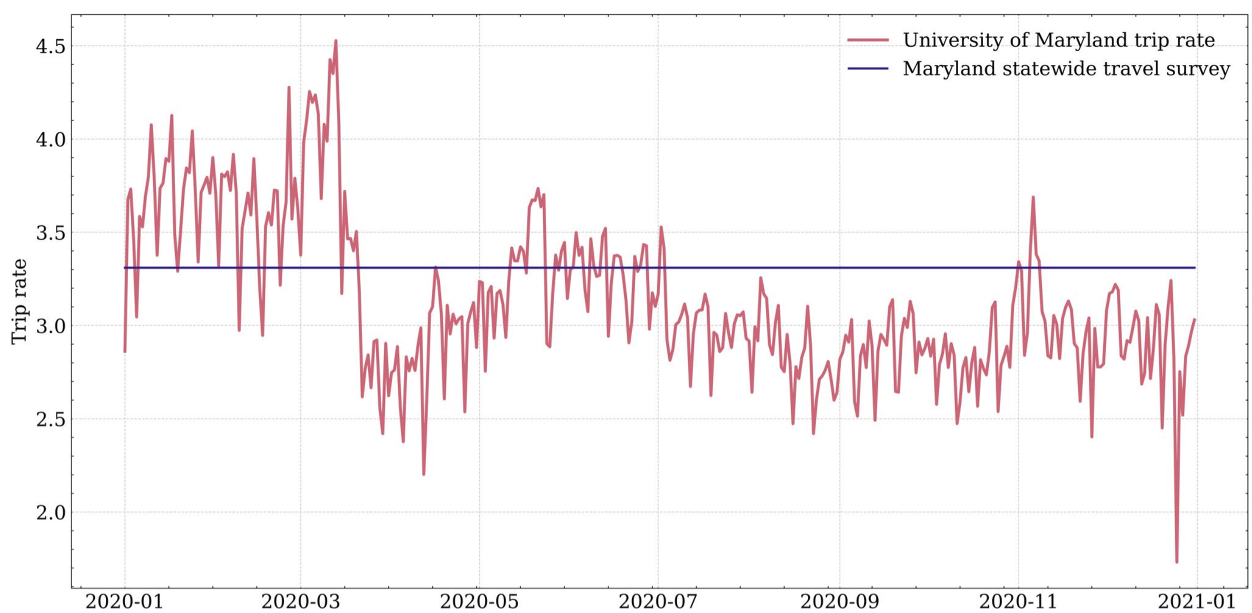


Figure 15. Comparison of trip rates per person between University of Maryland mobility data and 2018-2019 Maryland Statewide Travel Survey (MTS)

In January 2020, the MTS average trip rate was within the weekly fluctuation range of the UMD mobility data. The UMD estimated average trip rate per person in Maryland is 3.66 for January. This is a 10% overestimate. After January, excessively higher trip rates were estimated for February right before the beginning of the coronavirus pandemic (COVID-19). And then the UMD estimated trip rates dropped to lower than 3.0. Similar phenomena were also observed in other data platforms such as Google (Google, 2020, data shown in Figure 16). Overall, the estimated absolute value of trip rates per person is around the MTS survey-recorded weighted trip rates. The estimates before COVID-19 do show an overestimation. Several possible reasons could lead to this finding:

- The MTS excludes three most urbanized counties in Maryland: Montgomery, Prince George's, and Frederick while UMD mobility data reported here covers the entire state of Maryland.
- Location-based service data that UMD employs is passively collected and thus tends to capture more trips than a typical survey. This is found especially true in the shorter-distance bins of trips.
- The parameterization of the currently employed algorithms when processing the LBS data also influences the number of estimated trips. This is as highlighted in Section 3.

To study the fitness for use of the daily travel data for estimates of change over time, our team compares UMD mobility data with available evidence regarding the temporal trends on mobility. First of all, Google Community Mobility Report data (Google 2020) is employed. Instead of using one month of data, we use the entire year of 2020 in this study so the longer-term temporal trends can be assessed and compared.

Google, as well as a few other data providers, does not provide an overall estimate on the number of trips made by travelers. In Google's case, the median value of the first five weeks of 2020 is set as the benchmark. The daily values for the remainder of 2020 are then converted into estimates of mobility change over time, compared with the benchmark. To study the temporal trend, we calculate the UMD estimated mobility change in percentage based on the same method used by Google. The temporal trend of mobility change is visualized in Figure 16, together with Google's mobility change for retail & recreation, grocery & pharmacy, transit stations, and workplaces.

