The Lure of Big Data: Evaluating the Efficacy of Mobile Phone Data for Travel Model Validation

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ABSTRACT

The use of mobile phone location data to support transportation planning and travel behavior analysis is becoming common practice for many agencies, driven largely by the large sample size and lower costs for acquiring and processing the data. With recent successes to build from, these data are becoming more heavily marketed to transportation planning practitioners. The challenge is that these practitioners have few tools at their disposal for understanding data acquisition, data quality, data limitations, and data application issues. This lack of understanding can lead to situations where agencies invest in a product that does not fully meet their needs because they did not have a full understanding of the limitations, or conversely, that they purchase these data for a specific need but do not exploit these data to its full potential thereby not maximizing the return on their investment.

This paper attempts to address many of those questions through a detailed analysis of AirSage data in comparison to a household travel survey conducted during the same time period. Also presented is a methodology for performing reasonableness checks on the data for agencies who cannot afford to invest in both a household travel survey and the collection of mobile phone location data. Finally, this paper offers practitioners with valuable insights into using mobile phone location data to support travel model validation. Through this presentation of information, this paper contributes to the discussion of using big data as a low cost option for travel model validation.

INTRODUCTION AND MOTIVATION

The use of mobile phone location data to support transportation planning and travel behavior analysis is becoming common practice for many agencies, driven largely by the large sample size and lower costs for acquiring and processing the data. With recent successes to build from, these data are becoming more heavily marketed to transportation planning practitioners. The challenge is that these practitioners have few tools at their disposal for understanding data acquisition, data quality, data limitations, and data application issues. This lack of understanding can lead to situations where agencies invest in a product that does not fully meet their needs because they did not have a full understanding of the limitations, or conversely, that they purchase these data for a specific need but do not exploit these data to its full potential thereby not maximizing the return on their investment.

This paper attempts to address many of those questions through a detailed analysis of AirSage data in comparison to a household travel survey conducted during the same time period. Also presented is a methodology for performing reasonableness checks on the data for agencies who cannot afford to invest in both a household travel survey and the collection of mobile phone location data. Finally, this paper offers practitioners with valuable insights into using mobile phone location data to support travel model validation. Through this presentation of information, this paper contributes to the discussion of using big data as a low cost option for travel validation.

LITERATURE REVIEW

Travel modelers face many challenges when it comes to obtaining data for model estimation, calibration, and validation. Household travel surveys have been the staple of travel model development for decades. The data collected from these surveys help describe travel behavior and provide a framework for model estimation that captures local travel behavior and enables transportation planners to forecast future travel behavior. There are many new challenges with the traditional methods for travel survey data collection including rising cost, an increasing number of cell phone users in the population, and declining response rates [1]. The underreporting of trips in traditional household surveys is also becoming a concern. Comparisons of the number and pattern of trips collected using traditional household survey methods and those supplemented by GPS show significant differences between the two data sources that vary by purpose, model duration, and time of day [2]. This research further highlights the challenges with traditional household surveys, and shows the benefit of supplementing these surveys with GPS in an effort to better understand the patterns of travel behavior [2]. Another challenge with household survey data for travel model development is that while they are behaviorally rich, the sample size if also very small at a traffic analysis zone (TAZ) to TAZ level, limiting out understanding of origin-destination patterns at a sub-district level. With the cost of household surveys rising, and the challenges of recruiting participants increasing, it is not surprising that the ability to passively collect mobile phone data is gaining traction as a low cost data source to support travel model development.

The early use of mobile phone data in transportation analysis focused on travel time and congestion monitoring. One study shows that mobile phone technology is useful for collecting travel speeds on urban expressways and open highways where mobile phone collected data match well with observed conditions [3]. In another example, the Capital Area Metropolitan Planning Organization (CAMPO) in Raleigh, North Carolina used mobile phone data for speed and travel time validation to support the Triangle Regional Model [4]. Data collection covered over 800 centerline miles of roadway, 24 hours/day, for seven days per week during the entire month of March 2010. This approach yielded a significant cost savings over traditional methods, and provided the region with data that was useful for useful for travel time comparisons against regional model, volume-delay function development, and support of CAMPOs congestion management program.

