

Conducting Trade Area Analysis Using Mobile Data: The Case of Michigan's Super-Regional Shopping Centres

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Abstract

The increasing availability of spatial big data has revolutionized data analytics and provided valuable insights into consumer behaviour. Spatial big data has enabled retailers to optimize product assortment, pricing, site selection, and trade area analysis. Mobile location data has further enhanced the analysis of individual consumer mobility patterns, offering a more detailed understanding of movement in various contexts. However, using mobile location data for trade area analysis in retail remains understudied. This study aims to fill this gap by employing advanced methods of trade area analysis using mobile location data. Two research questions guide the study: 1) How effective is mobile location data in modelling shopping centre trade area activity? and 2) How reliable are the derived metrics in reflecting changes in trade area consumer traffic patterns during and after the global COVID-19 pandemic? By addressing these questions, this study enhances our understanding of the potential of mobile location data for trade area analysis in retail. It provides insights into consumer behaviour dynamics during the pandemic.

1. Introduction

The availability and use of spatial big data have significantly increased in recent years, creating unparalleled opportunities for decision-makers within various fields to leverage data analytics to understand consumer behaviours more deeply. Spatial big data has become ubiquitous in the retail industry, allowing retailers to optimize various business decisions,

including; merchandising, price optimization and site selection (Atkas and Meng, 2017). With the growth in mobile location data, it is becoming far easier to understand individual consumer mobility patterns over time (Aversa et al., 2022). Mobile location data facilitates the process of analyzing movement at the most granular level, which can be applied in various applications, such as traffic analysis (Herrera et al., 2010), identifying consumer travel patterns, and trade area analysis (Chen et al., 2018).

Mobile location data has gained considerable attention for its potential in trade area analysis, as it can provide valuable insights into customer travel patterns: pre-visit, during and post-visit to shopping destinations. Therefore, by leveraging this data, retailers can obtain a more comprehensive understanding of the origin of customers and their subsequent activities after leaving a retail establishment (Qu and Zhu, 2013). The literature on mobile location data for trade area analysis is scarce compared to other interdisciplinary mobile data-based studies. As such, this study aims to fill the gap by executing a nuanced method of Trade Area Analysis that relies on mobile location data. With this in mind, this study has the following two interconnected research questions: (i) How effective is mobile location data in modelling shopping centre trade area activity? and (ii) How reliable are the derived metrics in reflecting changes in trade area consumer traffic patterns during and after the global COVID-19 pandemic?

2. Research Context

2.1 Big Data and the Retail Environment

Given the unprecedented rate at which information is collected, the discussion around big data has garnered mass interest from industry and academia (Jin et al., 2015). The definitions for big data have varied over time; however, there is consensus regarding the three central qualities attributed to this type of data - the so-called 3Vs (Gandomi and Haider, 2014). The 3Vs of Volume, Variety, and Velocity refer to the size and magnitude of the data, their associated structural heterogeneity, and the speed or rate at which information is being collected and made available

(Lovelace et al., 2014). Other studies have added two additional Vs, Veracity and Value, to form the 5Vs (Rodríguez-Mazahua et al., 2015). Veracity is important when assessing big data, as the term refers to the inherent unreliability of some data sources (Gandomi and Haider, 2014) – a common feature of mobile location data. Big datasets contain a considerable amount of noise and errors, which raises questions about the quality, validity and overall process of assessing the value of acquiring such datasets. Value refers to the growing importance of assessing the costs and benefits of big data to extract meaningful insights. Taking the 5Vs into consideration is essential, especially when making business decisions, as adopting big data requires significant investment (Lovelace et al., 2016). From a practical perspective, big data can be defined as unconventional datasets in form and size and yield great difficulties in analysis using pre-established methods (Lovelace et al., 2016). Even though this definition contains no explicit mention of 5Vs, it can be assumed that these attributes are implicitly considered when assessing big datasets.

The usage and application of big data in the retail sector have garnered significant research attention (Atkas and Meng, 2017; Santaro et al., 2019; Sazu and Jahan, 2022; Silva et al., 2020), citing the potential that big data analytics provide for solving problems in several areas such as product assortment, design, procurement, and pricing (Atkas and Meng, 2017). Retail organizations can capitalize on big data to formulate strategies for the different facets of their operations, which factors heavily into location analysis and planning (Qu and Zhang, 2013).