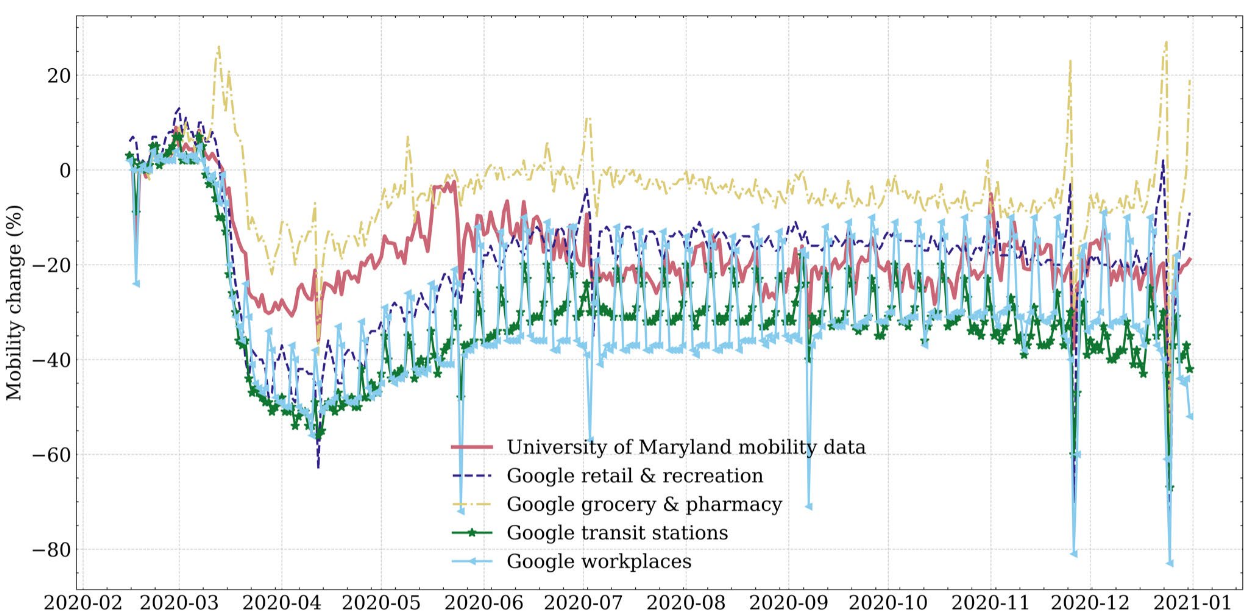


Figure 16. Comparison of mobility changes between University of Maryland mobility data and Google Community Mobility Report data

Google reports mobility changes based on different types of locations. Its estimates are based on location data collected mainly from app usage of Google Maps. As shown in Figure 16, significant mobility drop at transit stations and workplaces is observed in Google data during the pandemic onset, while the mobility drop at retail/recreation and grocery/pharmacy locations is not as dramatic. The curve of mobility change based on UMD mobility data is trending in the same direction of the four Google data curves, increasing during pre-pandemic, tumbling dramatically at the very beginning of the pandemic, then rebounding and staying stable. In terms of the magnitude of the mobility change percentage, UMD estimates are in between Google's high and low values.

In addition to comparison with other passively collected data, the temporal trend of UMD mobility data is also compared with traditional traffic data, i.e., the loop detector data obtained from the UMD RITIS platform. We collect 1,441 real-world loop detector data under the MDOT CHART program from Feb 1, 2021 to Feb 29, 2021 through the RITIS platform to measure the road traffic changes over time in the State of Maryland. Figure 17 shows the locations of these detectors. The data records the number of vehicles passing each travel lane, including a total of 9,239,029 rows for the entire February, 2021.