Recent examples show that the use of mobile phone data has expanded to support the development of origin-destination trip tables. This advance shows particular promise in capturing information about externals trips, trips missed in traditional household surveys, and for the validation of trip distribution models. One example of using mobile phone data for these purposes was in South Alabama where the Regional Planning Commission used passively collected mobile phone data to produce average trip patterns and travel movements, identify origin and destination points, validate the resident trip distribution model, and develop external trip tables [5]. In another example of using origin-destination trip tables for transportation planning, planners in Moore County, North Carolina used mobile phone location data to help evaluate the need for a bypass of the US 1 corridor through that county [6]. The study showed that very few travelers in the corridor were through trips, but rather that most travelers had either origins or destinations within the corridor.

Research conducted at the University of Kansas demonstrated the use of mobile phone data and Geographical Information Systems (GIS) to identify and track freight movements to and from a regional distribution center [7]. In this example, researchers analyzed the potential of cell phone positioning techniques in combination with GIS to identify truck movements and to map freight travel sheds. In a transit related application, researchers used mobile phone data to perform transit analysis and optimization that allowed them to develop a profile of existing ridership [8]. New candidate transit routes were also evaluated by extracting sequential travel patterns from individual call location data. The scope of mobile phone data to support transportation planning and travel modeling is continuing to expand with the growing popularity of GPS-enabled mobile phone devices. One recent study investigated the use of GPS-enabled mobile phones for collecting travel survey data [9]. Their study showed that GPS-enabled mobile phones provide location data of similar quality to standalone GPS devices, supporting the use of this technology for GPS enhanced household travel surveys. Yet another study showed the benefit of using mobile phone data to develop external trip models [10].

While there are many examples of interesting and innovative uses of passively collected mobile phone data to support travel analysis, the literature lacks direct references of comparisons that were made between this data and travel demand model outputs from a calibrated and validated model based on locally collected household survey data. The work presented in this paper provides such a comparison.

BACKGROUND

The work described in this paper was performed in cooperation with the French Broad River Metropolitan Planning Organization (FBRMPO) and the North Carolina Department of Transportation (NCDOT). The FBRMPO is located in the mountains of North Carolina covers the counties of Buncombe, Haywood, and Henderson. The model region for the MPO also includes the counties of Madison and Transylvania. The NCDOT and FBRMPO supported the collection of travel behavior data to support the development of a new generation model that reflects best practice for a community of this size in order to better respond regional growth and demands on the transportation system.

METHODOLOGY

Data

The data supporting this analysis includes mobile phone location data, a household travel survey, a fully attributed highway street system, and a traffic analysis zone system with population, household, and employment data.

AirSage Data

Cellular phone location data was collected by AirSage, Inc. for observed weekday travel patterns during the month of May 2013. Using proprietary procedures, these data were processed and expanded by AirSage to represent the population of the region. The data was provided as district to district trip pairs, including districts internal to the FBRMPO model region, and districts external to the region for a total of 150 districts. The district system used for the AirSage data collection was developed by WSP Parsons Brinckerhoff and reflects an aggregation of model traffic analysis zones (TAZs) such that the AirSage districts are larger than the model TAZs, but smaller than the super-districts used for processing the household survey data. The development of the 150 districts used for collecting the AirSage data took into consideration the current model TAZs, the location of external station roadways, street connectivity outside the modeled region, and land development patterns internal and external to the model.

Using proprietary algorithms for processing the data into trip purposes, AirSage disaggregated the average weekday trip tables into three trip purposes (home-based work, home-based other, and non-home-based) by time-of-day (AM-peak period, PM-peak period, and daily). The AM-peak period and PM-peak period match the peak periods in the travel demand model. The final data records were identified as resident (household location within the study area) or non-resident (household location outside the study area) trips. The final data product from AirSage was two separate data tables with different aggregations of the base data. One table included all the daily data records, and the second table included data records for the AM and PM peaks only. The data for both tables is in origin-destination (OD) format and reflects person trips, not vehicle trips.

Figure 1 provides a screenshot of the data format provided by AirSage. The data format for the AM and PM period is exactly the same with the exception of the Time_of_Day field. The data includes origin and destination zone, start date, visitor/resident flag, trip purpose, time of day, and expanded trip count. Scripts were written to process this data into observed trip tables by class and purpose for each time period.