Consumers in the retail sector generate vast amounts of data, which can be transactional and structured or behavioural and unstructured (Erevelles et al., 2016). Leveraging structured and unstructured data allows organizations to create new consumer insights to account for and address emerging consumer needs (Erevelles et al., 2016). By harnessing appropriate tools to analyze big data, retailers can proactively modify their practices and strategies, leading to enhanced sales performance. Retailers can gain valuable insights by analyzing larger datasets that encompass consumer-centric performance metrics such as consumer satisfaction, repeat visits, and conversion rates. Such performance metrics allow retailers to make data-driven

called 3Vs (Gandomi and Haider, 2014). The 3Vs of Volume, Variety, and Velocity refer to the size and magnitude of the data, their associated structural heterogeneity, and the speed or rate at which information is being collected and made available

decisions and optimize their operations to meet consumer needs better (Ying et al., 2020). Furthermore, big data allows retailers to potentially target new customers and facilitate insights that assist with retaining pre-existing customers to maximize sales.

2.2 Trade Area Analysis

Retail Trade Area Analysis (TAA) has been extensively utilized by practitioners and academics to understand the spatial dynamics of consumers, their behaviour, retail competition, and the overall market conditions that determine the success of retail locations (Hernandez et al., 2022). Generally, TAA emphasizes identifying a target market's characteristics to understand retail patronage (Dramowicz, 2005). Lea (1998) defines a trade area as the spatial area in the vicinity of the store in which a retailer retains its patrons. However, this definition falls short of capturing the overall essence of trade areas since it is too broad, given the fact that the attributes that define a trade area have evolved dramatically since the earliest conceptualizations of trade area by Reilly (1931).

Trade areas were traditionally conceptualized hierarchically based on the proximity around retail stores: the primary zone (closest to the store) and the secondary and tertiary zones (increasingly further from the store). For example, the primary zone could capture 60% of the closest customers; the secondary zone is the ring of the nearest 60% to 80% of customers; the tertiary zone contains consumers that travel considerable distances to reach a location, i.e., the ring beyond the closest 80% to 95% of customers.

Several normative methods are available for trade area delimitation, encompassing both straightforward and intricate approaches. These methods can be enhanced and refined to better suit specific requirements. (Hernandez et al., 2022). For example, simple methods include the ring model, which builds on Christaller's central place theory (1933). Here, the store location is used as a central point of interest, and rings are drawn around the centre to represent the service area for that location of interest visually. This is also known as the concentric morphological model (Applebaum and

Cohen, 1966), and it assumes that trade areas are made of non-isotropic distributions of consumers (Wang et al., 2016). Thiessen polygons, also known as Voronoi polygons, are another commonly used method for trade area delimitation. They delineate catchment areas based on the proximity to specific points of interest or service locations. (Wang et al., 2016). There are also empirical methods for trade area delimitation, such as using regression models to measure select parameters and correlate them to secondary variables – usually socio-economical and environmental (Wang et al., 2016). The most popular of the empirical methods is the Huff Model (1963), which proposes a consumer-choice probabilistic approach that assumes consumers shop at different stores. The Huff Model (1963) conceptualized a probabilistic surface that accounts for the likelihood of visiting certain locations based on their distance from the consumer. Huff Models have been extensively applied and refined in several bodies of work (Fueda et al., 2011; Liu, 2012; Suarez-Vega, 2015).

Mobile location data can be beneficial in deriving mobility patterns and facilitating an understanding of movement patterns at a granular level. Understanding how consumers travel, their patterns of retail location visitations, and the time they spend at retail locations is of the utmost importance. While there is almost no literature that applies granular-level mobile data for generating consumer insights, there is a vast amount of literature that discusses the applications of mobile data in the contexts of origin-destination flows (Calabrese et al., 2011), urban analysis (Ratti et al., 2006; Chen et al., 2018), and traffic analysis (Herrera et al., 2010). Utilizing mobile location data for trade area analysis allows researchers to gain an understanding beyond the currently utilized models, which would assist retailers in assessing the spatial-temporal patterns of consumers beyond their retail locations (e.g., mobile location data can be used to assess own-store and competitor store locations).