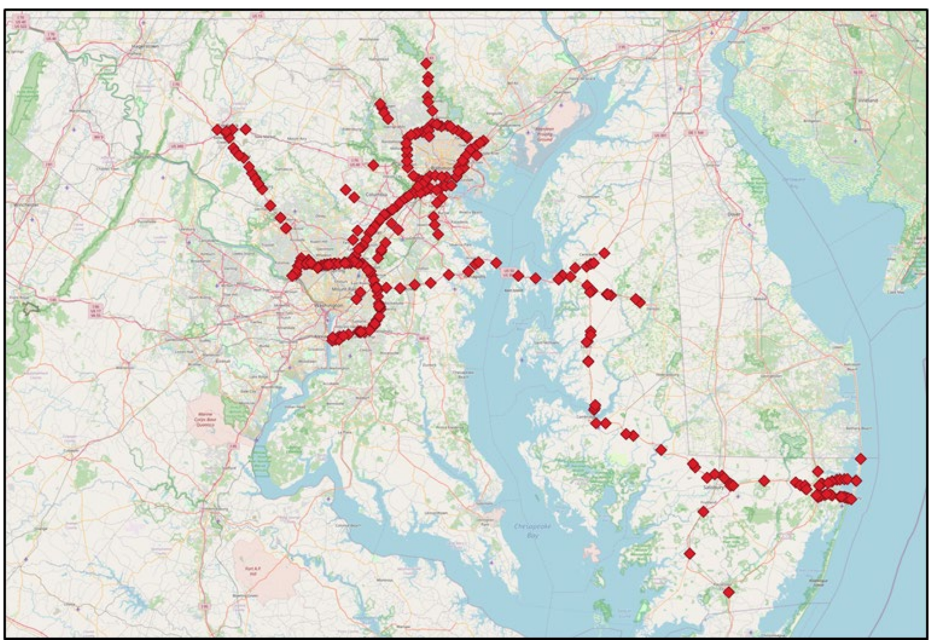
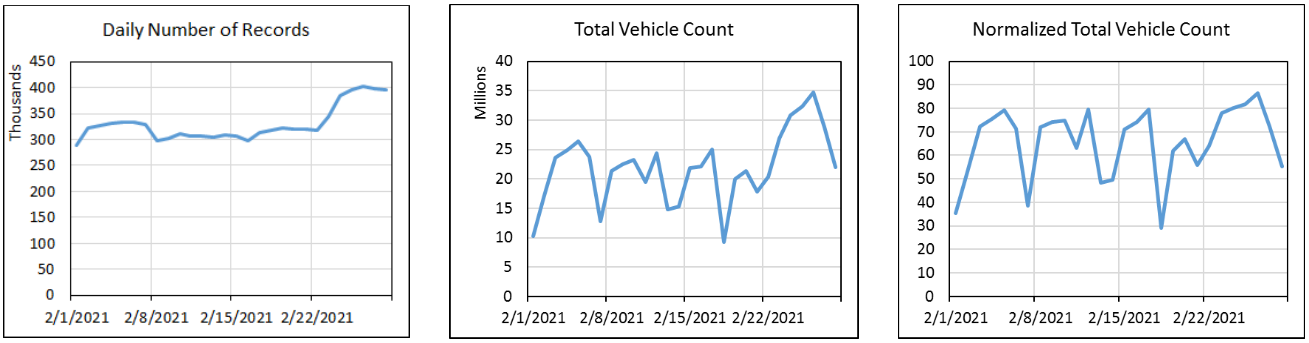


Figure 17. Spatial distribution of detector locations



(a) (b) (c)

Figure 18. Observations from RITIS data

The completeness of the RITIS data is firstly examined by counting the daily number of records, as shown in Figure 18(a). It can be seen that the daily number of records obtained from RITIS is relatively stable, while the daily number of detector data records is higher in the last week of February. The increase and decrease of the daily number of detector records are typical. The team normalizes the total daily vehicle counts (Figure 18(c)) based on the total unweighted counts (Figure 18(b)) for each day and the total daily number of records.

Then, our team evaluates the road traffic changes of February 2021 by calculating the relative ratio using February 3, 2021 (Wednesday) as the benchmark value. The same relative ratio is also calculated for the daily travel data. The equations for calculating the relative ratios are shown below:

$$Ratio\ i\ (Daily\ UMD\ Mobility\ Data) = \frac{Number\ of\ Trips\ on\ Day\ i\ -\ Number\ of\ Trips\ (benchmark)}{Number\ of\ Trips\ (benchmark)}$$

$$Ratio\ i\ (RITIS\ Count\ Data) = \frac{Normalized\ Total\ Vehicle\ Count\ on\ Day\ \ i\ -\ Normalized\ Total\ Vehicle\ Count\ (benchmark)}{Normalized\ Total\ Vehicle\ Count\ (benchmark)}$$

Figure 19 compares the relative ratios of the daily UMD mobility data and RITIS count data for the entire February 2021. Similar to the findings when conducting the comparison with LBS-based Google data, the trends of the two relative ratio curves are found consistent. The weekday-weekend fluctuations are found in an almost synchronized pattern, with a Pearson correlation value of 0.81. On the other hand, RITIS data captures a more dramatic decrease in road traffic during weekends, with the relative ratio during weekends mostly below -0.2 (including Feb 15, the Presidents' Day). While UMD mobility ratios do drop during weekends, the differences are not estimated at the same scale. It can be mainly explained by the fact that RITIS count data only captures the vehicle traffic passing certain sensors that are mainly located on major commute corridors such as I-95, I-270, and the two beltways of Baltimore and Washington D.C. During weekends and national holidays, the decrease of traffic on these major commute corridors is expected to be more significant. In comparison, the daily UMD mobility data includes multimodal travels on all streets and multimodal networks. When travelers are not commuting during weekends/holidays, their other trips, including but not limited to short-distance walk and long-distance rail/air travel, may fill their itinerary. These are part of UMD estimates but obviously cannot be captured by RITIS detector-based count data.