Origin_Zone	Destination_Zone	Start_Date	End_Date	Aggregation	Subscriber_Class	Purpose	Time_of_Day	Count
56	7	20130501	20130530	WD	Visitor	NHB	H00:H24	2.01
131	91	20130501	20130530	WD	Resident	HBO	H00:H24	13.54
73	56	20130501	20130530	WD	Resident	HBO	H00:H24	1.61
144	34	20130501	20130530	WD	Visitor	NHB	H00:H24	14.92
61	72	20130501	20130530	WD	Resident	NHB	H00:H24	18.38
71	76	20130501	20130530	WD	Resident	NHB	H00:H24	31.26
52	76	20130501	20130530	WD	Resident	NHB	H00:H24	7.7
63	148	20130501	20130530	WD	Resident	HBO	H00:H24	10

Figure 1 Sample AirSage Daily Data Records

Household Travel Survey

The FBRMPO in cooperation with NCDOT contracted with WSP Parsons Brinckerhoff and Westat, Inc. to collect household travel data to support development of the travel model. The survey was conducted in the late spring of 2013 and included a target sample size of 1,300 households, though the final sample exceeded this number, with 1,434 usable household survey records. The survey was administered as a multi-mode survey and included the collection of basic demographic and household level data along with individual travel behavior over a 24-hour period.

FBRMPO Travel Demand Model

The FBRMPO model includes 643 internal TAZs and 29 external TAZs. The model is an advanced trip-based formulation that includes a destination choice model in place of the standard gravity model, and a nested logit model for performing mode choice. Key data elements from the FBRMPO model supporting this investigation include socio-economic data by TAZ and an attributed highway network including traffic counts.

Approach

Reasonableness Checking

Having access to a household survey collected during the same time period as the mobile phone data provided a unique opportunity for comparing and contrasting the two data sets. The initial comparisons focused on regional level comparisons of trips by trip purpose and trips by time of day. Table 1 provides a summary of total trips by resident status and resident status by trip purpose. The majority of trips captured in the AirSage sample were trips made by folks with at least one end of the trip outside of the modeled region. The comparison of trips by trip purpose against the household survey (HHS) shows that the mobile phone data slightly overestimates home-based trips.

Table 1 Total Trips by Resident Status and Trip Purpose (AirSage Data)

Resident versus Non-Resident			
	Trips	Percent	HHS
Resident	951,204	34%	NA
Non-Resident	1,882,722	66%	NA
Total	2,833,926		
Trips by Trip Purpose (Resident Only)			
	Trips	Percent	HHS
HBW	184,551	19%	16%
HBO	548,748	58%	49%
NHB	217,905	23%	35%
Total	951,204		

Table 2 provides a summary of resident trips by time period and by trip purpose and time period. The AM period is defined as 6 a.m. to 9 a.m. and the PM peak is defined as 4 p.m. to 7 p.m. In this case the percentage of trips by period between the mobile phone data and the household survey are very close. The comparison of trips by time period is further explored by investigating the distribution of trips by trip purpose within each time period. The AM trips by purpose shows a close match between the mobile phone data and the household survey, while the differences are much greater in the PM. The percentage of HBW trips is similar between the two data sets in the PM period, but the HBO trips are 16 percent higher in the mobile phone data, and the NHB trips are 13 percent lower.

Table 2 Resident Trips by Time Period and Trip Purpose (AirSage Data)

	Total Trips by Time Period		
	Trips	Percent	HHS
AM	139,734	15%	14%
PM	176,733	18%	18%
Off Peak	634,737	67%	68%
Total	951,204		
	By Purpose and Time Period		
	Trips	Percent	HHS
AM			
HBW	47,538	34%	31%
HBO	65,769	47%	46%
NHB	26,427	19%	23%
PM			
HBW	29,861	17%	20%
HBO	102,116	58%	42%
NHB	44,756	25%	38%

Data Processing

After performing reasonableness checks of the data at a regional level, the next step involved processing the data for the purposes of generating several geographic comparisons, including county-to-county flows, district-to-district flows, and the creation of TAZ-to-TAZ trip tables in order to develop trip length distributions using the model highway network. For these comparisons external trips were excluded from analysis as the household survey is a survey of resident trips only.