2.3 Mobile Data and Visitation Patterns

While mobile location data and their respective analytical techniques have been studied extensively (Vassakis et al., 2018; Alsheikh et al., 2016; Yazti et al., 2014), there is a gap in retail-focused research. Much of the mobile location data research focuses on the tourism sector (Raun et al., 2016; Saluveer et al., 2020; Shmucker and Reif, 2022). For example, in a study focusing on tourist experiences in Maui, Hawaii, Brooker et al. (2020) identified the visitation experiences of tourists. The study identified different segments of visitors through a K-means clustering technique based on their activity choices. Additionally, Raun et al. (2016) used mobile location data to

understand tourism flows in Estonia, where their study showed that visitation patterns could assist with delimitating differentiating types of destinations and identifying the nationalities of visitors based on visitation patterns. Nyns and Schmitz (2022) used mobile location data to study why tourists choose different accommodation types for overnight stays. In essence, the tourism research body has extensively communicated the benefits of utilizing such data, as it allows planners and government officials to gain a more intimate knowledge of the patterns that tourists are subjected to when visiting specific destinations.

More contemporary issues have attracted the use of mobile data to assess visitation patterns, specifically the visitation activity of national parks during the global COVID-19 pandemic. Liang et al. (2022) investigated the validity of using mobile location data to assess the visitation patterns and demographics of Yellowstone National Park during the pandemic, where they reconciled estimates of the visitation trends from SafeGraph data with the American Community Service Survey to assess the validity of the data. The study highlighted the benefits and limitations of working with mobile location data. It argued that mobile location data should be used as a secondary source to complement traditional data sources such as official statistics. Similarly, Kupfer et al. (2021) also studied visitations to national parks in several states in the US. Contrary to Liang et al. (2022), they could highlight explicit spatiotemporal patterns due to government regulations and imposed closures. Lastly, Song et al. (2022) also used mobile location data to investigate the different landscape features affecting city parks' visitations in mid-sized US cities. The study correlated visitor counts with select landscape features and estimated a regression model predicting which landscape features could influence park visitations. This study further cites the data size as a limitation since it could not possibly reflect all the demographics of park visitors.

3. Data and Methodology

The focus of this study is placed on the City of Detroit and neighbouring cities and suburbs. Five super-regional shopping centres were chosen to assess consumer traffic and quantify trade area analysis metrics using mobile location data. As depicted in Table 1, the shopping centres are relatively close in size, except for Briarwood Mall. Shopping centres in the United States can be classified as super-regional if the total area in square footage exceeds 800,000 square feet and the mall is occupied by full-line department stores, mass merchants, discount department stores, and a food and beverage sector within the enclosed shopping centre as

defined by the International Council of Shopping Centres (ICSC, 2023).

Table 1. List of selected super-regional shopping centres

Shopping Centre Name	Location	Total Retail Floor Area
Somerset Collection Mall	Troy, MI	1,400,000
Fairlane Town Centre	Dearborn, MI	1,500,000
Twelve Oaks Mall	Novi, MI	1,500,000
Lakeside Mall	Sterling Heights, MI	1,500,000
Briarwood Mall	Ann Arbor, MI	983,000

To accurately assess the temporal variations in traffic and shopping mall visitations before and during the pandemic, data between March 21st, 2019, and June 3rd, 2022, were used to assess changing consumer behaviours. It should be noted that the cycle of lockdowns, closures, temporary re-openings, and complete re-openings of physical locations have been accounted for in this study. Residents of Michigan experienced a series of reoccurring stay-at-home orders that started from April 13th, 2020, to June 12th, 2020. This was due to the rising number of COVID-19 infections during the period, and the perceived threat of the virus spreading was at its peak. Subsequently, Michigan experienced an unconventional re-opening, as the United States Supreme Court ruled the Executive Orders carried by the Governor of Michigan as unconstitutional, resulting in a brief re-opening from October 2nd, 2020, to December 15th, 2020, which culminated in another lockdown ordered by the Governor in order to "pause to save lives". The second lockdown was marked by decreases in COVID-19 cases and an inevitable re-opening on May 15th, 2021, which marked the recommencement of traditional in-person visits to venues and retail locations.