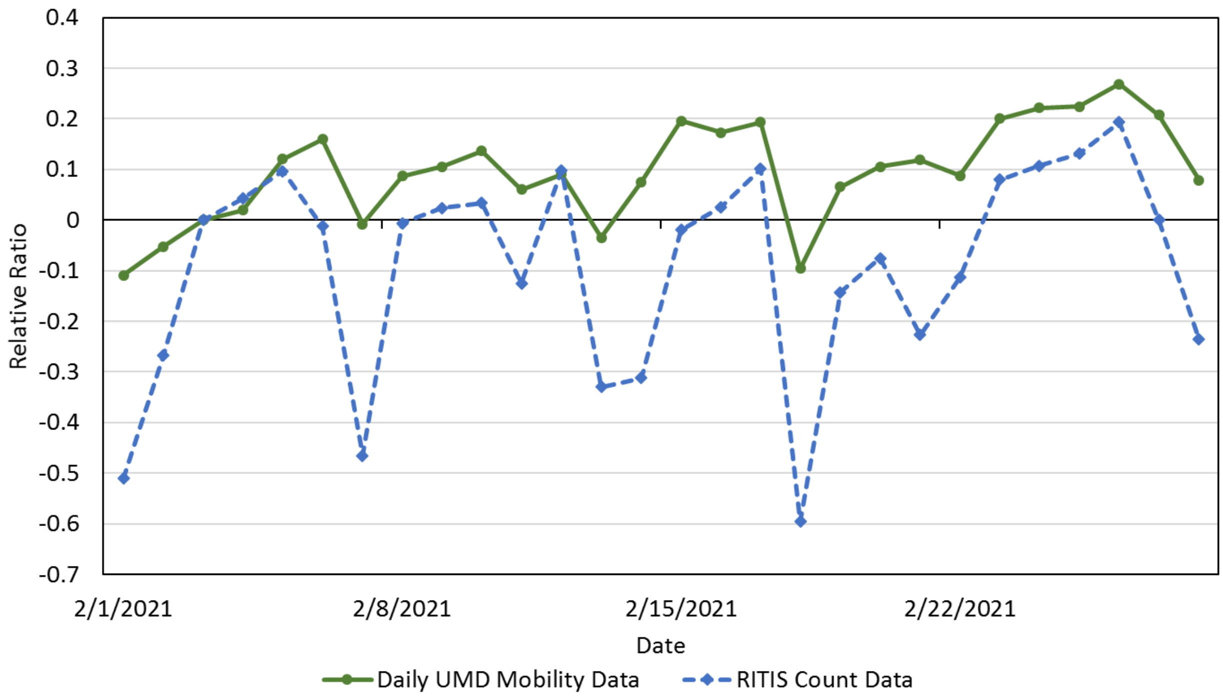


Figure 19. Comparison between UMD mobility data and RITIS count data

In summary, the team has collected and analyzed three sets of data in order to assess the fitness for using the daily UMD travel data for absolute estimates and for estimates of change over time. From the most recent Maryland Statewide Travel Survey, the team has extracted the average trip rates at the individual level. The survey only reports one day worth of data, which limits the assessment. Nevertheless, it is found the daily UMD travel data is within a 10% range of the survey reported trip rates. The slight overestimation can be attributed to limited comparable data, the nature of LBS data in capturing more trip records, and the parameterization of the team's algorithms. Again because of the lack of ground truth, the team is unable to expand in these directions. To fill the gap, it would be necessary to procure and compare with available trip-level data records from known third-party providers. The potential overestimation and parameter selection can be supplemented by a dedicated GPS-based multi-day travel survey data.

Regarding the mobility estimates of changes over time, the analyses with the Google mobility report and with Maryland traffic count data show highly consistent trends. Shorter-term weekly variations and longer-term monthly/seasonal trends are found in a comparable range with these external data sources. Again, the data discrepancy limits an exact comparison. For instance, Google reported mobility trends based on location types recorded by users' usage of Google Maps. UMD mobility data is passively collected and does not have explicit point-of-interest information. An imputation algorithm should be developed and plugged into the existing methodology to infer trip destination type and trip purpose. Similarly, travel mode imputation algorithm and network matching shall be developed and added to enable tabulations of mode-specific and route-specific trip sums. The UMD team is currently working on the development and validation of these additional algorithms and recommends updating the daily mobility data as well as this fitness assessment once the methodology is finalized.