The disaggregation of trips to the TAZ geography relies heavily on the underlying SE data. The AirSage data is provided in OD format requiring consideration of both population and employment in the disaggregation process. A measure of activity was calculated for each TAZ using the activity index shown in Equation 1. The ratio of regional population (Reg.Pop) to regional employment (Reg.Emp) is used to scale the contribution of employment in the activity index.

$$Activity\ Index = Population + Employment * \frac{Reg.Pop}{Reg.Emp} \qquad (1)$$

The Activity Index was calculated for each TAZ in the study area and used to disaggregate the AirSage district OD trips to TAZ OD trips. The process of disaggregation was applied twice, once for origins and once for destinations.

RESULTS

Several comparisons were carried out to assess whether the AirSage trip tables resembled the HHS trip tables. Since mobile phone data are often used as a data source for calibrating trip length distribution and district-to-district flows, the comparisons include these measures. Also included is a comparison at the county-to-county geography. This geography is the most aggregate and easy to visualize and understand. The household survey is weighted and expanded to county population, so it is at this geography where we would expect the comparisons between the two data sets to show the most similarity. The final comparison is designed to try and answer the question with respect to how well the AirSage OD trips table assigned to the highway network matches observed traffic counts. For this comparison, the AirSage trip table including all trips (internal and external) was assigned to the highway network and various measures of effectiveness were compiled.

Travel Time

The first comparison looks at the zone to zone travel times by trip purpose and time of day. Table 3 summarizes the average trip length in minutes. In general, the average trip length between the two data sets is comparable with the exception of the NHB trips, not surprising given the process for synthesizing the raw data into trip purposes. The process appears to be most effective for home-based trips as the home and work locations are easier to identify over the month long data collection. It is also possible that the NHB purpose has the highest level of error resulting from the triangulation process.

Table 3 Average Trip Length (minutes) for AirSage and HHS

Trip Purpose	Period	AirSage	HHS	% Diff
HBW	AM	13.6	13.3	2%
	PM	13.5	12.3	9%
	Off-Peak	12.6	10.9	15%
HBO	AM	9.9	9.6	3%
	PM	9.4	9.0	5%
	Off-Peak	8.9	8.9	0%
NHB	AM	11.1	9.5	17%
	PM	10.8	8.6	26%
	Off-Peak	10.3	7.3	42%

The trip length distributions by trip purpose for the AM and PM periods are shown in Figure 2. These curves show consistency between the AirSage data and the HHS data.