3.1 Data Source

The mobile location data in this project was acquired from a major mobile location data supplier. The data supplier's platform allows subscribers to pull individual-level pathing data from a user-defined geofence. For this study, pathing data instead of the more readily available aggregated data was imperative. Pathing data enabled the assessment of the accuracy of mobile big data without being influenced by standard data cleaning practices and aggregation techniques commonly employed by location data providers. These practices

often result in limited information being provided to the end user. By relying on pathing data, the project can ensure a more comprehensive and complete understanding of user movements and behaviours. Five geofences were created, each reflecting the boundaries of the shopping centres mentioned in Table 1. The subsequent data pulls were stored in five tab-separated files (TSVs) – one for each mall, containing reoccurring Hashed Device IDs, latitudes, longitudes, and the date and times of each mobile app-triggered observation.

3.2 Identifying Visitors

To be able to process and analyze the data, Alteryx was used due to its capabilities in handling, blending and processing large datasets. It was assumed that any movement sequence inside the boundary (geofence) of the shopping centre can be attributed to a visitor who intends to shop. It is important to acknowledge that the assumption in this context overlooks the various intentions of mobile phone users when entering a shopping centre, extending beyond simply patronizing the stores within the mall. While the primary motivation for visiting a mall is typically to acquire goods or services, it is essential to consider other potential purposes. Additionally, there are instances where movement sequences occur in the mall's perimeter (e.g., the parking pad). However, these individuals may not qualify as a visitor since these individuals do not enter the shopping centre building.

Establishing clear criteria is necessary to quantify shopping centre visitors effectively. In this case, the assumption is made that any user who enters the mall and has movement sequences within the strictly defined boundaries of the mall can be classified as a visitor. This criterion helps to delineate and identify individuals who can be considered genuine visitors to the shopping centre. Furthermore, a time constraint was applied to filter out potential non-visitors. Visits of more than 10 minutes and less than 240 minutes were filtered to identify valid patrons. Once the filtering was complete, trade areas were delimited using users' home locations and behavioural metrics were calculated from the valid paths, as outlined in Figure 1.

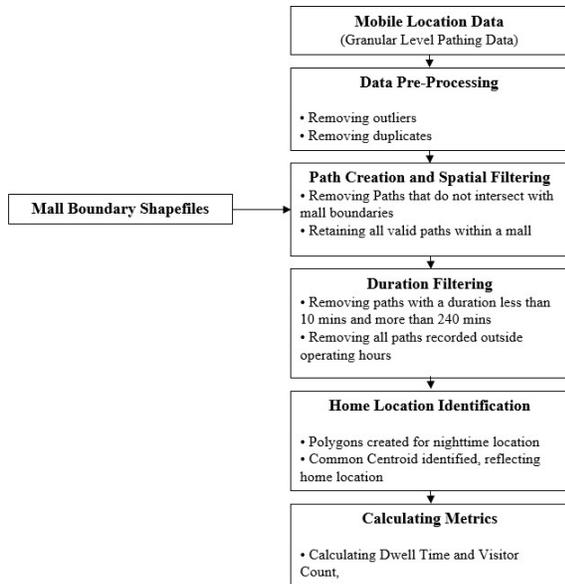


Figure 1. A depiction of the methodological process carried out

3.3 Trade Area Delimitation by Home Locations

After identifying valid visitors, the visitor movement datasets were filtered to identify home locations. Time filters were set between the hours of 2:00 AM and 4:00 AM. Again, these time limits are arbitrary, but it can be assumed that most visitors in the dataset are usually in their primary home locations during those hours. Additionally, the time limits were set in the early morning because it allows the elimination of activities that might occur in the late hours of the day (e.g., visiting a friend's house or partying). The recorded data points were subsequently filtered by distance to account for the spatial variations in pings that might occur for a device during those hours. Polygons were created for each day the device was observed during the time period of interest. Specifically, convex hulls were created for the 2 AM to 4 AM location of devices to account for the daily variations of nighttime location over the time period in which a device exists in a dataset. In order to precisely identify home locations, the distance was measured from the centre of the polygons created (per day) to a shared centroid. This approach ensures a reliable method for pinpointing the likely residential areas of the individuals under study. Qu and Zhang (2013) carried out a similar method, which is heavily adopted in this case to identify home locations. ArcGIS was subsequently used to delimit the trade area based on

the home locations of customers for each mall. Changes in trade area size were then calculated to reflect the changes in the shopping centre customer base.

3.4 Deriving Trade Area Metrics

Trade area metrics, such as visitor count and dwell time, were calculated from the processed valid paths. The paths of all valid visitors were used to calculate the visitor count. The paths were clipped by the boundary of the shopping centres to isolate the movement sequences inside malls, which were subsequently used to calculate the metric. The number of unique IDs was counted to report the number of visitors per day and was added up to represent a monthly summary of visitors at each of the shopping centres being studied in this project. Also, this process was replicated to tabulate the number of visitors per day for each mall.