6. Conclusion

This report assesses the quality of the University of Maryland daily mobility data submitted to the Bureau of Transportation Statistics (BTS) from five aspects. First of all, the team has conducted a thorough data evaluation to ensure the quality and representativeness of the raw location-based service data. The team assessed the device penetration rate across the nation. The results suggested a significantly higher device penetration rate compared to other competitors. In addition to overall penetration rate checks, the team also investigated the penetration rate variation for the regions with different socio-demographic characteristics considering income and race attributes. The outcome of this analysis suggests that either there is no clear bias toward any population group or the bias is minimal and can be handled through normalization methods. Finally, to provide a detailed statistical summary of the raw data, the team introduced twenty-four specific data quality metrics that can comprehensively summarize the quality of the raw data used to produce the data product.

Then, methods used for producing the daily mobility data are documented in detail. For the key parameters employed in identifying trips, sensitivity analyses have been conducted to assess the ranges of the estimated number of trips as well as its long-distance portion. For both unweighted and weighted results, the sensitivity analysis suggests that the most influential parameter is the time threshold followed by the speed and distance thresholds. Since mobile device location data can capture device movements more continuously, more long-distance trips are expected to be captured. The long-distance trip ratio estimated from mobile device location data is higher than that from both national and regional household travel surveys. However, the long-distance trip ratio after weighting becomes smaller compared with that from the unweighted results and that from the 2017 NHTS estimates. The unexpected decrease implies room for improvement in the weighting and data expansion framework. Further improvements include but are not limited to 1) establishing device-level weights by imputed socio-demographic groups to address the unequal representation of different socio-demographic groups in the mobile device location data; 2) establishing trip-level adjustment factors by imputed travel mode and time of day information to address the unequal representation of travel movements by different travel modes and in different periods; and 3) further calibration and validation of weighted trip estimates by imputed travel modes according to external ground truth data sources, such as the National Transit Database (NTD), the Airline Origin and Destination Survey (DB1B) database, and the Air Carrier Statistics database (T-100 data bank).

To assess the fitness of using the mobility data for absolute estimates and estimates of change over time, the team has collected and analyzed three sets of data. From the most recent Maryland Statewide Travel Survey, the team has extracted the average trip rates at the individual level. The survey only reports one day's worth of data, which limits the assessment. Nevertheless, it is found the daily UMD travel data is within a 10% range to the survey reported trip rates. The slight overestimation can be attributed to limited comparable data, the nature of LBS data in capturing more trip records, and the parameterization of the team's algorithms. Again because of the lack of ground truth, the team is unable to expand in these directions. To fill the gap, it would be necessary to procure and compare with available trip-level data records from known third-party providers. The potential overestimation and parameter selection can be supplemented by a dedicated GPS-based multi-day travel survey data.

Regarding the mobility estimates of changes over time, the analyses with the Google mobility report and with Maryland traffic count data show highly consistent trends. Shorter-term weekly variations and longer-term monthly/seasonal trends are found in a comparable range with these external data sources. Again, the data discrepancy limits an exact comparison. For instance, Google reported mobility trends based on location types recorded by users' usage of Google Maps. UMD mobility data is passively collected and does not have explicit point-of-interest information. An imputation algorithm should be developed and plugged into the existing methodology to infer trip destination type and trip purpose. Similarly, travel mode imputation algorithm and network matching shall be developed and added to enable tabulations of mode-specific and route-specific trip sums. These recommended methodological improvements conform with the findings in the sensitivity analyses. The team is currently working on the development and validation of these additional algorithms and recommends updating the daily mobility data as well as this fitness assessment once the methodology is finalized.

Last but not least, a summary of quality aspects regarding travel statistics following the domains and dimensions defined in "A Framework for Data Quality" developed by the Federal Committee on Statistical Methodology (FCSM, 2020) has been developed. In general, the team has been delivering a relevant, accessible, timely, and punctual data product in the required spatial and temporal granularity. The travel statistics are developed based on reliable raw data inputs from mobile device location data providers and estimated through rigorous and validated computational algorithms. During the entire process from raw data to final data products, the team carefully protects and ensures scientific integrity, credibility, computer security, and confidentiality. The team has also summarized a comprehensive list of potential threats in terms of each data quality dimension and will keep working on ameliorating the risks.

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