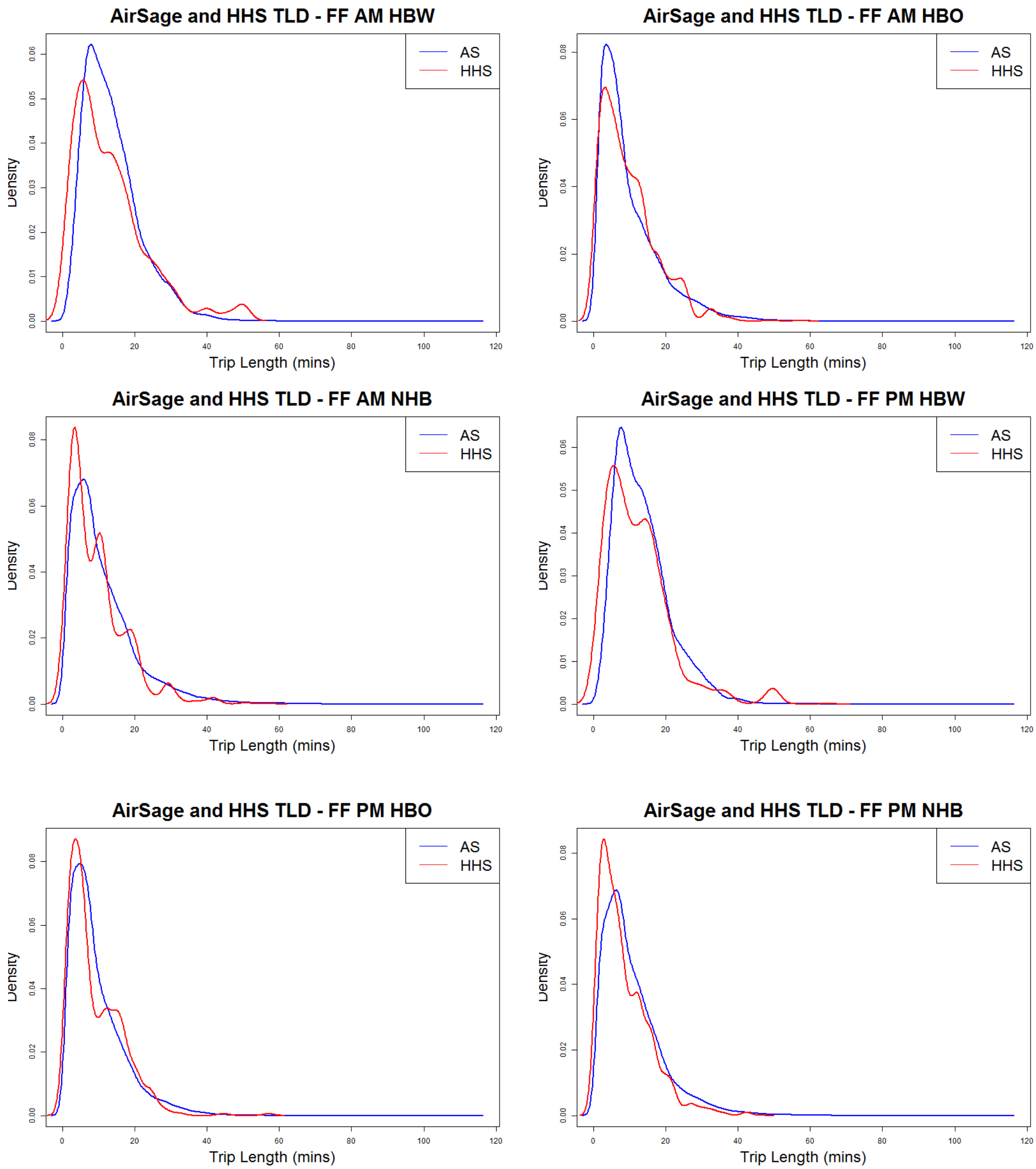


Figure 2 Comparisons of AirSage and HHS Data by Trip Purpose (AM and PM Peak)

District to District Flows

The next comparison considered differences in the district-to-district flows between the two sources. Figure 3 shows the FBRMPO district system, the comparisons in Figure 4 show the absolute error and the relative error for the district interchanges by trip purpose. Absolute error and relative error are defined as:

$$AbsoluteError = \left|Trips_{AirSage} - Trips_{HHS}\right| \quad (2)$$

$$RelativeError = \frac{AbsoluteError}{Trips_{HHS}} \quad (3)$$

The purpose of this comparison is to evaluate trip interchanges by both measures of error. The absolute error shows the absolute difference between the HHS trips and the AirSage trips, but does not give an indication of how significant the error is. The relative error gives an indication of how good the AirSage trip interchange is relative to the HHS trip interchange. Color coding is used to identify the trip interchanges with high absolute and high relative error, high absolute and low relative error, low absolute and high relative error, and low absolute and low relative error. The tables at the bottom of Figure 4 show the district interchanges for each trip purpose where both the absolute and relative error was is high.

The highest combined error is along the diagonal of the table, which are also the district interchanges with the highest number of trips. The diagonal represents trips that stay within a given district, and the districts with the highest absolute and relative error tend to be the districts in the less populated regions of the study area. The largest combined error for the inter-district flows are for flows to and from the districts within Buncombe County, the largest county in the region. In general, the household survey shows a much larger proportion of trips that stay internal to the districts, this is especially true for the district representing the City of Asheville across all trip purposes. Likewise, the mobile phone data shows more observed trip interchanges between districts across the region. This comparison seems to point out one of the underlying strengths of the large sample mobile phone data for understanding OD trip patterns at lower levels of disaggregation, as the household survey is constrained by a smaller sample size.

The correlation coefficient was calculated to further investigate the question of fit between the district-to-district flows. The correlation coefficient between the two data arrays is 0.77, suggesting a reasonable fit of the data between the two sources. Removing all of the intra-district flows increases the value to 0.88 further highlighting the intrazonals as the biggest difference between the two data sources.