Dwell time was computed to communicate how much time, on average, users spent in a shopping centre when they visited. The same process was carried out for the last two metrics, with a final step added to calculate dwell time. User IDs were grouped to the date time variable to isolate movement sequences for each user per visit. The maximum and minimum date and time were then subtracted to tabulate the net duration a visitor spent in the shopping centre.

4. Results

The first calculated metric, visitor count, describes seasonal variations in traffic for all shopping centres, as depicted in Figures 2 and 3. For example, Somerset Collection had approximately 13.5 thousand visitors in September 2019, which increased to 22.3 thousand in December 2019. The same pattern manifests in Fairlane Mall and Briarwood, which experienced increases in visitation by a couple of thousand counts in the same months. The same pattern is also present for Lakeside and Twelve Oaks, which experienced high traffic increases in the same time period.

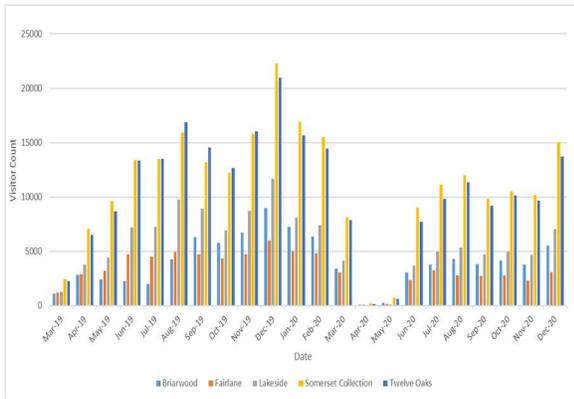


Figure 2. Seasonal Variations in monthly traffic before the pandemic

The occurrence of sales promotions can explain the increase in visitor count carried out during Black Friday and the Christmas shopping season during December. The declaration of COVID-19 as a pandemic affected consumer behaviour greatly, where significant decreases for all malls occurred during March 2020 and dropped to their lowest point during the introduction of regional lockdowns during April and May 2020.

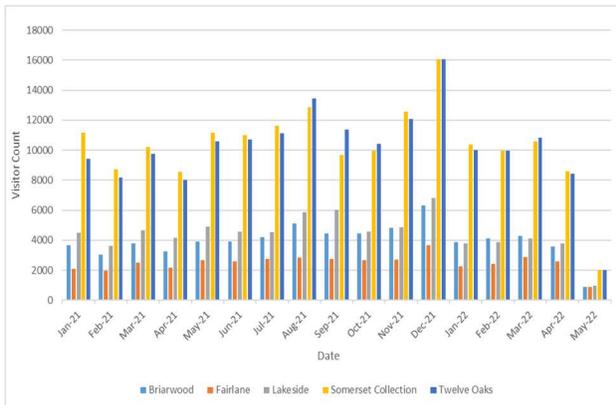


Figure 3. Seasonal Variations in monthly traffic during the pandemic and subsequent recovery period

Dwell time also exhibited seasonal variations during the study period. Figures 4 and 5 depict the monthly changes in dwell time during the study period. There are expected noticeable differences between the shopping seasons. For example, during the pre-pandemic period, Fairlane Mall experienced drops in dwell time during Christmas and the month leading up to it.

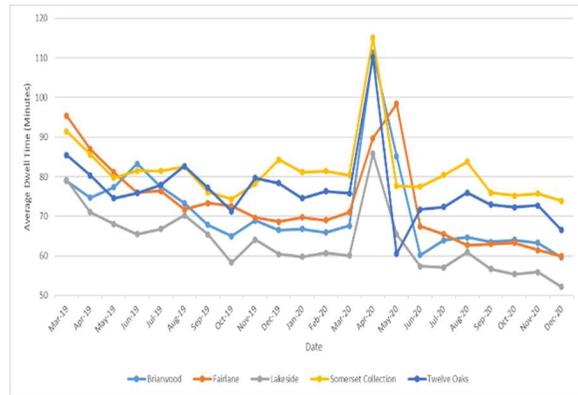


Figure 4. Seasonal variations in dwell time before the pandemic

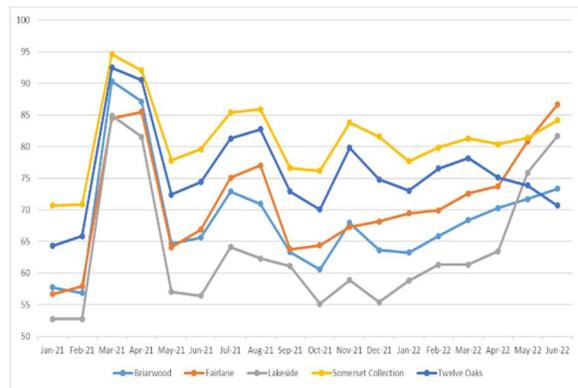


Figure 5. Season variations in dwell time during the pandemic and the following recovery period

Another interesting pattern is the spike in dwell times during April 2020, March 2021, and April 2021, which were all periods that coincided with the introduction, and the re-introduction of mandated lockdowns in the state of Michigan. This is likely caused by panic buying and product hoarding anticipating the lockdown. The remaining months for all shopping centres experienced minimal variations in the average dwell time, which makes it difficult to attribute the variations to any promotion that might affect dwell time.

Lastly, trade area sizes were calculated during the pandemic and recovery periods to quantify what changes occurred after the pandemic, as demonstrated in Table 2. Assessing the changing size and shape of trades area provide critical insights for shopping centre management and their retail and service tenants.

Table 2. Changes in Trade Area Size for each shopping centre

Mall Name	Pandemic TA Size (Km²)	Recovery TA Size (Km²)	Change in (Km²)
Twelve Oaks Mall	35,368.06	40,235.37	4,867.32
Briarwood Mall	26,958.71	36,099.87	9,141.16
Fairlane Mall	12,943.54	14,879.93	1,936.40
Lakeside Mall	17,724.11	21,236.71	3,512.60
Somerset Collection Mall	32,223.24	43,809.98	11,586.74

Trade area size increased for all shopping centres, most prominently Somerset Collection Mall, which experienced an increase of almost 12,000 km². Similarly, Briarwood Mall's trade area increased by almost 9,200 km². The increases for the remainder of the malls are smaller in comparison, which might indicate the economic health of certain shopping centres.

5. Discussion and Conclusion

Trade areas changed during the recovery period following the COVID-19 pandemic, indicating that the pandemic affected the distance consumers travelled to visit super-regional malls. The shrinkages in the primary trade areas in some malls during the pandemic and lockdowns can be attributed to the restriction of mobility since it is less intuitive for a visitor to travel to shopping centres that are farther as opposed to those that are within closer to proximity to a consumer's home location. The data source utilized in this study facilitated a nuanced method for trade delimitation, allowing for behavioural-based boundaries around a consumer home. Based on the graphical representations of the trade area limits over the period studied, a brief shift in consumer behaviour occurred during the pandemic, where individuals preferred to visit the super-regional shopping centres closer to their home locations instead of travelling to malls that were further from them. The preference for closer centres is most likely induced by the lockdowns since participation in hedonic shopping activities decreased due to the mobility constraints introduced by the lockdowns.

Mobile location data provides a more granular understanding of where consumers come from than using arbitrary measures to understand potential customers. Within this research's data acquisition

context, it is noteworthy that the selected data source was easily accessible. Multiple data providers offer mobile location data, hence its emergence as a highly sought-after resource. It empowers retailers to go beyond relying solely on private company data for acquiring addresses and postal codes required for trade area delineation. Furthermore, mobile location data is a valuable resource to go beyond own-store trade area delineation. It can be used to assess competition and potential retail cannibalization, eliminating the need for extensive survey work. By leveraging mobile location data, retailers can gain insights into consumer behaviour, movement patterns, and spatial interactions. Such analysis can provide a more comprehensive understanding of the market landscape, aiding retailers in making informed decisions and formulating effective strategies. While this study has demonstrated how mobile location can be used to create spatial-temporal trade areas, it should be noted that mobile location data has many limitations. The ubiquity of mobile location data does not lessen concerns over, for example, bias in the data, privacy, data accuracy and vendor sourcing and upscaling of mobile data. Further objective research is needed to critically ground-truth mobile location data to assess the fitness for purpose of the data. Developing best practices and industry codes of conduct is needed to ensure that the potential of mobile location data is fully realized.

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