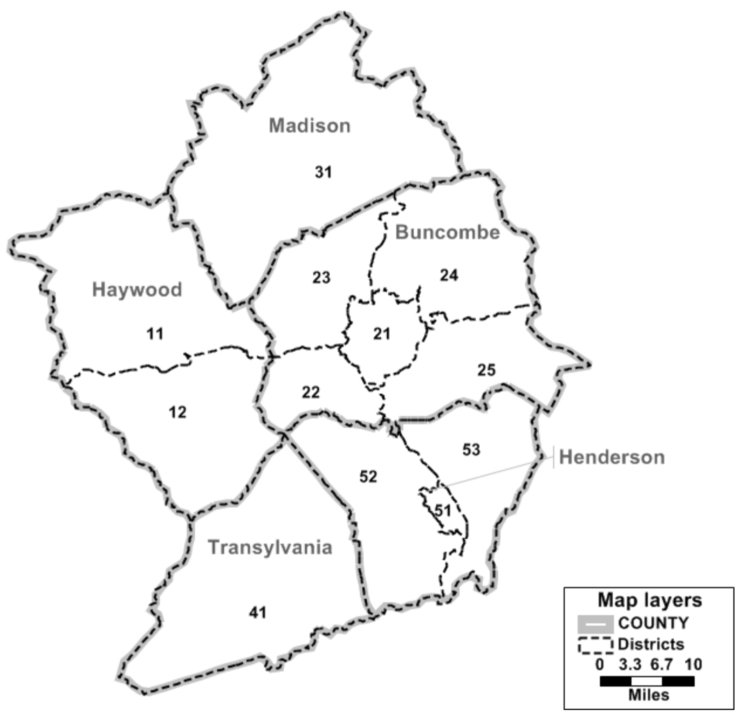
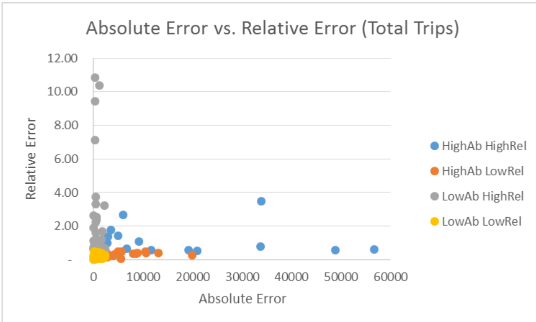
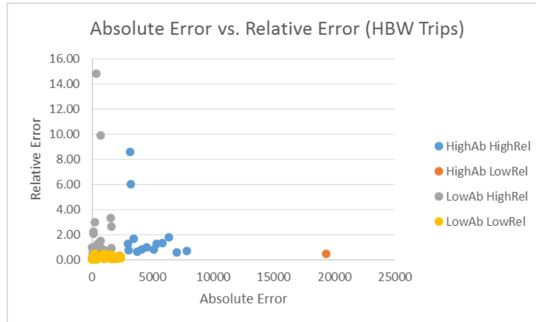
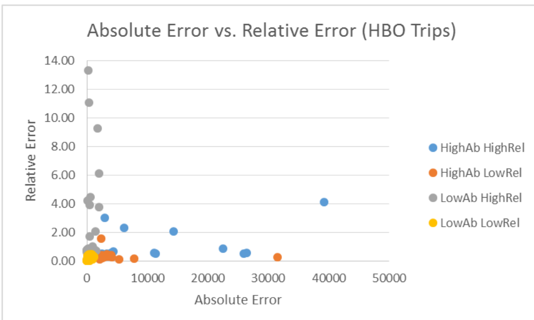
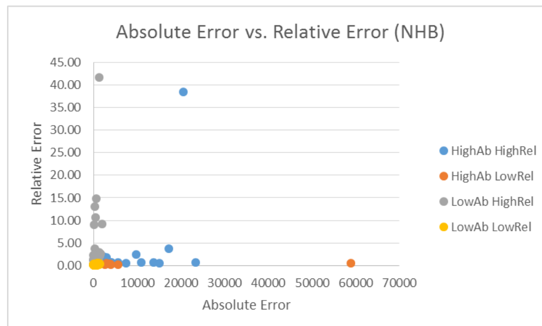


Figure 3 FBRMPO District System with County Lines









TOT	11	12	21	22	23	24	25	31	41	51	52	53
11												
12												
21												
22												
23												
24												
25												
31												
41												
51												
52												
53												

HBW	11	12	21	22	23	24	25	31	41	51	52	53
11												
12												
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53												

HBO	11	12	21	22	23	24	25	31	41	51	52	53
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NHB	11	12	21	22	23	24	25	31	41	51	52	53
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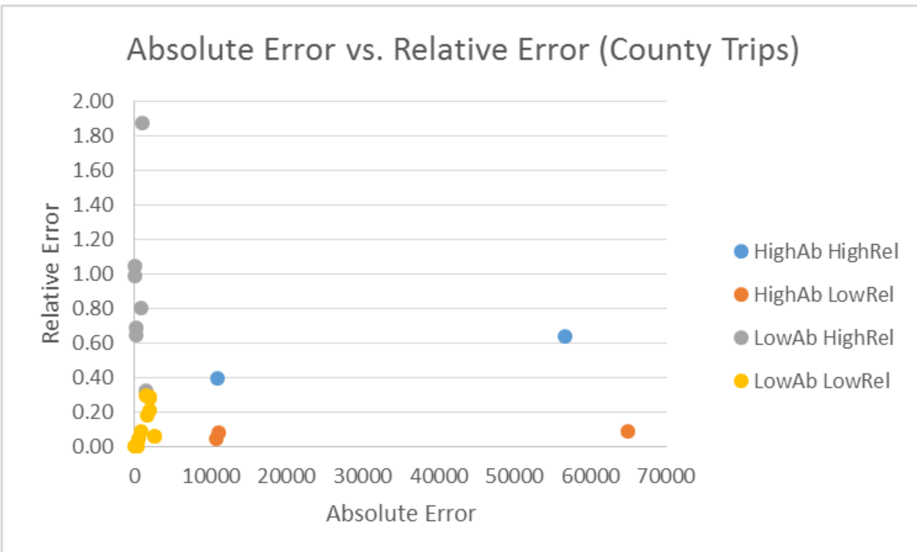
Figure 4 District to District Flow Comparisons

County to County Flows

It is during the comparisons of flows that the mobile phone data shines from the standpoint of number of observations. Even after aggregating the TAZs to 12 districts, there are still district interchanges with low or no trip observations, and this becomes more pronounced when the data are viewed by trip purpose. To overcome the sparseness of the HHS data at the district level, a county level comparison of flows was also conducted. Figure 5 shows the absolute error and the relative error for the county interchanges by total trips. Overall, the county-to-county comparisons are encouraging, with only two interchanges having both high absolute error and high relative error. These two interchanges are for intra-county trips for both Madison and Transylvania counties. Both counties are dominated by National Forests and have fewer than 100 persons per square mile. The collection of mobile phone data is heavily dependent on the placement of cell towers for picking up signaling data. When the population is sparse there are fewer cell towers available and the error in the mobile phone data increases as a result.



TOT	Buncombe	Haywood	Henderson	Madison	Transylvania
Buncombe					
Haywood					
Henderson					
Madison					
Transylvania					

Figure 5 County to County Flow Comparisons

Highway Assignment

The final comparison focuses on highway assignment metrics and how well the assigned mobile phone trip table compares to observed traffic counts. The assignment included the resident trips internal to the region, the external trips passing through the region, and all trips with one trip end within the region and the other trip end outside of the region. The highway assignment was performed for the AM, PM, and off-peak periods separately and then summed to a daily assignment for comparisons against traffic counts. A user equilibrium assignment was performed with user parameters set to 999 iterations and a convergence factor of 0.0001.

Table 4 provides a summary of performance metrics. In comparison to the counts, the mobile phone data performs best on freeway facilities and higher volume facilities both in terms of percent difference and percent root mean square error (%RMSE). Overall the mobile phone trip table is 16.6% low, suggesting that certain type of trips may be missing from the observed trip matrix. The %RMSE is also higher than desired at 50.7%, ideally this value would be 40% or lower.

Table 4 Highway Assignment Performance Measures for AirSage Trip Table

By Facility Type					
Facility Type	No. Counts	Count Volume	AirSage Flow	% Difference	%RMSE
Freeways	109	2,444,763	2,541,397	4.0%	23.3
Major Thoroughfares	352	3,718,053	2,653,541	-28.6%	52.9
Minor Thoroughfares	414	1,216,702	962,170	-20.9%	76.2
All Facilities	875	7,379,518	6,157,108	-16.6%	50.7
By Volume Group					
Volume Group	No. Counts	Count Volume	AirSage Flow	% Difference	%RMSE
Less than 4,999	435	889,503	812,448	-8.7%	98.7
5,000 – 9,999	176	1,278,406	793,222	-38.0%	58.6
10,000 – 19,000	153	2,145,973	1,737,840	-19.0%	46.5
20,000 – 39,999	107	2,881,132	2,658,483	-7.7%	23.6
Greater than 40,000	4	184,504	155,117	-15.9%	16.3

Findings and Benefits

Trip length distribution, average travel time, district-to-district and county-to-county flow comparisons between the AirSage trip table and the HHS trip table compare favorably. The findings from the comparisons presented in this paper suggest that mobile phone location data is a useful source of information for calibrating a trip distribution model for communities without a locally collected HHS. At the very least it can be asserted that the AirSage data are capable of depicting the same regional travel patterns as the household survey data.

The highway assignment outcomes also suggests that the AirSage data captured traffic flows on the highway network. In aggregate the AirSage assignment results are lower than the total volume reflected in the traffic count data, but within 16.6 percent of the observed data. The lower overall trips suggests the possible need to normalize the AirSage trip table to account for trips not well represented in the sample, but most importantly show the benefit of using mobile phone data to inform the model calibration and validation process.

The investigations presented in this paper benefit the travel modeling and transportation planning community by providing a documented case study supporting the efficacy of mobile phone location data in the calibration and validation of travel demand models. This is particularly beneficial to small and medium-sized communities who may not be able to afford the collection of household travel survey data, but may be uncertain of the value of mobile phone data in supporting travel model development. For communities that can afford to collect mobile phone data to supplement a household travel survey, this paper outlines several techniques for validating the mobile phone location data and for using the mobile phone data to develop a richer understanding of travel patterns at a more disaggregate level than that available from the household survey.

SUMMARY AND CONCLUSIONS

This paper reports on the findings of comparisons between trip tables generated from passively collected mobile phone location data versus those developed from household travel survey data. The investigations reported in this paper describe but one approach for validating mobile phone data to be used for model calibration through the comparison of an assigned mobile phone trip table to observed traffic counts. The mobile phone data used in this study were collected to support model development for the French Broad River Metropolitan Planning Organization (FBRMPO) in North Carolina. AM, PM, and daily trip tables were provided by AirSage, Inc. at a district level and where disaggregated into traffic analysis zones (TAZs). The analysis focused on assessing the usefulness of the mobile phone data for calibrating trip distribution models, and on validating the mobile phone data against household travel survey data and observed traffic counts. The metrics reported include trip length distribution, average travel time, district-to-district flows, and county-to-county flow. To validate the mobile phone data against traffic counts, the trip tables were assigned to the FBRMPO highway network attributed with traffic count data. The metrics reported include highway assignment summaries by facility type and volume group.

The investigation revealed that the travel patterns gleaned from the mobile phone data compared favorably to the trip length frequency distribution and trip tables from the household travel survey. Results show that the mobile phone data also validated well in highway assignment. In this case the AirSage assignment compared favorably to observed traffic counts using various performance measure metrics. The results demonstrate that mobile phone data can support travel model calibration and validation at a low cost relative to a household survey. These data are superior to a household travel survey with respect to sample size, especially when it comes to better understanding origin-destination flow patterns at a disaggregate level. However, mobile phone data do not provide the behavioral richness necessary for estimating behaviorally based travel models. The best approach appears to be one that combines passively collected mobile phone data with a household travel survey, as the former offers substantially greater insight into origin-destination patterns at a disaggregate level. This added level of validation may offer insight into the model and estimated travel patterns that might be missed through the use of traditional data alone.

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